An Approach to Modelling Learner Cognition for Technology Enhanced Learning

A thesis submitted to the
University of Dublin, Trinity College
for the degree of
Doctor of Philosophy
2013

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Victoria Macarthur

For Nick, Dad, and Charlotte.

Summary

In adaptive Technology Enhanced Learning (TEL) systems, the changing nature of learners' actions, responses, and characteristics are modelled. This information is assessed and traced in order to reason about the state of the learner and provide suitable personalised content or support. Metacognitive and self-regulatory strategies are now being addressed by these TEL systems. This is motivated by the goal of supporting learners to become pro-active, adaptive, and improve their educational outcomes. However, research in this area does not yet adequately address the modelling of metacognition. This thesis contributes a method for the modelling, tracing, and subsequently fostering cognitive competencies alongside a TEL environment. The focus is on regulatory metacognitive strategies that are antecedent to positive lifelong learning.

The first component of this thesis describes an analysis of psychological and pedagogical theories of learning, cognition and metacognition. Theories of cognition and metacognition are analysed in order to underpin an alternative approach to modelling cognition. An analysis of the state of the art adaptive TEL systems is also undertaken in order to understand their features, benefits and limitations. This includes an examination of the application of pedagogical and psychological theories to model and foster cognition and metacognition, analysis of user modelling for adaptation, distribution of adaptive TEL technologies as services, as well as an examination of TEL environments that provide metacognitive supports.

The requirements for a cognitive model that can be realised in a cognitive support service and work in symbiosis with a TEL environment are subsequently defined. The ETTHOS (Emulating Traits and Tasks in Higher-Order Schemata) model is specified in terms of research requirements, practical requirements, and ensuing system requirements. ETTHOS is responsible for modelling and tracing metacognition, and is reasoned over in order to select appropriate metacognitive supports, whereas a separate TEL service delivers the domain knowledge. With ETTHOS, a trait model traces the learner's progress over time using items from a metacognitive inventory. A baseline model, which holds the mean values assayed from the target population, is used to initialise the learner's model. A task model describes the activities

undertaken by learners when engaged in academic reading. These models are activated and acted upon in a manner analogous to schema theory, a theory of how knowledge is encoded and applied in human memory. ETTHOS is manifest in the Goby service as a test-bed system with which to analyse the educational outcomes, and suitability of the structure and approach taken.

This work advances the state of the art by building on the modelling and support features characteristic of adaptive TEL. ETTHOS contributes a novel, applied, and evaluated approach that describes the decomposition of the necessary models and processes required in a cognitive modelling service. An assessment of the baseline model compared to the Goby participants revealed that the two groups were on par, indicating that the baseline model was an accurate representation of the community. The accuracy of modelling afforded by ETTHOS in the Goby service was mixed with agreement reported for approximately half of the factors. Analysis revealed that participants, particularly those with lower prior knowledge, were motivated to reflect on and alter their metacognitive responses, seeing Goby as an ever-present tutor. Although there was no change in regulatory metacognition directly after the Goby experiment, there was an increase in learning gain reported. While it is difficult to generalise the learning gain results because of the size of this subset of participants, this points to the benefits of future use and evaluations of the ETTHOS model. Subsequent to this evaluation, this thesis concludes with a reflection on the research objectives and makes suggestions for future work.

"This is man-computer symbiosis at its best, where the computer program learns from the activity of human teachers, and its sensors notice and remember things the humans themselves would not. This is the future: massive amounts of data created by people, stored in cloud applications that use smart algorithms to extract meaning from it, feeding back results to those people on mobile devices, gradually giving way to applications that emulate what they have learned from the feedback loops between those people and their devices" (Tim O'Reilly, 2011).

Acknowledgements

There are so many people who have helped to make this thesis possible and whom I would like to thank. Owen Conlan has been a most inspiring supervisor. It was he who steered me in the direction of adaptive technology enhanced learning back when I was an MSc student who was interested in cognition and the Internet. His wisdom and guidance has made the PhD process a wonderful learning experience.

Doing a PhD is a long and sometimes selfish process that whisks you away for days, weeks, or months at a time. I could not have made it through without the support from my family and friends. It would have been a lot longer and a very lonely process if I didn't have Nick Grey at my side. His love, support, and impeccable logic helped me to reason my way out of many research pickles. He has endured my geek talk, working weekends, and dragged me out of bed when I needed to get back to work. Thanks to Sheila for opening her home to me. Her endless optimism and stylish outlook on life was always a welcome break.

I owe so much to my family - Dad and Charlotte thanks for the persistent belief that I would finish – a Macarthur is nothing if not stubborn and good at getting things done! My Aunty Mary was been a rock through hard times and helped me to stop to celebrate the good ones. Nana and Bill, combined you were two in a million - I only wish you could have seen me finish. I have a few special close friends of many years who have provided endless support. We've ended up together in Dublin and you were all helpful in so many ways – thanks Ashling, Barry, Caoilte, Gráinne, Helen, Kiera, and Laura.

The members of the Knowledge and Data Engineering Group (KDEG) in Trinity College have been a constant motivating force for me throughout the process. When I started the journey I was intimidated by their impressive minds and still they amaze me. KDEG has helped me to understand the PhD process and to develop into a researcher. Regular chats with Catherine were a welcome distraction from the thesis

and always put a smile on my face. Eileen and Ashling have been astute reviewers and helped to refine the syntax and formatting in my thesis.

The National College of Ireland (NCI) is also due thanks – to the faculty, associated faculty, and of course the students. NCI greatly influenced my research by instilling a student-centric approach and I have had so many thought-provoking discussions on the possibilities of web technologies and learning. Special thanks goes to the students for whom I was programme director - BSHCE, BSHBISE, and HCCE, especially those who put up with my pestering to complete surveys and experiments – without you this thesis would not have been possible.

Finally, I would like to express my gratitude to the Irish Research Council for Science, Engineering and Technology for partially funding the research detailed in this thesis.

Abstract

Adaptive Technology Enhanced Learning (TEL) combines pedagogical and psychological theory with technological approaches in order to support the learner as an individual. TEL environments have already begun to demonstrate significant positive results for the learner – knowledge gain, skill acquisition, and cognitive and metacognitive abilities can be improved through the introduction of these systems. However, the modelling of key cognitive skills such as metacognition and self-regulated learning, which are antecedent of positive lifelong learning, needs to be further addressed. Current systems address these skills as a by-product of the learning environment and those that explicitly address these skills do so in a way that is that is tightly coupled with a learning environment. There is no agreed mechanism with which to model, trace, and subsequently foster cognitive strategies that are complementary to learning in a manner that is logically separated from the learning environment. The original contribution to knowledge in this thesis is a model of learner cognition that can explicitly model metacognition, can be used to reason over how to provide metacognitive supports, and is implemented as a separate web service which works alongside a TEL environment. This thesis addresses the issue of modelling cognition by describing cognitive constructs in a manner that is measurable and implementable. The resulting system is logically separated from the learning environment, but works in symbiosis to deliver support that is complementary and aligned with its goals. The formulation and validation of this model and approach have been carried out through an analysis of related literature, an examination of typical metacognitive abilities in the target learner population, and through implementation and experimentation of a test-bed system to assess the perceived benefits for the learner, modelling precision, behaviour changes, cognitive gain, and knowledge gain. The result is a mechanism with which to explicitly describe learner metacognition in a measurable manner and which can be implemented as separate service that works in collaboration with a web-based TEL environment.

Table of Contents

CHAPTER 1 INTRODUCTION 1

1.1 MOTIVATION 1
1.2 RESEARCH QUESTION 6
1.3 RESEARCH AIMS AND OBJECTIVES 6
1.4 CONTRIBUTION 7
1.5 RESEARCH APPROACH 10
1.6 DEFINITION OF TERMS 11
1.7 THESIS ROADMAP 13

CHAPTER 2 METACOGNITION AND LEARNING 15

2.1 INTRODUCTION 15
2.2 THE ROLE OF COGNITION AND METACOGNITION IN LEARNING 16
2.3 LEARNING AND COGNITION 19
2.3.1 Constructivist Learning 20
2.3.2 Schemata – Our Mental Models 21
2.3.3 Declarative, Procedural and Metacognitive Knowledge 24
2.3.4 Processing Information in the Learning Environment 26
2.3.5 Cognitive Strategies for Reading 27
2.3.6 Psychosocial Aspects of Learning 29
2.3.7 Conclusion 31
2.4 METACOGNITION 32
2.4.1 Metacognition Background 33
2.4.2 Metacognition as a Component of Self-Regulated Learning 35
2.4.3 Two-Component Model of Metacognition 37
2.4.4 Supporting the Development of Metacognition 41
2.4.5 Measuring and Modelling Metacognition 43
2.4.6 Metacognition and Psychometrics 45
2.4.7 Conclusion 49
2.5 CONCLUSION 50

CHAPTER 3 COGNITION AND METACOGNITION IN TECHNOLOGY ENHANCED LEARNING ENVIRONMENTS 54

3.1 INTRODUCTION 54
3.2 COGNITION AND METACOGNITION IN TEL 55
3.2.1 Supporting Metacognition with TEL Environments 55
3.2.2 What are Adaptive TEL Environments? 55
3.2.3 Metacognition in Technology Enhanced Learning 58
3.2.4 Design of TEL to Support Cognition and Metacognition 61
3.2.4.1 Emulating the Human Tutor 62
3.2.4.2 Declarative, Procedural and Metacognitive Knowledge Support 62
3.2.4.3 Decomposition of Strategies and Knowledge into Components 63
3.2.4.4 Supports in the TEL Environment 64
3.2.4.5 Dealing with Individual Differences 65
3.2.5 Conclusion 66
3.3 USER MODELLING AND ADAPTATION 67
3.3.1 The User Modelling Adaptation Loop 68
3.3.2 User Modelling and Adaptation Characteristics 71
3.3.2.1 Dynamic and Static User Models 71
3.3.2.2 Explicit and Implicit Mechanisms for updating User Models 71
3.3.2.3 Adaptation On-The-Fly or Pre-Setup 72
3.3.2.4 Timing of the Support 72
3.3.2.5 Type of Support Target 73
3.3.3 Distribution of Adaptive and Modelling Services 73
3.3.4 Conclusion 76
3.4 METACOGNITION IN TEL ENVIRONMENTS 77
3.4.1 Scaffolding Metacognition through Dialog 84
3.4.2 Reflection and Open Learner Models 87
3.4.3 Reflection Before and After the Learning Task 91
3.4.4 Metacognition through Self-Assessment 93

3.4.5 Interactive Metacognition through Collaboration ... *95*
3.4.6 Scaffolding Help-Seeking Metacognition ... *98*
3.4.7 Conclusion ... *100*
3.5 DISCUSSION ... 100
3.6 CONCLUSION ... 103
3.6.1 Features of TEL Environments ... *104*

CHAPTER 4 DESIGN ... 111
4.1 INFLUENCES FROM THE LITERATURE ... 112
4.2 COGNITIVE MODEL REQUIREMENTS ... 118
4.2.1 Requirements from the Research – Design ... *119*
4.2.2 Requirements From the Research – Approach ... *119*
4.2.3 Practical Requirements – Personalised Learning Systems on the Web ... *120*
4.3 ETTHOS - EMULATING TRAITS AND TASKS IN HIGHER-ORDER SCHEMATA ... 120
4.3.1 The ETTHOS Model ... *121*
4.3.2 Traits [R1.1, R1.2] ... *122*
4.3.3 Progressive Modelling [R1.3] ... *126*
4.3.4 Tasks [R2] ... *126*
4.3.5 Mapping Traits to Tasks [R4.2] ... *129*
4.3.6 Schema Structure [R3] ... *130*
4.4 REALISING ETTHOS ... 132
4.4.1 Symbiosis with TEL Services [R4] ... *132*
4.4.2 Distributing TEL Services [R4.1] ... *133*
4.4.3 Dialog [R5] ... *134*
4.4.4 Baseline Model [R6] ... *136*
4.5 THE GOBY SERVICE ... 136
4.5.1 Goby Overview ... *136*
4.5.1.1 Scope ... 137
4.5.1.2 Software Context and Constraints ... 137
4.5.1.3 User Profiles ... 138
4.5.2 High-Level Goby Architecture ... *138*
4.5.3 Decision Engine [PR1] ... *139*
4.6 GOBY FUNCTIONS ... 140
4.6.1 [SR1] Model Learner Metacognitive Awareness ... *140*
4.6.2 [SR2] Model Reading Tasks ... *142*
4.6.3 [SR3] Map Tasks to Traits ... *143*
4.6.4 [SR4] Deliver Metacognitive Support and a TEL Service as Single Web Application ... *144*
4.6.5 [SR5] Initialise the Cognitive Model ... *145*
4.6.6 [SR6] Decide on a Trait Item to Trigger ... *146*
4.6.7 [SR7] Deliver Metacognitive Prompts and Questions ... *147*
4.6.8 [SR8] Provide a Visual Open Learner Model ... *148*
4.7 OPERATIONAL REQUIREMENTS ... 149
4.7.1 [SR9] Mashup with APeLS ... *149*
4.8 GOBY LOOK, FEEL, AND APPLICATION DESIGN [PR3] ... 150
4.8.1 [SR10] User-Centric Design ... *150*
4.8.2 [SR10.1] Site Navigation and Organisation ... *150*
4.8.3 [SR10.2] Ease of Use ... *150*
4.8.4 [SR10.3] Rich User Experience ... *150*
4.9 CONSTRAINTS AND ASSUMPTIONS ... 153
4.9.1 Solution and External Constraints ... *153*
4.9.2 Legal Requirements ... *154*
4.10 REQUIREMENTS TRACEABILITY TABLE ... 154
4.11 CONCLUSION ... 156

CHAPTER 5 IMPLEMENTATION ... 157
5.1 THE GOBY SERVICE ... 157
5.1.1 Traits ... *157*
5.1.2 Tasks ... *160*
5.1.3 Mapping Traits to Tasks ... *162*
5.1.4 Conclusion ... *164*
5.2 GOBY DEVELOPMENT ... 165
5.2.1 Goby Technologies ... *166*

5.2.2 Goby Mashup with APeLS ... *169*
5.2.3 Dialog Models ... *171*
5.2.4 Goby Functionality ... *172*
5.2.5 User Interface ... *175*
5.3 USER-CENTRIC DESIGN APPROACH TO DEVELOPING GOBY ... 176
5.3.1 Usability and Learnability ... *176*
5.3.2 Time to Complete ... *177*
5.3.3 Frequency of Prompts/Questions ... *177*
5.3.4 Goby Open Learner Model ... *178*
5.3.5 Conclusion From Analysis ... *178*
5.4 CONCLUSION ... 179

CHAPTER 6 EVALUATION ... 180
6.1 INTRODUCTION ... 180
6.2 EXPERIMENTAL SETUP ... 183
6.2.1 Assessing the Metacognitive Awareness of the Population ... *183*
6.2.1.1 Overview ... 184
6.2.1.2 Test Setup ... 184
6.2.1.3 Test Results and Summary Statistics ... 184
6.2.1.4 Conclusions from Analysis ... 185
6.2.2 The Goby Experimental Platform ... *185*
6.2.3 The Goby Experiment Design ... *188*
6.2.3.1 Admission Criteria ... 188
6.2.3.2 The Experimental Learning Environment ... 188
6.2.3.3 Participant Data Gathered ... 189
6.2.4 Goby Experiment Groups ... *190*
6.2.4.1 Experimental Group A ... 191
6.2.4.2 Experimental Group B ... 191
6.2.4.3 Experimental Group C ... 191
6.2.4.4 Summary Statistics for the Goby Experiment ... 191
6.3 SUPPORTING THE LEARNER ... 192
6.3.1 Evaluation of Learning Gains [R1] ... *194*
6.3.1.1 Overview ... 194
6.3.1.2 Test Setup ... 194
6.3.1.3 Summary Statistics of Knowledge Prior to Using Goby ... 195
6.3.1.4 Test Results and Summary Statistics for Knowledge Gain ... 196
6.3.1.5 Examining Influences on Learning Gain ... 197
6.3.1.6 Conclusion From Analysis ... 199
6.3.2 Assessment of Metacognitive Gain [R1.1] ... *200*
6.3.2.1 Metacognitive Skill Gain Post Interaction with Goby ... 201
6.3.2.2 Comparison of Metacognitive Awareness Between Groups ... 206
6.3.2.3 Metacognitive Ability when Comparing Prior-Ability ... 210
6.3.2.4 Conclusion from Analysis ... 211
6.3.3 Analysis of Learners' Qualitative Responses to Goby [R1.2, R4.2] ... *211*
6.3.3.1 Overview ... 212
6.3.3.2 Test Setup and Analysis Method ... 212
6.3.3.3 Results and Summary Graphs ... 214
6.3.3.4 Final Remarks from Participants ... 228
6.3.3.5 Conclusion from Analysis ... 230
6.3.4 Log Data Analysis to Examine Learner Behaviour and the Influence of Prior Ability ... *231*
6.3.4.1 Time Taken ... 232
6.3.4.2 Learning Efficiency ... 234
6.3.4.3 Responses to Metacognitive Dialog ... 234
6.3.4.4 Conclusion from Analysis ... 235
6.4 APPROACH TAKEN TO IMPLEMENT ETTHOS ... 237
6.4.1 Comparison of the Baseline Model to Goby Participants [R6] ... *238*
6.4.1.1 Overview ... 238
6.4.1.2 Test Setup ... 238
6.4.1.3 Test Results and Summary Statistics ... 239
6.4.1.4 Conclusion From Analysis ... 240
6.4.2 Approach Taken to Implement ETTHOS - Requirements and Features [R4.1 R4.3] ... *241*
6.4.2.1 Service-Oriented Architectural Pattern [R4.1] ... 241

6.4.2.2 Cohesion between Metacognitive Support and Learning Context [R4.1] ... 242
6.5 ETTHOS DESIGN ... 242
6.5.1 The Accuracy of Goby Modelling [R1, R1.2] ... *243*
6.5.1.1 Overview ... 243
6.5.1.2 Test Setup ... 243
6.5.1.3 Test Results and Summary Statistics Group A ... 244
6.5.1.4 Test Results and Summary Statistics Group B ... 245
6.5.1.5 Conclusion ... 247
6.5.2 Design of ETTHOS – Features and Requirements [R1.2, R1.3, R3] ... *248*
6.5.2.1 Psychometric Inventory to Structure the Technical Model [R1.2] ... 249
6.5.2.2 Temporal and Progressive Metacognitive Model [R1.3] ... 249
6.5.2.3 Technical Model Analogous to Schema Theory [R3] ... 250
6.6 RESEARCH LIMITATIONS ... 250
6.6.1 Task Model Limitations ... *250*
6.6.2 Trait Model Limitations ... *251*
6.6.3 Limitations of the Experiments Performed ... *251*
6.7 REQUIREMENTS TRACEABILITY TABLE ... 252
6.8 CONCLUSION AND DISCUSSION ... 254
6.8.1 Supporting the Learner ... *255*
6.8.2 Approach taken to implement ETTHOS ... *258*
6.8.3 ETTHOS Design ... *259*
6.8.4 Final Evaluation Remarks ... *260*

CHAPTER 7 CONCLUSION ... 262
7.1 REVIEW AGAINST ORIGINAL OBJECTIVES ... 263
7.2 CONTRIBUTION OF THIS RESEARCH ... 267
7.2.1 Main Contribution ... *267*
7.2.2 Secondary Contributions ... *268*
7.3 FUTURE RESEARCH DIRECTIONS ... 269
7.3.1 Rich Cognitive Support with Simulations ... *269*
7.3.2 Lifelong Centralised Modelling Services on the Cloud ... *270*
7.3.3 Dealing with the Cold Start Problem ... *271*
7.3.4 Temporal Open Learner Modelling ... *271*
7.3.5 Modelling Other Traits ... *271*
7.3.6 Modelling Other Tasks ... *272*
7.3.7 Multiple Models ... *272*
7.4 FINAL REMARKS ... 273

BIBLIOGRAPHY ... 274

APPENDICES VOLUME

APPENDIX A DECISION MAKING TECHNIQUES ... 1
APPENDIX B MAI - REGULATION OF COGNITION ... 5
APPENDIX C COGNITIVE TASK MODEL – REGULATION OF COGNITION ... 6
APPENDIX D GOBY WEB APPLICATION STORYBOARD ... 8
APPENDIX E BASELINE TRAIT MODEL ... 10
APPENDIX F TRAIT-TASK MAPPING ... 11
APPENDIX G SAMPLE LEARNER MODEL ... 14
APPENDIX H DIALOG MODELS ... 24
APPENDIX I MULTI-ATTRIBUTE DECISION MAKING IN GOBY ... 27
APPENDIX J GOBY SCREENS ... 28
APPENDIX K PARAMETRIC TO NON-PARAMETRIC ALTERNATIVE ... 32
APPENDIX L GOBY EXPERIMENT INFORMATION ... 41
APPENDIX M LOG DATA ANALYSIS ... 59

List of Figures

Figure 3.1 - Goals of Metacognitive Tutoring (from Koedinger et al., 09) 59
Figure 3.2 - Classification of AH methods and techniques (from Knutov et al., 09) 60
Figure 3.3 - "User Modelling - Adaptation" Loop (from Brusilovsky, 96) 68
Figure 3.4 - Adaptation Decomposed (from Brusilovsky et al., 01) 69
Figure 3.5 - MetaTutor (from Azevedo, Moos, Johnson et al., 10) 86
Figure 3.6 - SQL-Tutor Open Learner Model (from Bull & Kay, 08) 88
Figure 3.7 - CALMsystem (from Kerly et al., 07). 90
Figure 3.8 - QuizGuide (from Brusilovsky & Sosnovsky, 05) 91
Figure 3.9 - Betty's Brain Teachable Agent (from Kinnebrew et al., 2011) 97
Figure 3.10 - The Geometry Cognitive with Help-Seeking Tutor (from Aleven et al., 06) 99
Figure 4.1 - Model Components of ETTHOS 121
Figure 4.2 - Trait, Factor, Item relationship 123
Figure 4.3 - Traits in ETTHOS 125
Figure 4.4 - Task, Activity, Sub-Activity relationship 127
Figure 4.5 - Tasks in ETTHOS 129
Figure 4.6 – The Trait - Task Relationship Model 130
Figure 4.7 - Goby Service in Context 137
Figure 4.8 - Goby Architecture 138
Figure 4.9 - Multi-Attribute Decision Making Equation 140
Figure 4.10 - Modelling the learner 141
Figure 4.11 - Tracking the learners tasks 142
Figure 4.12 - Mapping tasks with traits 143
Figure 4.13 – Learning and metacognition mashup 144
Figure 4.14 - Initialise the Cognitive Model 145
Figure 4.15 –Select an item 146
Figure 4.16 - Contextualised prompts and questions 147
Figure 4.17 - Open Learner Model 148
Figure 4.18 - Master – Detail UI Pattern (from Neil, 10) 152
Figure 4.19 - Goby UI Layout 152
Figure 5.1 – ETTHOS Trait Component 157
Figure 5.2 - Goby Trait Component in Context 158
Figure 5.3 – XML Learner Trait Model 159
Figure 5.4 - Extract from the XML Descriptive Trait Model 159
Figure 5.5 – Extract from the XML Baseline Trait Model 160
Figure 5.6 – ETTHOS Task Component 161
Figure 5.7 – XML Descriptive Task Model 161
Figure 5.8 – XML Learner Task Model 162
Figure 5.9 – ETTHOS Trait-Task Mapping 162
Figure 5.10 - Example of the Trait - Task Mapping 163
Figure 5.11 - Extract from XML Trait - Task Mapping model 164
Figure 5.12 - Goby Technological Architecture 167
Figure 5.13 - Distribution of APeLS and Goby Web Services 169
Figure 5.14 – APeLS - Goby Interface 170
Figure 5.15 – Goby XML Question Chunk 171
Figure 5.16 - Extract from LO XML metadata in APeLS 172
Figure 5.17 - Multi-Attribute Decision Engine Process 174
Figure 5.18 - User Interface Walkthrough 175
Figure 6.1 - The Goby UI combines metacognitive notifications with a database course 186
Figure 6.2 - Goals of Metacognitive Tutoring (from Koedinger et al., 09) 193
Figure 6.3 - Boxplot of Experimental Groups before the SQL course 196
Figure 6.4 – Comparison of Knowledge Gain 196
Figure 6.5 – Planning after using Goby 207
Figure 6.6 - Information Management Strategies after using Goby 208
Figure 6.7 - Comprehension Strategies after using Goby 209
Figure 6.8 - Debugging after using Goby 209
Figure 6.9 - Evaluation Strategies after using Goby 210
Figure 6.10 - Likert Key 212

Figure 6.11 - Sample Bar Chart Figure 213
Figure 6.12 - Were you motivated by the popup content? 215
Figure 6.13 - Did the Goby prompts/questions help you while learning? 216
Figure 6.14 - Did you think about the prompts and questions? 216
Figure 6.15 - Did the prompts and questions help organise your time? 217
Figure 6.16 - Were the prompts and questions relevant to learning SQL? 219
Figure 6.17 - Were the prompts and questions relevant to learning CS? 219
Figure 6.18 - Were the prompts and questions relevant to the right section? 220
Figure 6.19 - Were there many times where the prompts/questions were not relevant? 221
Figure 6.20 - Did you feel as though the Goby interactions were more relevant over time? 222
Figure 6.21 - Would Goby be useful while learning other CS modules? 222
Figure 6.22 - Would Goby be useful for other domains? 223
Figure 6.23 - Did you feel that the Goby prompts added to the workload? 225
Figure 6.24 - Did you feel that the Goby questions added to the workload? 225
Figure 6.25 - Did you feel that the Goby prompts interrupted the flow of the work? 226
Figure 6.26 - Did you feel that the Goby questions interrupted the flow of the work? 227
Figure 6.27 - Did interactions with the Goby popup box add time to the learning task? 227

List of Tables

Table 1.1 - Definition of Terms 12
Table 2.1 Metacognitive Knowledge Components (Adapted from the Lai, 11) 37
Table 2.2 - Theories of Learning, Cognition and Metacognition 53
Table 3.1 - Azvedo's six characteristics of metacognitive tools 60
Table 3.2 - TEL Environments that Model or Support Metacognition 83
Table 3.3 - Features and Observations of How Theory Can Influence the Development of TEL Environments 110
Table 4.1 - Description of Keys 113
Table 4.2 – Extract from the Cognitive Task Model 128
Table 4.3 - Features Traceability Table 155
Table 6.1 - Regulation of Cognition - Descriptive Statistics 184
Table 6.2 - Goby Experiment Participant Data 192
Table 6.3 - Initial Database and SQL Knowledge Assessment 195
Table 6.4 - Comparison of Knowledge Gain 196
Table 6.5 - Group A: Planning scores pre and post Goby 202
Table 6.6 - Group A: Information Management Strategies scores pre and post Goby 202
Table 6.7 - Group A: Comprehension scores pre and post Goby 202
Table 6.8 - Group A: Debugging Strategies pre and post Goby 202
Table 6.9 - Group A: Evaluation scores pre and post Goby 203
Table 6.10 - Group B: Planning scores pre and post Goby 203
Table 6.11 - Group B: Information Management scores pre and post Goby 204
Table 6.12 - Group B: Comprehension scores pre and post Goby 204
Table 6.13 - Group B: Debugging Strategies scores pre and post Goby 204
Table 6.14 - Group B: Evaluation scores pre and post Goby 204
Table 6.15 - Group C: Planning scores pre and post Goby 205
Table 6.16 - Group C: Information management score pre and post Goby 205
Table 6.17 - Group C: Comprehension score pre and post Goby 205
Table 6.18 - Group C: Debugging scores pre and post Goby 206
Table 6.19 - Group C: Evaluation scores pre and post Goby 206
Table 6.20 - Comparison of Planning scores for group A, B and C post Goby 207
Table 6.21 - Information Management Strategies for group A, B and C post Goby 208
Table 6.22 - Comprehension for group A, B and C post Goby 208
Table 6.23 - Debugging Strategies for group A, B and C post Goby 209
Table 6.24 - Evaluation for group A, B and C post Goby 209
Table 6.25 - Participants impressions of the Goby service 229
Table 6.26 – Initialising the User Model - Planning 239
Table 6.27 - Initialising the User Model - Information Management Strategies 239
Table 6.28 - Initialising the User Model - Comprehension 239
Table 6.29 - Initialising the User Model - Debugging 240
Table 6.30 - Initialising the User Model - Evaluation 240
Table 6.31 - Group A: Comparison of Goby and user reported Planning 244
Table 6.32 - Group A: Comparison of Goby and user reported Information Management 244
Table 6.33 - Group A: Comparison of Goby and user reported Comprehension 244
Table 6.34 - Group A: Comparison of Goby and user reported Debugging 245
Table 6.35 - Group A: Comparison of Goby and user reported Evaluation 245
Table 6.36 - Group B: Comparison of Goby and user reported Planning 246
Table 6.37 - Group B: Comparison of Goby and user reported Information Management 246
Table 6.38 - Group B: Comparison of Goby and user reported Comprehension 246
Table 6.39 - Group B: Comparison of Goby and user reported Debugging 246
Table 6.40 - Group B: Comparison of Goby and user reported Evaluation 246
Table 6.41 – Requirements Traceability Table 254

Abbreviations

16PF	16 Personality Factor psychometric inventory
ACT-R	Adaptive Control of Thought – Reflection model
AD	Anderson Darling
ADAPT^2	Advanced Distributed Architecture for Personalised Teaching & Training
AEH	Adaptive Educational Hypermedia
AES	Adaptive Educational Systems
AH	Adaptive Hypermedia
AHS	Adaptive Hypermedia Systems
AI	Artificial Intelligence
AIED	Artificial Intelligence in Education
AJAX	Asynchronous JavaScript and XML
aLFanet	Active Learning For Adaptive interNET
APeLS	Adaptive Personalised eLearning Service
API	Application Programming Interface
AWS	Adaptive Web Systems
CA	Concrete Articulation
CALMsystem	Conversational Agent for Learner Modelling system
CBM	Constraint-Based Modelling
CBR	Case-Base Reasoning
CSS	Cascading Style Sheets
CTAT	Cognitive Tutor Author Tools
DB	Database
DBMS	Database Management System
DOM	Document Object Model
ECA	Event-Condition-Action
EER	Enhanced Entity Relationship modelling
EMT	Expectation and Misconception Tailored dialog
EOL	Ease Of Learning
ETTHOS	Emulating Traits and Tasks in Higher-Order Schemata
FOK	Feeling Of Knowing
HTTP	HyperText Transfer Protocol
IEEE	Institute of Electrical and Electronics Engineers
ImREAL	Immersive Reflective Experience-based Adaptive Learning

iSTART	Interactive Strategy Trainer for Active Reading and Thinking
ITS	Intelligent Tutoring Systems
JOL	Judgment Of Learning
JSP	JavaServer Pages
LISP	LISt Processing
LMS	Learning Management System
LO	Learning Object
LOM	Learning Object Metadata
MAD	Multi-Attribute Decision engine
MAI	Metacognitive Awareness Inventory
MAUT	Multi-Attribute Utility Theory
MARSI	Metacognitive Awareness of Reading Strategies Inventory
MSLQ	Motivated Strategies for Learning Questionnaire
NCI	National College of Ireland
OLM	Open Learner Model
OOP	Object-Oriented Programming
PAT	PUMP Algebra Tutor
PUMP	Pittsburgh Urban Mathematics Project
SaaS	Software as a Service
SOA	Service Oriented Architecture
SQL	Structured Query Language
SRL	Self-Regulated Learning
SUS	System Usability Scale
TA	Teachable Agent
TCD	Trinity College Dublin
TEL	Technology Enhanced Learning
TMS	Teachers' Metacognition Scale
UI	User Interface
UM	User Model
UML	Unified Modelling Language
VARK	Visual, Auditory, Read/Write, Kinaesthetic
XHTML	eXtensible Hypertext Markup Language
XML	eXtensible Markup Language
XML-RPC	XML - Remote Procedure Call

Chapter 1 Introduction

1.1 Motivation

Throughout the course of our lives, we accumulate knowledge, often pursuing self-development through traditional and distance education channels. This process of lifelong learning enables us to adapt to our circumstances and remain competitive in the economy (Coffield et al., 04). Lifelong learning can take many forms. It might be in the traditional classroom environment, on the job training, via distance or blended learning, or using web-based learning environments. However, we cannot simply attend course after course. Instead, we need to be equipped with competencies that help us to engage successfully in learning, encode new knowledge and skills, and adapt to new situations and challenges.

Learner autonomy, self-regulation, and more specifically, metacognition are crucial skills that enable us to learn from experience, adapt to the environment, and respond to cultural or social contexts (Ku & Lo, 10; Pintrich et al., 00; McNamara & Magliano, 09; Fischer & Scharff, 98). Development of these higher-order cognitive [1] competencies is antecedent of positive lifelong learning (Finley, Tullis & Benjamin, 10), and numerous studies have reported learning outcomes such as knowledge gains and improved ability to learn (e.g. Azevedo & Witherspoon, 09; Colineau & Paris, 10; Bednall & Kehoe, 11; Samsonovich et al., 10; Koedinger et al., 09). Metacognitive ability is an important component of self-regulation that enables us to engage in reflective thinking, and comprises of our ability to reason about our own cognition[2], knowledge, and the strategies that we have available to us (Flavell, 79; Brown, 78; Schraw & Dennison, 94; Tobias & Everson, 00; Magno, 10). Metacognitive ability is a precursor to successful prediction of performance, assessing knowledge or lack of it, and efficiently allocating cognitive resources and time (Gagné & Glaser, 87). Traditionally, educators have been seen as metacognitive professionals who can

[1] Higher-order competencies are complex skills that are developed through the expansion and incorporation of previously learned skills. For example, to respond critically to a text, we must first learn strategies to understand words and text.

[2] Cognition refers to the mental activities and functions through which human beings acquire and process knowledge including: perception, learning, memory, reasoning, and thought. This utility is mediated by biological, mental, emotional, and social influences (Bandura, 91; Vygotsky, 78).

incorporate scaffolds or learning into the curriculum that can support learners' cognitive and metacognitive abilities (Duffy et al., 09; Wilson & Bai, 10). Now, Technology Enhanced Learning (TEL) developers and researchers are starting to combine the learning objectives of the curriculum with strategies to support these skills (Koedinger et al., 09; Samsonovich et al., 10; Brusilovsky et al., 10; Ley et al., 10).

Adaptively supporting learners' cognitive needs while they engage with TEL systems has proven merit because these environments can accommodate the role that was traditionally provided by the human educator (Anderson et al., 84; Anderson et al., 95; Azevedo, Moos, Johnson, et al., 10; Brusilovsky, 04; Conlan & Wade, 04; De Bra & Pechenizkiy, 09; Kay, 08). For example, increase in learning gains, motivation, and engagement can result from altering course content depending on the learner's ability (e.g. a novice at SQL may be provided with hints on how to solve an introductory problem) or by providing supplementary material and scaffolds to help them to practise a difficult task (e.g. the same novice may be provided with related examples if they are struggling with an introductory problem). Adaptive TEL systems use mechanisms for user modelling with the functionality to carry out intelligent adaption reasoning to deliver a personalised educational experience that helps a learner to achieve learning objectives (Brusilovsky, 01; Knutov, De Bra & Pechenizkiy, 09; Graesser, Conley & Olney, 10). These educational systems incorporate psychological and pedagogical theory[3] with technological approaches in order to *detect*, *trace*, *model*, and *foster* learner ability and cognition (Azevedo, Moos, Witherspoon, et al., 09; Graesser & McNamara, 10; Ritter et al., 07; Ohlsson & Mitrovic, 07; Ruiz et al., 08). This means that TEL addresses the needs of the learner as an individual by monitoring and supporting their knowledge, skills, and cognitive ability (Azevedo, Moos, Johnson, et al., 10; Graf & Ives, 10; Brusilovsky & Millán, 07).

However, current adaptive TEL environments do not yet sufficiently support the modelling and acquisition of the metacognitive and self-regulatory skills that enable us to become autonomous learners and contribute to the knowledge-based economy. In order to become pro-active and adaptive citizens we need cognitive support

[3] Pedagogy refers to the art or science behind formal or informal learning and teaching. This includes both the theory behind and the practical application of processes, experiences, contexts, and outcomes (Beetham & Sharpe, 07). It traditionally had an etymological connection with children, however contemporary use of the term refers to learning and teaching as lifelong (Beetham & Sharpe, 07).

services that can directly model and foster these cognitive competencies. TEL environments that support metacognition or self-regulation often do so indirectly or by modelling learner cognition (such as their domain knowledge). For example, by engaging with the learner through dialog to encourage self-regulation (Ley et al., 10), or by using Open Learner Models (OLM) (Brusilovsky et al., 10), which enable the learner to reflect on the systems assessment and visual reification of their progress.

Some TEL environments do measure the learners' metacognition at explicit points during the learning activity, by using measures such as 'Feeling Of Knowing' (FOK) to assess how well a learner can evaluate their successes in a learning task. These can be useful for the learner, but are not sufficient for describing the cognitive traits in a measurable way that can be tracked by a learning system. Metacognition is a complex construct, that comprises more than the ability to judge learning. Rather, it can be described as a multiple component model. Metacognitive *knowledge of our own cognition* can be declarative as well as procedural – this means that we have an understanding of our cognitive capabilities and strategies. Metacognitive *regulation of cognition* can encompass strategies such as planning, comprehension and evaluation of the approach we take when engaged with a task or problem to be solved.

While there has been research on modelling these metacognitive regulatory strategies directly (e.g. Koedinger et al., 09), the supports provided are tightly coupled with the learning experiences. The assessment of learner metacognition is often carried out through algorithmic and intelligent reasoning that is tied to the specific tasks in the learning environment. This means that the metacognitive supports provided cannot be separated from the learning environment. However, these services need to be able to transfer and transport cognitive user profiles from one learning environment to the next to enable continuous progression of the model and the related support.

Although current TEL environments are web-enabled, making use of the SOA and SaaS patterns, the cognitive modelling is usually tightly integrated into the systems functioning with rules or algorithms to link to the model (Graf & Ives, 04; Conlan & Wade, 04; De Bra et al., 03). Recently, researchers have begun to distribute the user modelling process so that it runs on its own centralised server (Brusilovsky,

Sosnovsky & Shcherbinina, 05; Sosnovsky et al., 09; Kay et al., 06). These systems gather a large amount of noisy data and it can be difficult to handle the aggregated user data, but they can supply user information to multiple adaptive systems (Sosnovsky et al., 09; Berkovsky, Heckmann & Kufilk, 09). These types of cognitive models provide a useful mechanism with which to create OLMs to promote metacognition through reflection. However, the centralised user modelling approach has not yet been harnessed to explicitly model metacognition.

The research presented here is motivated by the need to further improve the state of the art modelling and support of abstract cognitive[4] aspects of a learner. Current technological approaches need to change in response to the needs of the lifelong learner (Bull & Kay, 08). Central to this is the development of supports for cognitive competencies that can enable learners to become self-regulated and autonomous as well as the progression towards developing a lifelong cognitive model. This work aims to begin addressing the requirements of lifelong user modelling. The lifelong user model needs to be discrete and separate from the TEL system (rather than being tightly coupled within the learning environment), while working in symbiosis with it in order to promote positive cognitive skills. In particular, metacognitive aspects of the learner, such as planning, information management strategies and comprehension are key factors that have been identified in successful learners. In order to foster these skills alongside TEL systems, it is necessary to define a model that can describe these components of metacognition.

Although there is much work on supporting metacognition and self-regulation, there is no agreement on how to model and foster learner metacognition in a manner that can be implemented as a service to work alongside TEL environments. There is still a need to improve the current learning services that are being delivered to better suit the modelling and fostering of self-regulatory and metacognitive facets of the learner. The advancement of approaches taken to deliver personalised support for lifelong learning is especially important (Bull & Kay, 08).

[4] This includes latent processes undertaken by a learner that are not directly observable. For example, to *analyse a text critically* can be considered an abstract cognitive process that has component strategies that are observable such as drawing a brainstorm diagram to analyse themes.

There are two challenges that must be addressed: first, how can we model the cognitive competencies that are antecedent to lifelong learning, in particular those that are complementary to their curriculum. This means providing a mechanism with which to model and measure learner metacognition and the components of metacognition that are complimentary to learning. The second is how can we create a user model that could travel and grow with the learner? This means overcoming the tight coupling between the learning environment and the metacognitive supports so that these two facets can be separate, yet work together effectively. This indicates that it should interoperate across a range of learning environments and be applied to a number of cognitive traits. Thus, the first step that needs to be taken is to develop a model of abstract cognition that provides a mechanism with which to provide measurements for metacognitive strategies as well as ensuring that this model can be logically discrete from a learning system. The changing nature of cognition needs to be addressed and the psychological and pedagogical learning theories, which underpin TEL research, examined in order to inform how this type of support should be implemented. It is essential that such a user model is developed that is both useful and actionable in order to successfully model and support facets of a learner's metacognition.

This thesis addresses the area of modelling and support of higher-order cognition in a manner that is logically separate from a TEL environment. It documents an investigation into the psychological and pedagogical theories of learning, cognition and metacognition that have informed traditional instructional strategies and have been applied in the development of TEL environments. The attributes of successful TEL environments that adapt to the learner and model and support metacognition are examined in order to inform the design and implementation of a model to represent and support metacognition. Subsequently, a technological approach to modelling, tracing cognition is described and empirical evaluations that were undertaken are discussed. The purpose of this chapter is to introduce the theories and criticisms associated with TEL and cognitive user modelling. It has set the scene for the current issues in the state of the art of cognitive modelling by introducing the application of these models in TEL environments. Having defined the thesis statement, it then discusses the research objectives and outlines the thesis organisation.

1.2 Research Question

This thesis proposes an approach to modelling cognitive aspects of a learner that can augment Technology Enhanced Learning. The research question posed in this thesis is:

> *How and to what extent can the cognitive aspects of a learner be modelled to support learning with TEL?*

In order to limit the scope of the research, metacognition has been identified as a suitable candidate skill as it is complementary to learning. In answering the research question, the following goals are addressed - (i) an *appropriate design* for a cognitive model that is separate while still aligned with TEL systems; that this model will result in (ii) *educational benefits* for knowledge gain and cognitive awareness; and describe (iii) an *architectural approach* to integrate this model with a TEL system for a successful learning experience.

1.3 Research Aims and Objectives

The aims of this research are to analyse the activities, principles or features, and theories that underpin TEL systems that model and support learner cognition. This analysis guides the formalisation, implementation, and evaluation of a model of learner cognition, which can be incorporated into a discrete cognitive support service. The motivation is to advance the state of the art modelling of learner cognition in TEL; promote positive metacognitive support in TEL by delivering a cognitive support as a service that can work with a separate TEL service; and shape the future of lifelong user modelling.

In pursuit of these aims, four objectives were identified:

1. Research and analyse cognitive and metacognitive aspects of learning. In particular, investigate the architectures, models, and the theory behind adaptive TEL, highlighting the strengths and problems that need to be overcome for successful cognitive modelling.

2. Formulate a set of requirements to inform the design of a model of learner cognition that can be implemented in a service that delivers metacognitive support.
3. Provide a high quality, innovative, and supportive approach to modelling learner metacognition.
4. Evaluate the extent of the success of this approach within a real system, and thereby assess its effectiveness to model, track, and foster learner cognition.

1.4 Contribution

The primary contribution of this work is the ETTHOS (Emulating Traits and Tasks in Higher-Order Schemata) model, which provides a mechanism with which to model, trace, and foster cognitive strategies that are complementary to learning. The main success of this model is that it provides a method with which to describe abstract cognition in a traceable way that is realisable in a cognitive support service that can work alongside a TEL environment.

Specifically, ETTHOS supports the regulatory metacognitive strategies including planning, information strategies, comprehension, evaluation, and debugging. An approach to implementing this model in a cognitive support service has been derived in order to allow for collaboration with a TEL environment. To this extent, ETTHOS can be leveraged to improve metacognitive behaviour in a TEL environment and subsequently promote better domain learning. As a proof of concept, ETTHOS was used to inform the development of Goby, a cognitive support service that works in collaboration with the APeLS learning service. Goby uses the ETTHOS model to represent the learner and subsequently interacts with the learner through dialog (prompts and questions) with the goal of prompting metacognitive reflection and updating the learner's metacognitive model. Evaluations with learners in situ revealed that they felt as though they changed their behaviour in response to the metacognitive support, particularly in low ability students. Although subsequent analysis pointed to learning gain, the small cohort means that it is difficult to generalise these results. Post hoc analysis showed that the supports offered in Goby did not result in an increase in learning time, time on page, or changes to the number of pages visited. This points to the potential for future use and evaluations of ETTHOS

as a tool for modelling learner metacognition as a service and the potential to explore the use of richer metacognitive supports.

A number of relevant publications have arisen out of this research:

- Macarthur, V., & Conlan, O. (2008). Higher-Order Cognition in Personalised Adaptive eLearning. *International Workshop on Cognitive Aspects in Intelligent and Adaptive Web-based Educational Systems, at ICCE08*. Taiwan.
    - This early workshop paper describes the need for supporting higher-order cognitive strategies as a third-party service that will work with TEL services in order to compliment the learning experience. The learning service is responsible for delivering domain knowledge, whereas the cognitive support service helps with 'learning to learn'.
- Macarthur, V., & Conlan, O. (2009). Using Psychometric Approaches in the Modelling of Abstract Cognitive Skills for Personalisation. *Lifelong User Modelling Workshop, at UMAP2009.* Trento, Italy.
    - This paper addresses the issue of modelling of abstract cognition by presenting the high-level components of the ETTHOS model. The use of psychometric inventories as a mechanism to codify the learner's cognitive model is presented and the need for a task model identified.
- Macarthur, V., & Conlan, O. (2010). Modelling Higher-Order Cognitive Skills in Technology Enhanced Distance Learning. *In Proceedings of the IEEE International Conference on Distance Learning and Education (ICDLE 2010)*. Puerto Rico, USA.
    - This paper addresses the issue of lifelong learning skills such as metacognition and self-regulation. A number of considerations for developing cognitive modelling service with ETTHOS are discussed.
- Moore, A., Macarthur, V., & Conlan, O. (2011). Core Aspects of Affective Metacognitive User Models. *Workshop on Augmenting User Models with Real World Experiences to Enhance Personalization and Adaptation, at UMAP2011*. Girona, Spain.
    - Metacognitive and affective aspects of a learner's cognitive repertoires are addressed in this paper. The content, form or structure, and source of the model are analysed in the context of current state of the art approaches.
- Macarthur, V., Moore, A., Mulwa, C., & Conlan, O. (2011). Towards a Cognitive Model to Support Self-Reflection: Emulating Traits and Tasks in Higher-Order

Schemata. *Workshop on Augmenting the Learning Experience with Collaborative Reflection, at EC-TEL2011*. Palermo, Italy.

- The trait, task, and mapping components of ETTHOS are discussed in this paper in the context of a cognitive support service. This paper makes suggestions for the future use of community models to initialise the learner model and for visualising the modelling data to prompt individual and collaborative reflection.

- Moore, A., Macarthur, V., & Conlan, O. (2012). Core Aspects of Affective Metacognitive User Models. *Lecture Notes in Computer Science, Advances in User Modelling Perspectives, Selected papers from UMAP 2011 workshops.* Springer.
  - This chapter is an extended version of the previous workshop paper of the same title. It expands on the content, form, and source requirements for modelling affective and metacognitive aspects of the learner.
- Macarthur, V. & Conlan, O., (2012). Addressing the Challenges of Survey Fatigue for Life-Long User Modelling: Initialising Baseline Models Using Community Psychometric Values. In *2012 IEEE 12th International Conference on Advanced Learning Technologies*. Rome, Italy.
  - This paper addresses the use of psychometric inventories to create baseline models, which may provide a solution to survey fatigue.
- Moore, A., Conlan, O. & Macarthur, V., 2012. SRL Tasks and Activities as a Model of Cognitive Behaviour within ETTHOS. In *International Workshop on Enabling Successful Self-Regulation in OLEs at ICALT 2012*. Rome, Italy.
  - This workshop paper describes how ETTHOS can be extended to support self-regulated learning tasks.
- Macarthur, V., Moore, A. & Conlan, O., (2013). Self-Regulation, Metacognition and Emotion in Technology Enhanced Learning Environments. In J. Jovanovic & Raymond Chiong, Eds. *Technological and Social Environments for Interactive Learning*. Santa Rosa, CA, USA. (In press): Informing Science Press.
  - This book chapter provides a synthesis of the literature and underlying theories for designing adaptive systems that address self-regulation, metacognition and emotion.

1.5 Research Approach

The research process undertaken that is described in this thesis comprises of:

- An initial review of the pedagogical and psychological theories of learning and cognition. In particular, this focuses on the role of metacognition in learning and the nature of the learning theories within which this concept has grounding.
- A review of TEL literature details an analysis of current state of the art approaches in user modelling, adaptation and personalisation, and outlines their benefits and limitations in order to inform the requirements needed to develop a loosely coupled metacognitive user model. In particular, this review focuses on existing approaches to designing adaptive systems that address cognitive and metacognitive modelling.
- The analysis of the literature informed the design of a novel approach to satisfy the requirements for developing a loosely coupled metacognitive user model. Requirements include both desired characteristics from current systems as well as requirements to overcome problems with these systems. Based on these requirements, the ETTHOS model and approach for implementing it was designed.
- A test system was implemented with a user-centric design approach in order to ratify the model. A number of evaluations were carried out to inform the metrics and testing of the system. The first evaluation surveyed participants in the target population's metacognitive awareness. A number of controlled experiments were carried out on the system in situ to assess the modelling approach, and to evaluate the benefit to the learner of incorporating such a model with a TEL system.
- Finally, the conclusion from the analysis of these results supports the claim that metacognition can be modelled separately from a learning system and be beneficial to learners. The contributions and limitations of this approach are discussed in order to stimulate future work.

1.6 Definition of Terms

Table 1.1 below provides definitions of the key terms that are referred to throughout this thesis:

Cognition	Cognition refers to the mental activities and functions through which human beings acquire and process knowledge including: perception, learning, memory, reasoning, and thought. This utility is mediated by biological, mental, emotional, and social influences (Bandura, 91; Vygotsky, 78).
Constructivism	Constructivism can be described as an approach to learning in which learners are provided the opportunity to construct their own sense of what is being learned in the context of their current and past knowledge (Harris et al., 96; Bruner, 86; Bruner 90). Constructivism is closely related to *self-regulated learning* and *metacognition* theories because in creating understanding of information and strategies, learners are required to monitor and regulate their own thinking (Gunstone, 94; Case et al., 01).
Higher-Order Cognition	Describes a set of complex skills that are developed through the expansion and incorporation of previously learned skills. Metacognition, critical thinking, and social cognition are examples of processes that control the regulation of learning and thinking and are considered examples of higher-order cognition (Magno, 10).
Metacognition	Metacognition (Flavell, 79; Brown, 78; Schraw & Dennison, 94; Tobias & Everson, 00) refers to the complementary psychological functions that actively monitor and consequently regulate cognitive processes according to the current state of an individual. It is viewed as a core component of self-regulated learning, which is responsible for controlling, monitoring and regulating cognitive strategies in order to meet the goals of the learner (Zimmerman, 89). This is commonly described as *cognition about cognition*, or *thinking about thinking.*
Pedagogy	Pedagogy refers to the art or science behind formal or informal learning and teaching. This includes both the theory behind and the practical application of processes,

	experiences, contexts, and outcomes (Beetham & Sharpe, 07). It traditionally had an etymological connection with children, however contemporary use of the term refers to learning and teaching as lifelong (Beetham & Sharpe, 07).
Psychometric Inventories	Psychometric tests are standardised measurement systems and inventories that are used to evaluate or examine cognitive functions.
Schemata	Schemata (Piaget 29; Anderson, 77; Anderson, 84; Bartlett, 32; Rumelhart 80; Ibrahim et al., 03; Derry, 96) are models (e.g. a process or information sets) that are applied to interpret events and solve problems. They can be understood as structured chunks or packages of knowledge that are organised into an overall framework of knowledge that influence how people comprehend tasks or solve problems.
Self-Regulated Learning (SRL)	SRL is the process whereby learners deploy strategies to respond to (and subsequently regulate) their current status within a learning task. Through self-assessment and practice of regulatory strategies, they can become autonomous and improve their understanding of both the learning material as well as their own cognitive abilities (Schraw et al., 06; Graesser, D'Mello & Person, 09; Zimmerman, 94).

Table 1.1 - Definition of Terms

1.7 Thesis Roadmap

This thesis is organised as follows:

Chapter 2 –Metacognition and Learning

This chapter examines theories of learning, cognition, and metacognition and provides background to the learning theories applied in adaptive TEL environment development. Metacognition is of particular interest because it is a cognitive skill that is complementary to learning with TEL. This chapter explores the role of metacognition in learning and the nature of the learning theories within which it has implications and grounding. It also provides the background to the psychological theories that have been harnessed in the development of the ETTHOS model.

Chapter 3 –Cognition and Metacognition in Technology Enhanced Learning Environments

This chapter reviews the adaptive TEL environments that address cognitive and metacognitive modelling. A review is carried out to examine how TEL systems harness learning theories to support learning and to analyse the features as well as examination of the functions of user modelling and adaptation used in personalising learning experiences. TEL environments that support metacognitive aspects of learners are specifically addressed to assess the current mechanisms and limitations in the state of the art.

Chapter 4 – Design

The design chapter outlines the design of an approach to modelling cognition in TEL. It describes the requirements that have been identified based on good practice and the problems associated with the current state of the art TEL systems. This includes requirements from the research question, practical requirements from the state of the art, and subsequent system requirements for developing a cognitive modelling service. These requirements have two roles – the first is to define the requirements for a new computational approach to cognitive modelling. The second is to define the requirements for a test-bed system that will serve as proof of concept. The research requirements are realised in the ETTHOS model (Emulating Traits and Tasks in Higher-Order Schemata), which used in symbiosis with a TEL system and realised with a pseudo-dialogic approach. A detailed specification of the components and

activities is provided, including the approach necessary to implement the architecture.

Chapter 5 – Implementation

Chapter 5 outlines how the architecture was implemented in a test-bed system in order to evaluate its appropriateness. The prototype implementation is called the Goby system. This system was integrated with the APeLS learning environment (Conlan & Wade, 04; O'Keefe et al., 06). A brief overview is included which outlines the technological decisions and the user-centric design process that was taken.

Chapter 6 – Evaluation

The evaluation chapter provides an in depth discussion of the experimentation and analysis undertaken in order to ratify the proposed modelling solution introduced in the design chapter. This chapter verifies that ETTHOS can be considered as a suitable model to technologically represent learner cognition. The results from early studies are used to inform the baseline user model, and each of the evaluations on the model in situ are presented and findings discussed. The most significant set of evaluations were carried out on the Goby service, in order to assess the modelling accuracy, metacognitive support, and learner knowledge gain. Supporting qualitative and quantitative analysis is presented, along side analysis of the learners' log data and critical analysis of ETTHOS.

Chapter 7 – Conclusion

Chapter 7 summarises the contributions of this thesis, discusses the successes and limitations of the work, and makes suggestions for future work.

Chapter 2 Metacognition and Learning

2.1 Introduction

This chapter addresses the major psychological and pedagogical underpinnings of the work presented in this thesis. Adaptive TEL environments offer new ways of presenting course material and learning support that are adaptive and personalised for each individual learner. In order to model the learner's cognitive strategies when engaged in academic reading, substitute the traditional tutor with intelligent system support, and represent learner metacognition in a technical model, it is first important to have an understanding of the psychological theories within which these concepts have significance and grounding.

This chapter opens with an introduction to the concepts of cognition and metacognition and their role in learning and successful development. There are two main components of this chapter – the first includes a discussion of cognition and learning which is necessary to describe the cognitive strategies and mental models that influence the ETTHOS[5] model as well as understand the learning theories and instructional strategies that can be harnessed when implementing ETTHOS in a TEL environment. This includes a discussion on how we represent our internal mental models, knowledge and cognitive processing, cognitive strategies for academic reading, and theories of learning as an individual and through social interactions. Secondly, a discussion of metacognition is included which analyses its components, its importance for reading, and strategies for supporting and modelling metacognition. The chapter ends with a summary of the aspects of cognitive strategies, metacognitive modelling, and mental model theory from which the ETTHOS model draws.

[5] Emulating Traits and Tasks in Higher-Order Schemata - ETTHOS draws from (or Emulates) metacognition by modelling it with a psychometric (Traits), cognitive strategies used when reading academic texts and resources (Tasks), and uses mental models as an analogy (Higher-Order Schemata) for representing these constructs in an Object-Oriented environment.

2.2 The Role of Cognition and Metacognition in Learning

As individuals, we are continually learning – to be successful within the culture and environment in which we live as well as within our individual context we must acquire a rich repertoire of knowledge and intellectual skills. The intellectual ability to be proactive and adaptive is regarded as crucial for successful lifelong performance (Fischer & Scharff, 98). These skills comprise of learner autonomy, self-regulation, and metacognition, so that we can learn from experiences, adapt to the environment and respond to cultural or social contexts (Ku & Lo, 10; Pintrich et al., 00; McNamara & Magliano, 09; Fischer & Scharff, 98).

Cognitive theories of learning posit that learning involves conscious and reasoned thinking processes, the use of cognitive strategies, and deliberate application of learning strategies. Cognition is a broad construct used to describe our internal (mental) processes and functions – it refers mental behaviours such as thinking, reasoning, learning, self-reflection, adaptation, insight, social strategies, organisational behaviours and beliefs (Sternberg & Sternberg, 09). Our cognition is malleable, meaning that knowledge and strategies can be acquired, shaped and increased through various types of interventions (Jensen, 09). *Cognitive strategies* are mental functions called upon to attend to, acquire, process, represent, and recall information, whereas *learning strategies* are specific cognitive strategies that learners use to enhance comprehension, learning, and retention of information. Successful students characteristically possess numerous learning strategies of great variety (Bednall & Kehoe, 11) and better students report a larger range than less proficient students (Zimmerman, 89).

Metacognition, in particular, is an essential higher-order thinking[6] skill that supports learning because it enables learners to engage in reflective thinking, become more aware of their learning strategies and gain control over how they acquire new knowledge and skills. Metacognition (Flavell, 79; Brown, 78; Schraw & Dennison, 94;

[6] *Higher-order cognition* describes a set of complex skills that are developed through the expansion and incorporation of previously learned skills. This comprises of non-algorithmic, complex and effortful cognition, whereby the individual engages self-regulated tasks that require reasoning and the creation of meaning when dealing with uncertainty (Resnick, 87). This means that higher-order thinking is necessary when handing new situations and solving problem. It is particularly important for learners who can be considered self-regulated.

Tobias & Everson, 00; Magno, 10) is about knowing what you know, knowing what you need to know, and knowing how to actively regulate your approach to a task. This is commonly described as *cognition about cognition*, or *thinking about thinking.*

What is the difference between cognition and metacognition? Cognition comprises of the processes and strategies that are activated to solve a problem or complete a task. In contrast, metacognition is the knowledge and awareness of processes and the monitoring and control of such knowledge and strategies (Tarricone, 11). Not only does this encompass knowledge of your own thoughts, it refers to knowledge of the cognitive factors that underlie your own thinking. This means that two processes occur simultaneously in a learner as they *monitor* their progress as they learn and make changes or *regulate* their cognitive and learning strategies if they perceive that they are not on the path to achieving their learning goals.

Metacognition is *at the heart* of self-regulation (Borkowski, et al., 92; Baker & Cerro, 00). It is a vital component of successful *Self-Regulated Learning* (SRL) (Zimmerman, 89; Brown, 78; Tarricone, 11) in that it drives the control, monitoring and regulation of strategies in order to meet the goals of the learner (Zimmerman, 89). An ideal learner is self-regulated – this means that they formulate learning goals, track the progress toward their goals, assess their errors, debug contradictions, self-question, search for missing or new information, make inferences or analogies, and work towards deep understanding (Schunk & Zimmerman, 98; Graesser & McNamara, 10). Conceptually, there is an overlap across the discussion of metacognition versus SRL. In the literature, these are divergent and overlapping constructs that are used to describe learning, cognition and control. In this thesis, SRL refers to learning in which the individual has self-responsibility and is intrinsically motivated, self-directed and displays strategic control of their learning (Schunk, 89). On the other hand, metacognition is viewed as a core component of self-regulated learning, which is responsible for controlling, monitoring and regulating cognitive strategies in order to meet the goals of the learner (Zimmerman, 89). Learners who engage in active self-regulation and use metacognitive knowledge and regulatory strategies have been shown to be better at interpreting multiple situations in order to solve problems, to better apply their existing knowledge to novel situations, are more motivated, and demonstrate better learning outcomes (Brown et al., 83; Zimmerman, 89; Schunk &

Zimmerman, 98; Graesser & McNamara, 10; Chase et al., 09; Tarricone, 11; Illustre, 11; Afflerbach, 02; Hamadan et al., 10; Shunk, 94).

In developing the ETTHOS model of learner cognition that can work alongside a TEL environment[7] two aspects of learner cognition are represented – the first is learners' metacognition (traits) and second are the cognitive strategies that they undertake (tasks) at different stages in the learning environment. This is because ETTHOS has been created to describe a metacognitive model, which can be used in the design of a metacognitive modelling and support service (Goby) that is loosely coupled with a TEL environment (APeLS). This means that the two services are delivered in the form of a mashup web application, which delivers SQL learning alongside metacognitive modelling and support. In developing such a service it has been necessary to examine both *'learning and cognition'* and *metacognition*. This chapter investigates the attributes of learning and cognition in order to examine the psychological and pedagogical theories that influence the design of TEL environments, inform the design of a cognitive model, and the primary content of that model. Metacognition is explored in greater depth, as it is the construct that is to be supported by ETTHOS. This means examining its background, its role as a component of self-regulation, the components of metacognition (knowledge and regulation of cognition), and the questions that arise when supporting and measuring metacognition.

[7] In particular, an AEH environment that is delivered as a service on the web.

2.3 Learning and Cognition

Cognitivism or *cognitive science* is a general approach to psychology and pedagogy that is concerned with our mental functions, belief systems, and social behaviour[8]. From this perspective, learning and mental functioning is not just a process of observed events and behaviours – instead mental strategies, processes and knowledge also have a role to play in how knowledge and skills are acquired. The *cognitive learning perspective* (Piaget & Inhelder, 73) involves transformation of information from the environment or domain into new or refined knowledge that is stored by the learner. Cognitive learning theories are comprised of ideas of how individuals process information, attention, memory, thinking and cognitive processes. The *social cognitive perspective* (Vygotsky, 78; Vygotsky, 62; Langer & Applebee, 86; Bandura, 91; Bandura, 97) examines the process of how individuals learn from observing others in the context of their environment or culture. The *constructivist learning perspective* (Harris et al., 96; Jonassed, 91; Gagné, 65) draws from both cognitive and socio-cognitive theories, with the key focus on how knowledge is constructed by the individual – from this perspective, the acquisition of knowledge structures requires active learning towards their learning goals. This development of their knowledge and strategy repertoire is unique and idiosyncratic to the learner because prior understanding impacts the learning process (von Glasersfeld, 90; Tarricone, 11; Brown, 87). Metacognition is an important construct in constructivist learning because in building meaning from their learning environment and responding to learning tasks, learners are required to monitor and regulate their own thinking (Curwen et al., 10; Pressley, 02).

This section will examine the psychological and pedagogical theories of learning and cognition that have influenced both metacognitive theory and the development of instructional strategies that inform TEL research. Having established that

[8] The cognitive movement (Piaget & Inhelder, 73; Vygotsky, 78; Vygotsky, 62; Langer & Applebee, 86) was a progression from the behavioural psychology approach and can be described as the study of how people learn, structure, store and use knowledge (Miller, 56; Lutz & Huitt, 03). Behaviourist psychologists (Skinner, 45; Skinner, 38; Watson, 13; Pavolv, 27) take the approach that objective psychology can only be carried out on observed behaviour in individuals. The focus of behaviourism is on how stimuli leads to observed responses (e.g. an environmental event such as a pin prick to the finger results in an overt reaction when the individual quickly moves their hand away). The cognitivism field is multiple disciplinary in that it draws from psychology, linguistics, anthropology, neuroscience, and artificial intelligence (Bednar, et al., 92).

constructivism is closely related to self-regulation and metacognition theories and that there are two influencing paths to constructivism (both cognitive and social cognitive), this section first addresses the cognitive theories. After an examination of schema theory as a mechanism with which to describe how we represent knowledge as mental models, it inspects the types of knowledge we can possess (declarative, procedural, metacognitive), the influences on how we process information to create unique and idiosyncratic knowledge (through practice, reinforcement, and with limited cognitive load resources), and specifically examines the cognitive strategies we engage in when reading. Social cognitive theories of learning are subsequently examined as the roles of the traditional tutor (such as scaffolding the learner in order achieve learning goals that are beyond their immediate ability and to become autonomous and self-regulated) are often emulated in TEL environments. It concludes by suggesting that although we possess individual differences in our knowledge and cognitive approaches, the application of social theories of learning is an important tool when designing instructional strategies.

2.3.1 Constructivist Learning

Constructivism can be described as an approach to learning in which learners are provided with the opportunity to construct their own sense of what is being learned based on their current and past knowledge (Harris et al., 96; Bruner, 86; Bruner 90). Constructivism is a theory of learning that describes how individuals construct meaning and acquire knowledge and supports the belief that learners construct new ideas or concepts that are influenced by existing knowledge, social interactions and motivation. Constructivism is closely related to *self-regulated learning* and *metacognition* theories because in creating understanding of information and strategies, learners are required to monitor and regulate their own thinking (Gunstone, 94; Case et al., 01). Constructivist views of learning require learners to consciously undertake an informed and self-regulated approach to recognising, evaluating and deciding whether to reconstruct their existing mental models and beliefs and respond to their environment (Gunstone, 94; Perkins, 91; Jonassen, 99; Harris & Graham, 94; Driscoll, 05).

There are a number of core principles that are common among most constructivism-based approaches to instruction (Sjøberg, 07; Taber, 06; Harris et al., 94; Jonassed, 91):

- Learning is something engaged in by the learner to enable them to actively construct knowledge rather than simply passively receiving the information.
- Learning is influenced by prior knowledge – learners' schemata that influence learning can be well-developed and difficult to change or may be ad hoc or unstable.
- Learners have their own individual viewpoint, however they also share common patterns in their ideas that are socially and culturally accepted.
- Knowledge is represented as conceptual schema structures that can be modelled and described.
- Learners construct their knowledge through interaction with their environment, social setting, cultural and linguistic environment.

There are two main paths towards constructivism[9] - cognitive psychology and socio-cognitive psychology. With his contributions to cognitive development, ideas of higher-order cognitive development in the formal operation stage, and schema theory from adolescence, Piaget is often accredited with being the driving force behind cognitive (or individual) constructivism, while Vygotsky's focus on the social and collaborative nature of learning has been accredited with influencing the development of social constructivism (Sjøberg, 07).

2.3.2 Schemata – Our Mental Models

Piaget described cognitive development as being initially facilitated by *schemas* or mental models. Schemata (Piaget 29; Anderson, 77; Anderson, 84; Bartlett, 32; Rumelhart 80; Ibrahim et al., 03; Derry, 96) are models (e.g. a process or information sets) that are applied to interpret events and solve problems. They can be understood as structured chunks or packages of knowledge that are organised into an overall framework of knowledge that influences how people comprehend tasks or solve problems. Schemata are organised patterns of behaviour or mental representations

[9] There are numerous philosophical differences in constructivism theories including cognitive constructivism, radical constructivism, social constructivism, cultural constructivism and constructionism (Harris et al., 94; Dougiamas, 98). This thesis focuses on the two main principles of constructivism - the social and cognitive components. This is because we perceive events, objects and problems from our own experiences, schemata and abilities as well as through social interaction in the context of culture.

that organise knowledge, skills and rules, and are used to understand and interact with the world.

The development and acquisition of successful models rely on the learner engaging in a range of learning scenarios. Materials within schemata are related to one another; concepts that commonly co-occur in a particular context are related to each and can influence perceptions or expectations. Through learning from our environment, we construct and reconstruct unique and idiosyncratic meaning in response to our world. Schemata are *activated* in order to understand new events or solve problems (Rumelhart, 80; Derry, 96). A schema will be activated into consciousness (into our short-term memory) if the information perceived can provide a suitable trigger or schema *signal*. This means that further information can be accessed in order to complete the picture. Cognitive development occurs through three processes of equilibration: the *assimilation, restructuring* and *accommodation* of knowledge and strategies (Piaget & Inhelder, 73; Rumelhart, 80).

As a learner assimilates (accretion) or transforms information from their environment, they position it within their own existing mental models. This process is particularly important for children who *organise*, group and combine knowledge about their experiences into categories. This organisation provides them with ways of describing how the world works. In response to understanding a new event, current schemata can be expanded, so that new information is remembered. For example, they may combine their schemas for dogs and horses into a larger scheme for mammals that breathe oxygen.

Accommodation involves the *adaptation* or fine-tuning of information stores to allow new input. The *fine-tuning* of a current mental model means that it is altered to become more consistent with real world experience. As individuals acquire new information, they are often required to adapt in order to achieve their goals or solve a problem. This involves modifying existing schemas to include more refined rules with which to understand the environment. For example, learning that a dolphin is a mammal even though it looks like a fish, would require modification of the mammal schema. Present conceptions can be thrown out of balance by disparities between prior experiences and new observations. The *restructuring* or creation of a new

schema may be required in order to replace an old one. This might mean that some aspects of the old schema are incorporated, but the model as a whole is more representative of the real world. This is demonstrated by the way that new understanding can be developed by analogy.

A learner's ability to control their model is limited - it is difficult to build new strategies and control the development of successful models. This is because our mental processing capabilities are limited and our mental models and are often incomplete (Norman, 83) because the experiences and stimuli processed are never sufficient to completely convey the world. Concepts (declarative knowledge), and strategies (procedural and conditional knowledge) are not necessarily as accurate or precise as a problem requires (Norman, 83). However, this generalisation is useful because a learner can reuse or *transfer* their strategies across a variety of contexts. The matching between the environment and schema memory is quite powerful, since one concept can trigger another (Norman, 83). In this context, prior knowledge and skills can facilitate and enhance the transfer of learning across domains and environments.

Schema signals can be introduced into a learning scenario. Since learners can rely on schema signals to provide a basis for reasoning, there are instructional implications for the educator who has the role of activating learners' prior knowledge or appropriate schemata. Signals help the learner to activate prior knowledge, often highlight important segments, and activate suitable encoding strategies (Derry, 96; Ibrahim et al., 03). Potentially this also means challenging preconceptions, in order to restructure or redefine them. Establishing meaningful learning scenarios can improve learners' abilities to regulate learning and thought processes (Derry, 96).

According to schema theory, cognitive development occurs through organisation and equilibration as the learner actively adapts their schemata (Piaget 29; Rumelhart 80; Ibrahim et al., 03; Derry, 96). Piaget also proposed *stages* of cognitive development, each of which is prerequisite for the next. Although this view of development as a set of distinct stages is now considered a simplified view of how cognitive development occurs, it is a useful framework with which to understand the progression of innate and simple cognitive functions into more complex abilities. Schema theory has a role

to play in cognitive constructivism, whereby our mental models are used to make sense of our experiences (Derry, 96). From the cognitive constructivist perspective, learners actively engage their cognitive structures in schema building when processing information from their environment.

By reflecting on our experiences, engaging with our environment through inquiry, and learning through experience, we can actively construct our own understanding of our environment (Bruner, 90). This is because knowledge is constructed in our schemata in unique and idiosyncratic ways rather than being simply reproduced (von Glasersfeld, 90; Tarricone, 11; Brown, 87; Aleven, McLaren, Roll et al., 10). When we encounter something new, we construct new understanding and knowledge, through experiencing things and reflection on these and prior experiences. This means that we may need to reconcile new knowledge or experiences with previous ideas, and that our schema may be updated, discarded, or new information identified as irrelevant. Learning requires us to adjust our mental models to accommodate new experiences and derive new meaning from our environment and cumulative experience (Bednar et al., 92). Over time, individuals develop sophisticated internal representations of the world around them, and gain control of their own learning and thinking approaches thereby becoming capable of complex interactions between thought and behaviour (Williams & Atkins, 09; Schraw et al., 06; Zimmerman, 89; Vygotsky, 78; Piaget, 83).

2.3.3 Declarative, Procedural and Metacognitive Knowledge

Knowledge refers to the set of understanding or body of information possessed by an individual that is innately available or experientially acquired[10] (Chomsky, 84). Successful learning depends on a range of individual influences that can change with cognitive development or through instruction, including levels of declarative, procedural knowledge and metacognitive skill (Zimmerman, 89; Pressley, 87; Graesser et al., 10; Zimmerman, 89).

[10] The concepts of *memory* and *knowledge* are closely connected, with the terms often used interchangeably (Rogers, 06). Knowledge is more than a collection of conditioned responses, instead it comprises of material such as ideas, facts, strategies stored in our memory. These range from factual declarations (e.g. the ability to declare that the a dog is an animal) to the capacity to carry out complex patterns of behaviour (Anderson, 93; Taatgen & Anderson, 09). Our *memory* is the mental storage system for storing information, skills and strategies. The concept comprises of a number of theoretical facets to describe how information is attended to, processed, and stored.

Declarative knowledge (knowing that, factual knowledge) is factual knowledge about our world (Zimmerman, 89; Siegler, 82; Dienes & Perner, 99; Anderson, 83). This is the type of information that an individual can communicate to others through explicit statements (or declarations) about the content or material. This is synonymous with *explicit memory*, whereby an individual is consciously aware of material previously presented and can *recall it* or *recognise it* against alternatives (Dienes & Perner, 99)[11]. *Procedural knowledge* (or knowing how, practical knowledge) is often learned in this fashion because it is non-declarative knowledge that is in the form of skills and cognitive strategies (Dienes & Perner, 99; Anderson, 83). Procedural knowledge is organised around the conditions and actions needed to complete a task or solve a problem. This includes operational knowledge that is used to guide our behaviours when we engage in tasks, guide us to solve problems, and make decisions (Zimmerman, 89; Dienes & Perner, 99).

Metacognitive knowledge has both procedural and conditional qualities (Schraw & Dennison, 94; Schraw et al., 06). This is because it comprises of knowledge about our internal cognitive strategies as well as strategies for regulating our approaches towards completing goals. Knowledge can be considered as metacognitive if it is actively used in a strategic manner in order to achieve a goal. For example, self-regulated learners employ strategic planning to guide their efforts when solving a problem. Their plans may change over time as they assess feedback from the task at hand as well as by assessing how well they have implemented the plan (Zimmerman, 89). Metacognitive and cognitive knowledge can overlap, because the same strategy can be used in multiple ways. For instance, a learner's ability to engage in metacognitive decision-making requires the learner to assess the effects of their learning strategies and metacognitive processes on their progression towards a learning goal. Self-questioning may be employed while reading as a way of obtaining information (cognitive) or as a way to monitor comprehension (metacognitive) (Yang et al., 09).

[11] Not all knowledge is available to consciousness. The process of learning, which happens, independent of awareness, is termed *implicit learning* and is seen in the process of socialisation and language learning (Chomsky, 84).

2.3.4 Processing Information in the Learning Environment

In cognitive theories of learning and psychology, knowledge is viewed as symbolic, mental models that are stored in our mind. Learning processes have been described in a general processing model where knowledge is created by the individual rather than discovered. The *Information Processing* theory (Miller, 03; Ashcraft, 94; Gaines & Shaw, 03; Proctor & Vu, 06) of cognitive development describes individual functioning and thought in a manner analogous to computer processes. *Input* information (or information that *perceived* by the learner) is *processed* (encoded), *stored* (in memory) and *retrieved*. Just as a computer has limited processing power and memory capabilities, so too does our mind. Our *cognitive load* is limited – this is because the capacity of sensory and working memory is limited, meaning that cognitive strategies need to be used in order to make better use of the resources (e.g. rehearsal or chunking) (Sweller, 04; Chandler & Sweller, 91; Bendall & Kehoe, 11; Ohlsson & Mitrovic, 07). The introduction of too much information, or too many problem tasks to be solved simultaneously during a learning task results in the learner being unable to process this information (known as cognitive overload) (Chandler & Sweller, 91; Bendall & Kehoe, 11). The capacity limitations of working memory ensure that alterations to our long-term memory are slight. From an instructional perspective, it is important for students to be given the chance to *practice* or reiterate new knowledge and abilities to ensure that learning occurs (Sweller, 04). Learning is strengthened through *practice*. Through repetition, behaviour is *reinforced* and over time these skills can become automatic (Vygotsky, 62), which means that more *cognitive resources* are available to the learner.

Knowledge and memorial processes are extremely complex and different tasks or problems to be solved require the activation of different knowledge. Material stored in memory is typically linked with the context within which it was learned. This contextualisation means that it can be difficult to *transfer* the knowledge or strategies learned in one situation to another situation (Bransford et al., 00). In situations where there is an overlap between tasks (e.g. equations in maths and accountancy), knowledge or skills acquired during the earlier task assist with carrying out subsequent tasks. Positive transfer can result in increased performance and reduce the amount of cognitive load required from learners if they can activate previously encoded strategies or knowledge (Butcher & Aleven, 99). In situations that are

dissimilar, it is more difficult to transfer abilities even if the principles learned in one situation could be applied to another.

2.3.5 Cognitive Strategies for Reading

The process of understanding texts requires the reader to actively construct a representation of the information through numerous processes (e.g. inference making, noting connections) (Pressly & Afflerbach, 95; Jones et al., 87; Wiliams & Burden, 97; Brown & Paliscar, 84). Success when learning in a range of subject areas is very much dependent on the efficiency and effectiveness of learners' comprehension of reading materials and related resources (McNamara, 09; Illustre, 11; Pressly & Afflerbach, 95). Reading material, including text, prose and related tables and figures are a major source of information for students, whether they are in the form of textbooks, related course material (such as journals, articles, etc.), online content or other independently researched material. An understanding of the cognitive strategies for reading is important in the context of this research, because in modelling learner metacognition, the research model will also represent the general stages undertaken by the learner when reading academic text online[12].

The skilled reader employs an extensive repertoire of cognitive tasks and activities. Reading can be characterised as constructively responsive (Pressly & Afflerbach, 95). This means that successful readers actively construct knowledge as they interact with and respond to new information that is presented to them while reading. Reading a piece of academic work incorporates text, examples, diagrams and sample solutions (Pressly & Afflerbach, 95). Expert readers employ similar thought processes to learning, mathematics and problem solving (Rules, 06) – for example activating prior knowledge, setting reading goals, monitoring comprehension and employing strategies. Expert readers possess metacognitive knowledge about reading strategies, meaning that they are aware of their strategies and can employ them in the right context (Pressley & Gaskins, 06).

[12] A general model of cognitive strategies for reading will be used in the ETTHOS model to contextualise when metacognitive supports are offered. A general model can tell us at what stage the learner should be at in the reading process, and describes the series of actions typical learners take. For instance, before the reading task learners should most likely engage in planning whereas at the end of the task it may help to engage in evaluation.

Pressly and Afflerbach (1995) have published an extensive model of reading protocols. The result of protocol analysis carried out on 38 primary research studies is a comprehensive list of the cognitive activities undertaken by the successful reader. They have summarised *cognitive strategies* undertaken while responding to reading academic text through a survey of self-report literature from diverse disciplines and reporting standards (Pressley & Afferlbach, 95). Seven main categories of task emerge from the protocol analysis; an overview of these is outlined below:

1. *Before the task* – Good readers plan before beginning a text in order to construct goals. This might involve skimming the text in order to note structural characteristics that point to important information or to determine what to ignore.
2. *Salient behaviours during initial reading* – Initially the reader might read a chunk of content from front to back, focusing on the important components, repeating if necessary or pausing to reflect on the text.
3. *Identifying important information* – Readers look for information that is relevant to their goal or the learning goals. Information can be perceived as novel, or important, or dismissed if it is does not fit with their goal.
4. *Conscious inference making* – Readers incorporate the knowledge they have gathered while reading with their own mental models or schemas by relating prior knowledge, their goals, and new information.
5. *Integrating different parts* – In order to construct meaning out of new information, readers need to be able to make inferences across disparate parts of the text.
6. *Interpreting* – Interpreting refers to the creation of overall meaning from the text. This might mean visualising concepts and their relationships or constructing alternative perspectives.
7. *Activities after reading* – On completion of the text, good readers undertake a mental review of the process. They might also reread after the first iteration or self-question or self-test to establish their level of understanding.

The main limitation of this protocol model is that it is constrained to what the individual has reported. As individuals learn new procedures and become more expert they become progressively automatic. Although think-aloud studies can be applied in conjunction with retrospective reports, they would be subject to introspection. This means that the individual might speculate about what they

thought they should be doing rather than the actual process itself. Accordingly, Pressley and Afflerbach (1995) reported current thinking of participants, rather than incorporating subjective reflection to the model. Another limitation is that although the tasks have been described with a linear approach - in reality the process can be recursive and interactive. Some activities are prerequisite or preclude others. However, this model has the potential to model a limited view of reading activities, to tell us what stage the learner should be at in the reading process, and describe the series of actions typical learners take.

2.3.6 Psychosocial Aspects of Learning

Vygotsky's social and cultural views on development posit that our cognitive abilities increase through working with others and that we learn in a cultural context (Vygotsky, 78; Vygotsky, 62; Langer & Applebee, 86). Interactive events are at the heart of learning, whereby the tutor initially mediates the process and governs the learner's participation until they internalise the new knowledge or strategies. Social constructivism (Vygotsky 62, 78; Eberle, 92; Berger & Luckman, 67) is rooted in Vygotsky's psychosocial theory, drawing from the idea that knowledge can be socially and culturally constructed. Individual cognition and responses are mediated by social contexts where knowledge is not simply transmitted, but actively constructed in the learner's mind.

Scaffolding (Bruner, 75; Dickson et al., 93) involves providing assistance to a student in order to move into their *Zone of Proximal Development* (ZPD) and achieve learning goals that would normally be outside of their individual abilities. The ZPD can be defined as the gap between the learner's current abilities (development level) and their potential development level that can be achieved under the guidance or support of a tutor or educator (Vygotsky, 86; Langer & Applebee, 86). The ZPD is continually changing as the student bridges this gap and acquires new knowledge and skills. Scaffolding harnesses the social nature of learning and the potential abilities of the learners. It involves instruction through systematic sequencing of social supports, prompted content, material, problems or tasks with support in order to optimise the learning outcomes. This can be achieved through a number of instructional strategies such as activation of prior knowledge (schema signals), providing new background or landscape knowledge and intervening at difficult stages of a task to provide hints.

This support is given for novice learners, until they have internalised the material or skills and can apply them independently (Langer & Applebee, 86). As students begin to demonstrate task mastery, the responsibility of the learning should be given to the learner and less support provided. Social constructivism promotes social and communication skills by introducing learning environments that emphasise collaboration and exchange of knowledge and strategies. Learning is aided by social interaction with peers and tutors in real world experiences. There are a number of instructional strategies for enabling social constructivist learning including: scaffolding, cognitive apprenticeship, tutoring, cooperative learning, negotiating group perceptions, group discussion, and small-group collaboration (Wood et al, 95).

Of these, human *tutoring* is recognised as the most effective form of instruction (Bloom, 84; Koedinger, 01; VanLehn, 06; Graesser, D'Mello & Cade, 09; Cohen, Kulik & Kulik, 82; Cohen, Kulik & Kulik, 82). This type of support is especially important if a student is underachieving or struggling. Traditional human tutoring generally involves working with an individual student, instructing them through a problem or concept, and where necessary providing feedback at each stage along the way (Graesser, Conley, Olney, 2010). Graesser and his colleagues have reported a number of observations that characterise successful tutors (Graesser, D'Mello & Person, 09; Graesser, Conley, Olney, 10):

1. The tutor adaptively supports the learner to correct errors in their knowledge and skills. This means that the tutor needs to have the flexibility to *adapt* their own cognitive strategies have the ability to adapt their student.
2. Short *feedback* is given after most stages of a task or problem. This feedback is usually elaborated with explanations or hints.
3. Good tutors give *hints* to encourage the learner to engage in the material or a conversation about it. These are statements, questions, or more comprehensive discourse.
4. Tutors who have expertise facilitate more effective tutoring. In particular a tutor needs to be responsive to the cognitive and emotional state of each tutee, and possess a wide range of teaching strategies, as well as understanding of which strategies are most suitable for different situations.
5. Effective human tutoring is costly.

A number of instructional strategies that can be used by tutors to effectively enable scaffolding have been derived to support students to become independent learners, including appropriateness (e.g. offering examples that could be imitated), structure (the learner can mimic the task even though they may not have a complete understanding of it), collaboration, (the learner needs less direction, and can eventually self-regulate and take control of their learning), and fading (Larkin, 01; Langer & Applebee, 86). Over time, support is *faded* so that the students assume responsibility for their learning as the tutor provides less support. As the learner takes responsibility for the learning task, the eventual goal is to enable them to become self-regulated (Langer & Applebee, 86).

2.3.7 Conclusion

Self-regulated learning and *metacognition* are considered to be integral parts of constructivist learning because in actively constructing meaning from their learning environment and responding to learning tasks, learners are required to monitor and regulate their own thinking (Gunstone, 94; Case et al., 01; Curwen et al., 10; Pressley, 02). Over the course of our cognitive development we develop individual and idiosyncratic knowledge and strategy repertoires – our mental models, how we think, and interact with the learning environment varies compared to the next person because we develop our own individual differences or cognitive style (von Glasersfeld, 90; Tarricone, 11; Brown, 87). Our ability to understand and respond to our environment becomes more able (and more complex) over time as we learn how to better process information, build declarative knowledge, acquire procedural or strategic knowledge and develop metacognitive knowledge that enables us to reason about our own cognition. Success when learning in a range of subject areas can be dependent on the efficiency and effectiveness of learners' comprehension of reading materials and related resources (McNamara, 09; Illustre, 11; Pressly & Afflerbach, 95). Learning environments that allow us to practice skills or cognitive strategies reinforce this knowledge and free up cognitive resources for new learning tasks. Learning is not just an individual process however; we make meaning from our peers and the people around us. Tutoring makes the most of this social aspect of learning, whereby tutors support and scaffold learners in order to achieve their learning potential whilst being sympathetic to their cognitive load. Through the structure

provided by scaffolding, learners are guided towards an independent, autonomous, and self-regulated competency of skills.

2.4 Metacognition

Metacognition encompasses a learner's *knowledge* about their own cognitive process and the *regulatory strategies* employed by them for the purpose of control (Flavell, 79; Brown, 78; Schraw & Dennison, 94; Tobias & Everson, 00)[13]. Metacognition is associated with intelligence because it is a critical component of learning. It refers to the higher-order thinking that an individual engages in while learning and the active control taken over the cognitive processes triggered during learning (Sternberg, 86). Cognitive strategies are activated to solve a problem or complete a task (e.g. recall of information during an exam). In contrast, metacognitive strategies control the monitoring and regulation of our cognitive strategies and evaluation of our progress towards achieving a learning goal (e.g. the ability to reflect on how well you answered an exam question).

This section examines metacognition because it has been identified as a cognitive construct that can result in positive learning outcomes. In conjunction with an understanding of cognitive theories discussed above, it describes the development of metacognitive theory and its role in self-regulated learning. Having shown how knowledge of cognition and regulation of cognition are important facets of the regulatory process that enables learners to become autonomous, it discusses the issue of supporting and measuring metacognition. It concludes by recommending that metacognition is an important higher-order strategy when learning and reading and that regulatory components of metacognition can be effectively measured using a psychometric inventory.

[13] Several terms have been used to describe the same processes are used interchangeably in the literature (e.g., meta-memory, meta-learning, meta-attention, self-regulation, executive control) (Brown, 87; Kayashima & Inaba, 03). Here, metacognition is defined as one's knowledge and control of one's own cognitive system (Flavell, 79). While most commonly referred to as a two-component model, in the history of study researchers have posited varying views on how to define metacognition, expanding it's remit to greater number of components (e.g. White's (1998) four component model which added knowledge about metacognition and readiness to apply the ability) or reducing it to simply knowledge about cognition (e.g. Paris & Winograd, 00).

2.4.1 Metacognition Background

Research on metacognition in academic domains has been carried out on reading and studying, mathematics, writing and science (Afflerbach, 00; Baker & Brown, 84, Baker & Cerro, 00). Consistent findings have been that students who are more successful in a learning environment or domain exhibit higher levels of metacognitive knowledge about the domain and have greater skills for regulating their own cognitive processes (Baker & Cerro, 00).

The concept of metacognition draws from constructivist roots in cognitive and social-cognitive theories. In particular, it draws from theories of cognitive development, reflection, higher-order reasoning, self-regulation, mental models and memory. Piaget's theory of cognitive development supports the role of metacognition in the development of cognition and intelligence through reflection and self-evaluation. Reflection is the process of thinking about our own cognition, whereas metacognition is about the awareness of thinking and reflection. Reflective thinking is a clear element of abstract thinking in Piaget's formal operation stage, which is needed to enable learners to engage in logic, reasoning and abstract thought processes (Inhelder & Piaget, 58). It is at this stage that individuals begin to develop higher-order reasoning. For instance, knowledge of self, self-control and self-correction are higher-order processes that enable reasoning. Reflective thought, awareness and purposeful thinking in adolescence and beyond are seen as contributions to the development and use of metacognition. This implies that metacognitive processes come into existence in adolescence and adulthood and are reliant on the individual having knowledge about their own cognitions and being able to reflect on this knowledge (Tarricone, 11). The abstract reflective process is considered to be a powerful form of metacognition that not only helps to direct cognitive process but also enables individuals to actively reconstruct their mental models and deepen their understanding (Tarricone, 11).

Complex abstract situations require higher-order reflection and reasoning processes to be activated in order to create inferences and make informed judgements. The social construction of knowledge has contributed to reflective theory and metacognitive theory because reflection can be socially mediated through communication with others as well as internal verbalisations (Vygotsky, 62;

Habermas, 87). Although Vygotksy (1962) did not use the term metacognition, he described education as primarily enabling students to engage in consciousness and deliberate control of their cognitive processes (Bruner, 85; Tarricone, 11). Instruction goes beyond curriculum delivery to influence the development of higher functions that are useful in a range of subjects. While courses may be delivered as a formal discipline, each facilitates learning in others because the psychological functions stimulated by them develop into one complex process (Vygotsky, 62).

As we have seen, social cognitive interactions can create zone of proximal development by determining the gap between the actual development and potential development. During problem solving both verbalisation and internal verbalisation promote progression into this learning zone. This type of reflective dialectical process when problem solving is an integral part of metacognition because it promotes reasoning about the relationships between problems, the problem solving process and the effectiveness of the strategy used (Bruner, 85; Tarricone, 11). The learning process should then move from a predominantly social cognitive process to a metacognitive process whereby learners are in control of their own cognitive strategies and become autonomous (Tarricone, 11). Scaffolds can enable learners to make this progression (Bruner, 90). For instance, enabling learners to engage in reflection and introspection facilitates the development of knowledge about their internal processes, which is fundamental to metacognition (Tarricone, 11).

The study of metamemory (Kreutzer, Leonard & Flavell, 75) is the historical foundation of metacognition theory (Tarricone, 11). Metamemory refers to the ability to monitor and reflect on memory and mnemonic strategies in order to acquire, store and retrieve information. The metamemory framework is the foundation for the two-component metacognition model. This comprises of higher-order knowledge, including declarative and procedural knowledge (and conditional or sensitivity knowledge) that can be categorised into person, task and strategy variables (Flavell & Wellman, 77) and is influenced by cognitive development, learning experiences and reflection (Trricone, 11).

2.4.2 Metacognition as a Component of Self-Regulated Learning

Metacognition is a vital component of successful self-regulation (Zimmerman, 89; Brown, 78; Tarricone, 11) as it drives the control, monitoring and regulation of strategies in order to meet the goals of the learner (Zimmerman, 89). Metacognitive strategies help learners to become aware of their learning strategies and to gain control over how they acquire knowledge and skills. Self-Regulated Learning (SRL) refers to our ability to understand and control our learning environment (Schraw et al., 06). An ideal learner is self-regulated – they formulate learning goals, track the progress on their goals, assess their errors, debug contradictions, self-question, search for missing or new information, make inferences or analogies, and work towards deep understanding (Schunk, 96; Schraw et al., 06; Schunk & Zimmerman, 98; Graesser & McNamara, 10). Few students are fully self-regulated, however support for self-regulation of study or tasks have shown significantly positive benefits to learners (Bednall & Kehoe, 11; Azevedo & Witherspoon, 09). For instance, individuals with better self-regulation skills typically learn more with less effort and report higher levels of academic satisfaction (Schraw et al., 06; Zimmerman, 00).

SRL theory originated with Bandura's theory of social cognition and his theory of *reciprocal determinism* – this approach suggests that learning is the result of personal, environmental, and behavioural factors and their interplay[14] (Bandura, 91; Bandura, 97). Self-regulated learning consists of three main components: cognition, metacognition, and motivation[15] (Schraw et al., 06; Graesser, D'Mello & Person, 09). Metacognition is of particular importance because it enables learners to monitor their current knowledge and skill levels, plan and allocate limited cognitive resources with optimal efficiency, and evaluate their progress toward their learning goals (Schraw et al., 06). Each of these three components has an important role to play in successful self-regulated learning (Schraw et al., 06). For example, learners who have cognitive skills but are unmotivated to use them do not perform to as high a standard as their peers who have cognitive skills with motivation (Zimmerman, 00; Schraw et al., 06). Effective learners are able to determine the utility of their learning strategies and

[14] Personal factors include a learner's beliefs and attitudes that affect learning. Environmental factors include the quality of instruction, instructor feedback, and material available. Behavioural factors include the effects of prior performance. According to reciprocal determinism each of these three factors influences the others (Schraw et al., 06).

[15] Motivation includes beliefs and attitudes that affect the use and development of cognitive and metacognitive skills.

calibrate their approach in order to achieve their goals (Schunk & Zimmerman, 98). Consequently, self-regulated learners are proactive and adaptive in their approach to learning.

Zimmerman (1994) proposed that self-regulation is comprised of a three-phase cycle including forethought, performance and subsequent regulation. Learners have declarative, procedural, and metacognitive knowledge about learning strategies and how to implement them. With forethought, learners can describe and apply strategies, and can recognise the conditions when they should be used. Learners then monitor and regulate their *performance* during the task. Learners also monitor their progress and internal cognitive strategies during *performance***,** making judgments about their performance and ability to achieve their goal. This phase is critical for self-regulation, as it sets up the enactive feedback loop and motivates them to set higher goals in proceeding tasks (Schnuck & Zimmerman, 94; Bandura, 91), comprised of: Observing performance, comparing performance to the goal, and subsequently adjusting performance if needed in response to the perceived difference. The final phase of the SRL cycle is *self-regulation*. This involves self-evaluation and the estimation of the success/failure of personal performance. Results from self-regulation should influence the planning and monitoring phase in order to improve future learning tasks (Zimmerman, 94).

The development of self-regulatory learning skills is dependent on a range of requirements; the learner should be provided with a range of problems or tasks in a variety of contexts. In order to practice self-regulation, learners should be allowed to control their learning, set their own goals, and chose a variety of learning strategies (Driscoll, 05). Three types of feedback (Bednall & Kehoe, 11) drive SRL - *feedback from cognitive processes* such as metacognitive monitoring, and judgments of learning, *motivational processes* such as feelings of self-efficacy, and *external cues* such as tutor feedback. It is the learner's role to activate useful and applied cognitive strategies to undertake a task. This means that metacognitive understanding of both the suitability of strategies and an awareness of their own personal cognitive functioning is prerequisite for optimal learning.

2.4.3 Two-Component Model of Metacognition

Metacognition is often described as a *two-component model* that includes both *knowledge of cognition* (knowing about your thinking) and *regulation* of cognition (controlling your thinking) (e.g. Baker & Cerro, 00; Schraw et al., 06; Brown, 87, 80). Several theories have been defined which categorise the types of knowledge related to metacognition. Table 2.1 below provides an overview of these knowledge types, and the related researchers responsible for their development, and puts them into the context of metacognition.

Metacognition Component	*Knowledge Type*	*Knowledge Variable*	*Illustrated By*
Knowledge of Cognition	Knowledge about own cognitive processes and factors affecting learning	Person & Task Knowledge	Flavell, 79
		Self-Appraisal	Paris & Winograd, 90
		Declarative Knowledge	Brown, 87; Schraw & Dennison, 94
	Awareness and management of cognition, including knowledge about strategies	Procedural Knowledge	Schraw & Dennison, 94
		Strategy Knowledge	Flavell, 79
	Knowledge about why and when to use a given strategy	Conditional Knowledge	Schraw & Dennison, 94; Case et al., 01
Regulation of Cognition	Identification and selection of appropriate cognitive strategies	Planning	Tobias & Everson, 02; Brown, 87; Paris & Winograd, 90; Schraw & Dennison, 94; Whitebread et al., 09
	Attending to and regulation of comprehension and task performance	Monitoring or Regulation (including information management strategies and personal debugging)	Tobias & Everson, 02; Brown, 87; Paris & Winograd, 90; Schraw & Dennison, 94; Whitebread et al., 09
		Cognitive Perception	Flavell, 79
	Assessing the progress towards learning goal and level of success of cognitive strategies, and revising learning goals	Evaluating	Tobias & Everson, 02; Brown, 87; Paris & Winograd, 90; Schraw & Dennison, 94; Whitebread et al., 09

Table 2.1 Metacognitive Knowledge Components (Adapted from the Lai, 11)

The *knowledge* component of metacognition refers to an individual's knowledge and beliefs about their own cognition. Knowledge is considered to be metacognitive if it is actively used in a strategic manner to ensure that a goal is met. There are three aspects of types of metacognitive knowledge that can be used for self-regulated learning: *declarative knowledge:* the ability to describe some thinking strategies*;*

procedural knowledge: knowledge of how to use the selected strategy*;* and *conditional knowledge:* knowledge of when to use it (Schraw & Dennison, 94; Schraw et al., 06)[16]*.*

Declarative knowledge includes our knowledge about our internal processes that we use as learners and what factors influence our performance. For example, most adult learners know the limitations of their information processing abilities and can plan accordingly. Procedural knowledge refers to knowledge about strategies and other procedures. Most adults possess a basic repertoire of useful strategies such as skimming unimportant information, using mind-maps, summarising course content, and periodic self-evaluation. Finally, conditional knowledge includes knowledge of when to use a particular strategy and why it should be used. Prior metacognitive knowledge fundamentally influences how learners engage with learning, whether this knowledge is explicit or not (Case et al., 01). For instance, individuals who have a large repertoire of conditional knowledge are better able to assess the demands of a learning situation or problem and, in turn, select the appropriate strategy (Schraw et al., 06).

Flavell categorised knowledge of cognition into *person variables*, *task variables*, and *strategic variables*, and the interaction of these three (Flavell, 79; Tarricone, 11). *Person variables* encompass individuals' self-assessment of their own cognition (Flavell, 79). More experienced learners display a better understanding of their memory and cognitive strategies than novice learners because they can allocate their cognitive resources with more precision (Flavell, 79). Metacognitively aware learners have greater control of personal factors such as cognitive ability, personality, and self-concept (Baker & Cerro, 00; Tarricone, 11). An individual's self-awareness and knowledge about their own abilities is mediated by self-efficacy, self-concept, and beliefs about ability (Tarricone, 11). *Task variables* encompass factors such as task complexity, performance, and related prior knowledge (Flavell, 79; Tarricone, 11). These variables are indicative of an understanding of how metacognitive strategies are context dependent. This means that individuals can apply contextually

[16] This model of metacognitive knowledge originated from metamemory, whereby declarative metamemory is described as knowledge of memory and awareness of what is known and not known. Procedural metamemory involves knowledge of the application of specific strategies in different contexts towards information storing. Conditional metamemory, termed *sensitivity,* involves actively knowing when to use deliberate, goal orientated strategies to memorise information and when to allow spontaneous passive use of memory strategies in different task situations (Tarricone, 11).

appropriate strategies. *Strategy variables* are initiated by the learner, and relate to knowing how to monitor and alter their approach to a task. Ideally learners should know about their cognitive strengths or weaknesses and the nature of the task in order to regulate learning. For example, a student may plan how to approach a programming exam: "I know that I (person variable) have difficulty with data structures problems (task variable), so I will answer the algorithm problems first and save the data structure problems for last (strategy variable)." They implement the plan and monitor its success to determine if it led to the desired goal. If it did not, they may need to try to find out where the issue is and attempt to remedy the situation.

Our knowledge of cognition is late developing and is often lacking in both young and adult learners (Graesser, D'Mello & Person, 09). Adults tend to have more knowledge about their own cognition and are better able to describe that knowledge than children and adolescents (Alexander et al., 95; Schraw et al., 06). The successful learner needs to be aware, not only of their cognitive strategies and disposition, but also of their metacognitive processes (Facione, 90; Ku & Ho, 10). Metacognitive knowledge is an important indicator for positive self-regulation and higher-order thinking (Ku & Ho, 10). This involves the application of appropriate skills and strategies to best suit a situation. Indeed, many adults cannot explain their expert knowledge and performance but can still harness metacognitive knowledge implicitly to better perform (Butler & Winne, 95). There is proven merit for trying to support the acquisition of metacognitive knowledge - metacognition is considered complementary to learning, and research has recorded a causal relationship between level of metacognitive knowledge and subsequent ability to transfer strategies across tasks (Schraw & Dennison, 94). This is because greater metacognitive knowledge results in a more flexible cognitive strategy repertoire. Consequently; the individual can be more strategic and perform better (Schraw & Dennison, 94; Butler & Winne, 95).

Metacognitive *regulatory strategies* include the planning, awareness, monitoring, and subsequent regulation of cognitive processes. The ability to know what you do or do not know requires a large amount of cognitive ability. Metacognitive regulation also involves the ability to monitor progress towards learning goals, correcting mistakes, analysing the effectiveness of the learning strategies you have used and changing

strategies when necessary. Regulation of cognition typically includes at least three components, planning, monitoring, and evaluation (Schraw et al., 06; Paris & Winograd, 90; Tobias & Everson, 00; Tobias & Everson, 02) and has been expanded in some models to include information management strategies and personal debugging (Schraw & Dennison, 95).

Planning involves the selection of appropriate strategies and the allocation of resources (Paris & Winograd, 90; Schraw et al, 06). Planning includes goal setting, pacing, self-questioning before beginning a task and scheduling appropriate time (Schraw & Dennison, 95). Experts are more self-regulated compared to novices due to more effective planning; particularly planning that occurs prior to beginning a task (Schraw et al., 06). *Monitoring* includes the self-testing, attention to and awareness of comprehension and task performance (Schraw et al., 06; Paris & Winograd, 90). Comprehension monitoring is carried out at both a global level (an overall problem to be solved) as well as at each individual component item to be solved within a problem (Schraw et al., 06). Flavell (1979) describes comprehension monitoring in the context of *cognitive experiences*, which are insights or perceptions experienced during a task. For instance, you may reflect, "I'm not understanding this", and change your learning strategy in response to this insight. These experiences serve as quality control checks that help learners revise their strategies and goals (Flavell, 79). Information management strategies can be used to support monitoring in order to process information more efficiently (e.g. organising, elaborating, summarising) (Schraw & Dennison, 95). *Evaluation* refers to assessing the processes and results of the regulatory processes used while learning and revisiting and revising learning goals where necessary (this revision can also be described as personal debugging). For instance, this could include the ability to know how well you do on completion of a test, or asking if you have learned as much as you could have once you have finished a task (Schraw & Dennison, 95).

Strategy instruction improves self-regulated learning (Butler & Winne, 95) and metacognitive regulation (Alexander et al., 95; Schraw et al., 06). Procedural competence in the form of expert problem solving and complex processing of information becomes increasingly more important as learners are required to engage with more complex topics and become autonomous learners (Schraw at al., 06).

These regulatory processes (including planning, monitoring, and evaluation) are important for the self-regulated learner and may not be conscious or explicit in many learning situations (Butler & Winne, 95; Schraw et al., 06). This is because through practice, these processes have become automated. Some of these processes may develop without any conscious reflection and subsequently it can be difficult to report to others. Also, there is often not a readily available language for students and teachers to communicate about such issues (Schraw et al., 06).

2.4.4 Supporting the Development of Metacognition

Metacognitive ability can differentiate successful learners from their less successful peers (Schraw et al., 06). The ability to monitor one's own comprehension and understanding of the learning environment and use that self-evaluation can influence the level of success (Tarricone, 11). For instance, metacognition is an integral part of effective reading comprehension and understanding academic material (Brown, 94; Illustre, 11). Successful readers use more cognitive strategies, use them more frequently, and have enhanced metacognitive awareness of their own use of strategies and what they know, which in turn leads to a greater reading ability and proficiency (Afflerbach, 02; Hamadan et al., 10). Expert readers use targeted metacognitive strategies before, during and after reading to aid their comprehension and understanding (Pressley & Afflerbach, 95; Hamadan et al., 10). Planning, monitoring and evaluation of cognition increase a reader's ability to construct meaning and understand and evaluate the text (Case et al., 01; Hamadan et al., 10). These metacognitive strategies enable readers to construct meaning while reading, monitor their learning while reading, and make connections with prior knowledge.

While most individuals can engage in metacognitive regulation when confronted with effortful cognitive tasks, some individuals are more metacognitive than others (Veenman et al., 06). Metacognitive deficiencies often result from inexperience in new and difficult problem situations (Brown, 80). Also, although many learners have the ability to implement learning strategies, they tend to have lower ability to be strategic about the learning and thinking itself (Hamadan et al., 10). Those who lack knowledge of their own strengths and weaknesses will be less likely to adapt to different learning environments, regulate their learning and control their information processing and mental models (Hamadan at al., 10; Tarricone, 11).

As learners become more skilled at using metacognitive strategies, they gain confidence and become more autonomous and self-regulated. Autonomy can lead to ownership as metacognitive knowledge helps learners to realise that they can acquire information to enhance their intellectual capabilities. Through scaffolding, educators can support this autonomy by encouraging awareness and enabling learners to engage in metacognitive regulatory strategies (Brown et al., 83).

Increasing the quantity and quality of metacognitive knowledge and monitoring skills through systematic training is desirable because it enables individuals to take conscious control of their learning (Flavell, 79; Schraw et al., 06). Professional educators display abilities to formulate tasks or problems to be solved that can scaffold learners' cognitive and metacognitive abilities (Wilson & Bai, 10). Educators can be described as *metacognitive professionals* (Koedinger et al., 09) because it is commonly reported that educators have a rich understanding of metacognition, both to regulate their own cognitive processes as well as to enable learners to become more metacognitively aware (Wilson & Bai, 10). They are said to possess adaptive metacognition in order to monitor their efforts in the classroom and respond to groups or individuals (Duffy et al., 09). They also possess an awareness of metacognitive and regulatory processes that are beneficial to the learning process and construct learning scenarios to enable learners to practise these strategies.

Metacognitive instruction enhances metacognition and learning in a range of students, particularly helping poor students (Veenman, et al., 06). There are a number of instructional strategies which can foster metacognition and self-regulation, including inquiry based learning[17], collaborative support (such as tutoring or reciprocal teaching), strategy instruction, and strategies for helping learners to construct mental models and to enable them to tackle preconceptions (Graesser et al., 09; Schraw et al., 06). These strategies can be successful when they promote explicit

[17] Bruner's constructivist instructional strategy prompts learner inquiry through invitation, exploration, explanation and allowing them to practice (Bruner et al., 86). Other instructional inquiry models include puzzling, hypothesising, the BSCS 5E (engage, explore, explain, elaborate, evaluate) model, PQ4R (Preview, Question, Read, and Reflect, Recite and Review), and IDEAL (Identify, Define, Explore, Act and Look) (Bybee et al., 06, Thomas & Robinson, 72, Jonassen, 97).

metacognitive awareness in order to support students to self-regulate their learning (Schraw et al., 06).

Three fundamental principles for successful metacognitive instruction include: connection of metacognitive instruction with the subject content, informing learners about the usefulness of metacognitive activities to motivate them to exert the initial extra cognitive resources, and allowing learners to reflect on and practice metacognitive strategies (Veenman at al., 06). For instance, during a learning session, educators can label and discuss a particular metacognitive strategy when it is useful for learning. This explicit prompt creates awareness of the strategies and encourages learners to recognise such strategies when they appear in other situations. Educators can also teach learners to *self-question* in order to facilitate metacognition. Through practice of self-questioning, students learn to monitor their own cognition, and make judgments about their learning, knowledge, and success of regulatory functions (Schraw at al., 06; Tarricone, 11). This type of monitoring and self-evaluation enables the learner to adapt according to their learning environment, make corrections to behaviours where needed and subsequently develop more understanding of both the task at hand and their cognitive processes. Feedback is particularly important as it can increase learners' self-regulatory skills and metacognition because it enables learners to overcome preconceptions and accommodate new information (Schraw et al., 06).

However, it is important to use appropriate scaffolds during learning because learners cognitive load is limited. For example, in a web-based learning experiment designed to encourage self-feedback (Bednall & Kehoe, 11), prompts for student self-assessment degraded performance. Requiring metacognitive reflection can produce split attention, by dividing the cognitive resources of the learner (Bednall & Kehoe, 11). This is indicative of the importance of ensuring that extra support does not overburden the learner.

2.4.5 Measuring and Modelling Metacognition

Assessment of metacognitive knowledge and regulatory strategies by educators and researchers has been carried out using formal (e.g. questionnaire and interviews) and informal (e.g. encouraging students to engage in self-evaluation) approaches

(Pintrich, 02; Pintrich et al., 00; Tarricone, 11). Educators who discuss metacognitive knowledge as part of their normal classroom teaching can become aware informally of the general level of metacognitive knowledge and will be able to judge the level and depth of students' metacognitive knowledge. Metacognition can also be assessed informally by providing students with the opportunity to self-evaluate their own strengths and weaknesses through discussion, interviews, through developing reflective portfolios, or concurrent think-aloud (Pintrich, 02). While these approaches can provide rich information about the learner's metacognitive strategies there are several limitations. Feedback is limited to what the learner can report - as learners become more expert their cognitive strategies can become automatic. Although think-aloud studies can be applied in conjunction with retrospective reports, they can distrust the cognitive process and are subject to introspection (Pressley & Afflerbach, 95). Also, this type of feedback results in large amounts of qualitative data, making it difficult to compare learners to their peers of previous performance.

There are also a number of formal methods for assessing facets of metacognitive theory such using a number of psychometric inventories and response metrics. Metacognitive monitoring has been examined under metrics such as Judgment Of Learning (JOL), Feeling Of Knowing (FOK), and Knowledge Monitoring Assessment (KMA), which compare confidence in response judgments to subsequent test results (Pintrich et al., 00; Azevedo & Witherspoon, 09; Serra & Metcalfe, 09; Tobias & Everson, 00; Tarricone, 11). These types of measurements involve asking a learner how well they think that they answered or could answer a question/solve a problem and subsequently compares their belief to the actual test result (Tarricone, 11). Although these measurements can provide useful product measures, they are limited in the insight that they can provide about the individual's knowledge, their cognition, and the regulatory strategies available to them (Veenman et al., 06).

There are a number of psychometric inventories, which have been constructed to specifically measure metacognitive facets of cognition. These address a range of specific metacognitive knowledge and regulatory factors – for example the Motivated Strategies for Learning Questionnaire (MSLQ) (Pintrich et al., 91), Self-efficacy and Metacognition Learning Inventory-Science (SEMLI-S) (Thomas et al., 08), State Metacognitive Inventory (SMI) (O'Neil & Abedi, 96), and the Metacognitive

Awareness Inventory (MAI) (Schraw & Dennison, 94). The MAI is used in this research as a vehicle for modelling and tracking learner metacognition. This specific inventory will be discussed in greater depth, however first it is necessary to examine the qualities of psychometric inventories and the factor analysis methodology with which it was developed.

2.4.6 Metacognition and Psychometrics

Psychometric tests are standardised measurement systems and inventories that are used to evaluate or examine cognitive functions. The derivation of psychometric inventories was motivated by the progression in psychology towards the scientific method (Kline, 08). Principles of mathematics and statistics are used to describe cognition and differences between individuals. The aim of psychometrics is to quantify human functioning so that it can be subjected to experimentation (Cattell, 81). This involves describing our cognitive strategies, emotional traits, and personality characteristics in an observable and quantifiable way. There are a multitude of higher-order skills that are similar in their importance to learning, yet difficult to quantify, for example, the abstract cognitive skills that control the monitoring and regulation of learning. These complex cognitive skills are external, yet supportive of the academic domain, and are unique due to the nature of the learning they support.

Over one hundred psychometric inventories are currently available for clinical, educational and organisational or occupational evaluations e.g. 16PF, Big Five, and Myers Briggs. They are concerned with the measurement of a number of things including numerical ability, verbal ability, memory span, spatial relations, conformity, occupational tests, depression, anxiety, empathy, and metacognition (Kline, 95). For example, in studying personality, an investigator is likely to use a self-report survey such as the Big Five or 16PF.

Factor analysis (Spearman, 1904; Caroll, 93; Kline, 08) is a process commonly used to construct psychometrics. Factor analysis can be described as compressing a large number of related observed variables into a smaller set of descriptive, but latent variables. In order to create a new test (Kline, 95), the first step is to generate a pool of observable items that are likely to be related to a particular trait or variable. These

items are administered to a large sample that are representative of the population. Subsequently, the correlation between items is subjected to factor analysis. Taking into account measurement error, where a group of variables is highly correlated, they measure one thing. Items are selected which are related to only one factor, and new items can be generated where necessary. These items are administered to new samples in order to derive a reduced set of descriptive factors and their observable items. The combinations of these factors in a correlation matrix describe an overarching trait or dimension. In essence, there is a hierarchical relationship as each trait may have a number of latent descriptive factors, and each factor is represented by a number of component items. Items that correlate highly with each other represent a single factor. Inventories employed by psychologists require individuals to respond to each of these items with yes/no or responses on a scale from strongly agree to strongly disagree, often categorised along a Likert scale.

The importance of these tests is their useful predictive and comparative power. However, psychometric tests do not give a single true value or provide an all-encompassing perspective (Kline, 08). For example, you cannot say that a person is 60% metacognitive. When it comes to cognition or personality scales there is no real zero. The power of these inventories is as representational tools, on which progress may be measured over time. They measure a subset of factors that describe a potential cognitive skill – for example, planning and debugging are component factors of metacognition.

For a psychometric test to be considered good, it should possess the following characteristics (Kline, 08):

1. Test-Retest reliability - For components that are not expected to change over time the test should yield the same score for subjects.
2. Internal consistency – Inventories should be univariate, measuring only one construct to ensure that items are created with only one goal.
3. Validity – The test measures what it is meant to measure. Tests can be compared with others that are similar to see if there is a correlation between them and whether there is construct validity. They should also demonstrate predictive power.

5. High discriminatory power – Meaning that subjects should not all receive the same score on a test. Instead, the test needs to demonstrate that it can be used as a tool to understand individual differences.

The MAI is well cited in the literature as a measurement system for describing our underlying metacognitive traits (Schellings, 11; Canella et al., 10; Young & Fry, 08; Sperling et al., 02). Metacognitive awareness and regulatory strategies play an important role in complex tasks and problem solving, and can be predictive of performance of monitoring accuracy (Schraw & Dennison, 94). The MAI was derived through the process of factor analysis (Schraw & Dennison, 94) and has been validated as a reliable test for metacognitive awareness among older students. It is a 52-item instrument that represents the two-component model of metacognition that includes knowledge and regulation of cognition. Knowledge of cognition represents individual's awareness of their cognitive strategies, where their strengths lie and when and how to implement them. Knowledge of cognition is represented by three factors - declarative, procedural and conditional knowledge. Regulation of cognition refers to five factors; evaluation, debugging strategies, comprehension, information management strategies, and planning. Each of these factors is assessed using a number of items. For example, in the MAI *planning* comprises of observable items such as '*I pace myself while learning in order to have enough time*"; "*I think about what I really need to learn before I begin a task*"; and "*I set specific goals before I begin a task*." The items depict learning situations in which awareness of one's knowledge and awareness of one's skills are related to effective monitoring and regulation (Mango, 10).

The validity of the MAI has been ratified through comparing scores with other measurements related to metacognition such as monitoring ability, performance on tests, and the ability to monitor progress (Schraw & Dennison, 94; Young & Fry, 08). Significant correlations have been found between the knowledge of cognition and the regulation of cognition (Schraw & Dennison, 94; Sperling et al., 04). Subsequent analysis by Yildiz explored the eight factors MAI solution proposed by Schraw and Dennison (Yildiz et al., 09). Their factor analysis extracted the same eight-factor solution and further confirmed these factors using Confirmatory Factor Analysis

(CFA). The results of the CFA revealed that all items had significant relationships to their specific factors.

The results of the studies in which the MAI was used to assess metacognition and compared it to educational outcomes point to a correlation with overall course scores and GPA rather than specific continuous assessment results. Significant correlations were found between the MAI and broad measures of academic achievement (Young & Fry, 08). For instance, both regulation and knowledge of cognition have been related to GPA and end of course scores (Young & Fry, 08; Everson and Tobias, 98; Nietfeld et al, 05; Schraw, 94). These results also provide support for the validity of the MAI as it relates to academic measures. However, correlation to single test scores within a course is not as certain, as found between the MAI and SAT math scores (Sperling et al., 04) and results on continuous assessment tests (Young & Fry, 08). In other cases knowledge of cognition on the MAI has been significantly related to higher test performance, whereas regulation of cognition was not (Schraw & Dennison, 94). This is because there may be confounding issues other than utilisation of metacognitive regulation and knowledge skills. From this perspective, the MAI is better correlated to broad measures of academic achievement such as GPA and end of course grades rather than single measures (Young & Fry, 08).

However, there is support for modelling the MAI and using it as a basis for prompting learners to active items in the model. At a broader level, educators can use MAI scores to flag students who obtain low scores on the MAI and determine what type of metacognitive knowledge and regulatory skills the student reportedly underuses while learning (Young & Fry, 08). Success has been reported in improving discrete test scores by prompting these items. Pseudo-dialog using static questions derived from the MAI has been used to prompt learners during a learning task (Saadawi et al., 11). These prompts provided learners with an opportunity to assess their own past performance and also suggested ideas for new learning strategies. The results show that immediate feedback using the MAI is associated with an improvement of overall feeling of knowing (FOK) accuracy and an increase in the learner's ability to distinguish correct and incorrect responses (Saadawi et al., 11). These findings are consistent with results from other researchers who claim that metacognitive prompting increases learning performance through activation of reflection and

strategy knowledge (Chatzipanteli & Digeldis, 11; King, 92; Davis, 00; Lin & Lehman, 99).

2.4.7 Conclusion

Metacognition is an essential higher-order thinking skill that comprises of knowledge about cognition and regulatory strategies and can differentiate successful learners from their less successful peers (Schraw et al., 06). It is a key component of self-regulated learning because it enables learners to engage in reflective thinking, become more aware of their learning strategies, and gain autonomy over how they acquire new knowledge and skills. These strategies are particularly important for the lifelong learner because through self-assessment and practice they can improve their understanding of course material, tasks to be completed, their own cognitive abilities, and perform better in the learning environment (Tarricone, 11; Schraw et al., 06). Metacognition is an integral part of effective reading comprehension and understanding academic material because successful readers use more cognitive strategies, use them more frequently, and have enhanced metacognitive awareness of their own use of strategies and what they know (Brown, 94; Illustre, 11; Afflerbach, 02; Hamadan et al., 10). Metacognitive instruction can include connection of metacognitive instruction with the subject content, informing learners about the usefulness of metacognitive activities to motivate them to exert the initial extra cognitive resources, and enabling learners to reflect on and practice metacognitive strategies through dialog with tutors and peers as well as internal dialog through reflection on progress in a learning task. Assessments of metacognitive knowledge and regulatory strategies by educators and researchers have been carried out successfully using the MAI, which has been validated as a reliable test for metacognitive awareness among older students. The items on the MAI have also been used to create static metacognitive hints that prompt the learner during a learning task (Saadawi et al., 11). This type of metacognitive prompting has been shown to increase learning performance through activation of reflection and strategy knowledge (Chatzipanteli & Digeldis, 11; King, 92; Davis, 00; Lin & Lehman, 99). Increasing the quantity and quality of metacognitive knowledge and monitoring skills through systematic support is desirable because it enables learners to take conscious control of their learning (Flavell, 79; Schraw et al., 06).

2.5 Conclusion

This chapter described the psychological and pedagogical learning theories that play an important role in learning, cognition and metacognition and have influenced the development, as part of this research, of a model to support metacognition in the context of a TEL environment. In particular, it has examined *learning, cognition* and *metacognition*. Over the course of our cognitive development, we construct unique and individual knowledge and cognitive capabilities. Schema theory describes our individual mental models as influencing how we perceive the learning environment and as being malleable - knowledge is assimilated, restructured and accommodated into our existing knowledge stores. Our ability to understand and respond to our environment becomes more able and complex over time as we acquire greater declarative knowledge, procedural or strategic knowledge and develop metacognitive knowledge. As strategies and knowledge are practiced and internalised, this frees up our cognitive resources and enables us to re-evaluate our subsequent learning goals.

Although we possess individual knowledge and strategies, we also learn within a social context. Tutoring and scaffolding supports offered by tutors have been recognised as the most effective form of instruction, because the tutor can engage with the learner as an individual in order to guide them towards achieving their learning potential and autonomy. Metacognition is an integral part of self-regulation, which enables us to actively monitor and subsequently regulate our approach to learning tasks and reading comprehension. The concept of metacognition draws from constructivist roots in cognitive and social-cognitive theories, in particular theories of cognitive development, higher-order reasoning, reflection, self-regulation, mental models and metamemory. It is a skill that comprises of knowledge about cognition and regulatory strategies and can differentiate successful learners and readers from their less successful peers. Metacognitive instruction can happen through scaffolding by motivating learners by explicitly discussing the usefulness of metacognitive activities. This often happens by enabling learners to reflect on and self-assess their own capabilities, ability within a domain and their progress when engaged in a task. Reflection is often triggered by dialog with tutors and peers as well as internal dialog as learners reflect on their goals and cognitive abilities at different stages of learning – this may be prior to a learning enterprise in order to set goals that are within their

reach, during their learning task as they assess their progress, and after the learning task to reflect on how well the strategies they implemented aided them in achieving their goals. There are many of approaches to assessing metacognitive capabilities. While metacognitive monitoring assessments such as FOK can provide useful product measures, they are limited in the insight that they can provide about individual's knowledge about their cognition and the regulatory strategies available to them. On the other hand, psychometric inventories such as the MAI specifically assess learners' knowledge about cognition and regulation of cognition capabilities. This means that it is possible to decompose regulatory strategies into a set of factors (such as planning, self evaluation and debugging strategies). Thus, the MAI can be used as a tool with which to flag learners who obtain low scores and determine what type of strategies the learner reportedly underuses while learning.

The problem of modelling and fostering cognitive aspects of the learner to support learning with TEL is challenging. The modelling, tracking, and support of metacognition as students engage in learning activities needs to be addressed. From this perspective, there is a need for an approach to model and support learner cognition that can be logically discrete and separate from a TEL learning environment. There are a number of issues that need to be addressed when developing a metacognitive support that is logically separated from a TEL environment. First, there is the question of design – how can a learner be modelled using a separate service? This requires an understanding of the ways in which we model our own knowledge, how we engage in learning environments (tasks, or the cognitive strategies for academic reading), and how to model and foster metacognition (traits, in particular the regulatory cognitive strategies that are antecedent to positive learning). The second question is about the approach taken to implement this model. Currently, there is lack of consensus on how to model cognition and support metacognition in TEL. In the next chapter, a review of adaptive TEL environments that model learner cognition, provide adaptive instruction and feedback, and deliver metacognitive support is presented.

An overview of the core theories and features that have influenced the design and implementation of ETTHOS is presented in Table 2.2 below. The *key* here will be referred to in future chapters in order to link back to the TEL features and the

concepts taken under consideration when developing the components of and implementation strategy for the ETTHOS model. The *description of the concept* provides a brief summary of the concept, in order to serve as a road map with which to understand the psychological and pedagogical theories under investigation in this thesis. The *illustrated by* column provides references for these concepts.

Key	***Description of Concept***	***Illustrated By***
L1	***Learning is a constructivist process***, whereby the process of learning is active and involves the processing of information from our environment to derive meaning from experience, form hypotheses, make decisions and respond to the learning environment.	Gunstone, 94; Perkins, 91; Jonassen, 99; Harris & Graham, 94; Driscoll, 05
L2	***Knowledge and abilities strengthen with practice and use***, which frees up our cognitive resources for more complex or novel tasks. Our ability to understand and respond to our environment becomes more able (and more complex) over time as we learn how to better process information, and build a rich knowledge and strategy repertoire.	Sweller, 04; Piaget & Inhelder, 73; Zimmerman, 89; Siegler, 82; Dienes & Perner, 99; Anderson, 83
L3	We possess ***unique and individual differences in our cognitive and metacognitive styles***. Over the course of our cognitive development we develop individual and idiosyncratic knowledge and strategy repertoires – our mental models, how we think, and interact with the learning environment varies compared to the next person.	von Glasersfeld, 90; Tarricone, 11; Brown, 87
L4	There are ***differences between novice and expert learners***. As individuals learn new procedures and become more expert they become progressively automatic. Expert readers possess metacognitive knowledge about reading strategies, meaning that they are aware of their strategies and can employ them in the right context. ***Scaffolding support given to novice learners enables them to internalised new or difficult material and strategies so that they can apply them independently***.	Pressley & Gaskins, 06; Langer & Applebee, 86
L5	***Cognitive load is limited***, but this can be buffered through scaffolds and learning supports. As students begin to demonstrate task mastery as they acquire more complex mental models, the responsibility of the learning should be given to the learner and less support provided.	Sweller, 04; Chandler & Sweller, 91; Bendall & Kehoe, 11; Ohlsson & Mitrovic, 07
L6	***Schemata (mental models) are organised patterns of behaviour or mental representations*** that organise knowledge, skills and rules, and are used to understand and interact with the world. Schemata can provide the impetus for reflective thinking and enable learners to transfer strategies across domains according to cognitive constructivist theories.	Ibrahim et al., 03; Piaget 29; Anderson, 77; Anderson, 84; Bartlett, 32; Rumelhart 80; Derry, 96
L7	Knowledge is the set of understanding or body of information possessed by an individual that is innately available or experientially acquired. ***Knowledge can be described as declarative*** (factual), ***procedural knowledge*** (strategic) and ***metacognitive*** (knowledge about cognition and regulation of cognition).	Zimmerman, 89; Pressley, 87; Graesser et al., 10; Zimmerman, 89; Chomsky, 84; Brown, 87; Schraw & Dennison, 94

L8	***Cognitive strategies and metacognition are particularly important when reading***. Successful readers use more cognitive strategies, use them more frequently, and have enhanced metacognitive awareness of their own use of strategies and what they know, which in turn leads to a greater reading ability and proficiency. Expert readers use targeted metacognitive strategies before, during and after reading to aid their comprehension and understanding.	McNamara, 09; Illustre, 11; Pressly & Afflerbach, 95; Hamadan et al., 10;
L9	Learning is not just an individual process however; we make meaning from the people and our peers. ***Tutoring is the most effective form of instruction***, whereby tutors support and scaffold learners in order to achieve their learning potential whilst being sympathetic to their cognitive load.	Vygotsky 62, 78; Eberle, 92; Berger & Luckman, 67
L10	Through the structure provided by ***scaffolding***, learners are given personalised ***feedback and support towards independent and self-regulated competence*** of skills.	Bruner, 75; Dickson et al., 93
	SRL is important to enable learners to become autonomous and self-directed. Learners who apply effective self-regulation during learning activate more suitable schemata for the task at hand, but also activate schemata responsible for monitoring which consequently regulates their own performance at that task.	Schunk, 96; Schraw et al., 06; Schunk & Zimmerman, 98, 00; Graesser & McNamara, 10
L11	***Scaffolds can enable learners to make the progression from dependent to self-regulated learners***. For example, enabling learners to engage in reflection and introspection facilitate the development of knowledge about their internal processes, which is fundamental to metacognition.	Bruner, 90; Tarricone, 11
L12	***Positive transfer can result in increased performance and reduce the amount of cognitive load*** required from learners if they can activate previously encoded strategies or knowledge. Greater metacognitive knowledge results in a more flexible cognitive strategy repertoire.	Schraw & Dennison, 94; Butcher & Aleven, 99
L13	***Metacognition is antecedent to positive lifelong learning***. It is a component of self-regulated learning that can be described as comprising of knowledge of cognition and regulation of cognition.	Flavell, 79; Tobias & Everson, 02; Brown, 87; Paris & Winograd, 90; Schraw & Dennison, 94; Whitebread et al., 09
L14	***Educators are metacognitive professionals*** who can scaffold metacognitive strategies along with traditional supports for domain learning. The prompting of metacognitive reflection during learning has proven beneficial to learners self-evaluations and learning outcomes.	Duffy et al., 09; Wilson & Bai, 10
L15	***Psychometric inventories*** provide a mechanism with which to quantify cognitive functioning. The ***MAI in particular has been validated and ratified as an inventory that can describe the knowledge and regulatory components of metacognition***.	Schraw & Dennison, 94; Young & Fry, 08; Yildiz et al., 09

Table 2.2 - Theories of Learning, Cognition and Metacognition

Chapter 3 Cognition and Metacognition in Technology Enhanced Learning Environments

3.1 Introduction

This chapter investigates the attributes of adaptive TEL systems that address cognitive and metacognitive modelling. It first provides an introduction to adaptive Technology Enhanced Learning (TEL) environments, the goals and characteristics of metacognitive supports in TEL and the questions that need to be asked when developing supports in this context. After an examination of the influences of cognitive science on TEL environments, this chapter inspects user modelling and adaptation approaches that can influence the development of a novel reference model for modelling, assessing and fostering learner metacognition. It then shows that cognitive modelling can be decomposed across web services and that adaptive supports can be provided using algorithmic rule-based reasoning. It subsequently focuses on environments that support metacognition, elaborating on these systems in order to consider their mechanisms, successes, and limitations. Having established that most TEL environments do not directly model components of metacognition and those that do are tightly tied to a learning environment meaning that they can not be reused for lifelong learning supports across multiple environments, it concludes by recommending that metacognitive modelling and support can be provided as a service for use with a TEL environment. This will be achieved through dynamic and static models of both metacognition and cognitive strategies (that the learner is expected to engage in when learning in a TEL environment). In particular, this means modelling of learner (traits) using the structure of psychometric inventories (MAI) and bridging the gap between the metacognitive service and the TEL environment by describing the phases (tasks e.g. planning during the introduction and self-evaluation during the conclusion) of learning.

3.2 Cognition and Metacognition in TEL

3.2.1 Supporting Metacognition with TEL Environments

TEL environments that adapt to the learner do so through modelling, adaptation, and personalisation techniques that are grounded in computational processes and underlying pedagogical and psychological theories (Azevedo, Moos, Witherspoon, et al., 09; Graesser and McNamara, 10; Ohlsson and Mitrovic, 07; Ruiz et al., 08; Brusilovsky, 01; Knutov, De Bra & Pechenizkiy, 09; Graesser, Conley & Olney, 10. Adaptive TEL environments personalise the content and delivery mechanisms of course materials, supports, and scaffolds in order to suit the needs of the learner as an individual. This means that each learner experiences content that is tailored to their needs or actions as opposed to the '*one size fits all*' approach in traditional learning environments (Brusilovsky, 01; Walsh et al., 11). This adaptive approach has proven merit for the learner, exemplified in the learning gains that can result from altering course content depending on the learner's ability or by providing supplementary support (e.g. prompts or hints) (Brusilovsky, 04; Aleven et al., 06). In doing so, they address the need for learner supports that were traditionally available to the learner in the classroom via the educator, tutors, and peer interactions.

TEL research reports a range of approaches for capturing and classifying learner cognition, which vary in their complexity, level of granularity, pedagogical or psychological perspective (Azevedo, Moos, Witherspoon et al., 09). Accordingly, the design of educationally responsive learning environments requires two lines of enquiry: pedagogical theory and technological approaches. This chapter focuses on TEL environments that '*adapt*' to the learner – unless explicitly highlighted it will discuss adaptive TEL environments. Here, two issues in the problem of modelling cognition and metacognition are introduced. First, an overview is provided of the characteristics and functions of adaptive TEL. Secondly, the concept of metacognition in the context of learning, and the goals and characteristics of metacognitive supports are introduced.

3.2.2 What are Adaptive TEL Environments?

Adaptive TEL environments have three main functions – they combine a mechanism for *user modelling* with the functionality to carry out *adaption reasoning* (Brusilovsky,

01; Knutov et al., 09; Graesser, Conley & Olney, 10) in order to deliver *personalised support to the learner*. Adaptive TEL systems employ techniques such as eye tracking, keystroke, navigational analysis, performance analysis, and dialog interactions in order to model the learner (Azevedo, Moos, Johnson, et al., 10). These techniques can be used to create a limited model of the learner, and can be combined for a more complete representation of the learner. Researchers, who have developed TEL environments have reported successes such as improvements in knowledge gain, decreased time to successfully complete tasks and increased motivation (e.g. Azevedo, Witherspoon, Chauncey, et al., 09; Labuhn, Zimmerman & Hasselhorn, 10; Ley, Kump & Gerdenitsch, 10; Kerly, Ellis & Bull, 08; Kinnebrew & Biswas, 11; Conlan & Wade, 04; Brusilovsky, Sosnovsky, et al., 10).

This chapter explores two main categories of adaptive TEL environments - Intelligent Tutoring Systems (ITS) and Adaptive Educational Hypermedia [18] (AEH) environments[19]. *ITS* generally structure their models and adaptation strategies differently to *AEH*, however recently there has been crossover between the two with the development of hypermedia-based tutoring systems (Azevedo, Witherspoon, Chauncey, et al. 09; Mitrovic & Martin, 07). ITS often incorporate Artificial Intelligence (AI) methods from education[20] (Robinson, McQuiggan & Lester, 09; VanLehn, 06; Alves, Amaral & Pires, 06), pedagogical models (Koedinger, Aleven & Heffernan, 03) and mathematical models (VanLehn & Lynch, 05), and draw from cognitive science (Graesser, Conley & Olney, 10). In ITS the problem solving tasks are typically decomposed into sub components or activities. Instruction is provided for each step or activity needed to solve a problem or complete a task. Overall information and feedback is provided. The tutor actively exposes the goal of the task by illustrating the separating of components with feedback, hints and support. Although ITS have started to become web-enabled, they are generally delivered as services, for example using Java, Flash, or using other simulation environments

[18] There are a number of descriptions of AEH technologies found in the literature, each of which can have slightly different connotations, including *Adaptive Hypermedia (AH), Adaptive Web Systems* (AWS) (Brusilovsky & Millán, 07), *Adaptive and Intelligent Web-Based Educational Systems* (AIWBES) (Brusilovsky & Peylo, 03), *Adaptive Educational Systems* (AES) (Brusilovsky & Millán, 07), and *Adaptive Hypermedia Systems* (AHS) (Brusilovsky, 07; Knutov, De Bra & Pechenizkiy, 09). There are a number of different types of AH systems, including educational systems, information systems, help systems, information retrieval and systems for managing personalised views in information spaces, and instructional hypermedia (Brusilovsky, 96; Brusilovsky, 01).

[19] Researchers have carried out significant evaluations on the effectiveness of ITS tutors over the last 35 years (Graesser, D'Mello & Cade, 10), and adaptive hypermedia systems for around 17 (Brusilovsky, 01). As a result of their successes, ITS and AEH are now being deployed in schools and universities worldwide (Avezedo et al., 10; Brusilovsky et al., 10).

[20] Referred to as the Artificial Intelligence in Education (AIED) domain.

(Heffernan & Koedinger, 02; Aleven et al., 09). Unlike Adaptive Hypermedia (AH) however, they generally do not take advantage of the logical decomposition of web pages into nodes or pages and related hyperlinks[21]. AEH provide DOM[22] based personalisation and server-side processing, allowing the learner to refer to the support while they tackle the next step. For example, a learner can be provided an extra sample activity on the web page that assesses the same learning objective. At the heart of AH systems is the user modelling approach, which originated in ITS (Knutov et al., 09) in order to tailor the user experience to suit the needs or preferences of the individual (Brusilovsky, 01; Brusilovsky, 96; De Bra, Stash, Smits et al., 07), however they combine *hypermedia-based adaptation* with adaptive instructional approaches.

In this context an AH system needs to satisfy three criteria (Brusilovsky, 96). Firstly, it should be a *hypertext/hypermedia* system. Hypertext or hypermedia systems generally refer to a collection of web-based pages (nodes) and links (hyperlinks) between them. More recently, this has meant AEH take a service-oriented approach (Brusilvosky, 03). This means that AEH environments can be delivered as a service, in order to incorporate them with other services such as LMS and course management tools. This means that learners often have a greater range of material available to them than they do when using an ITS. Secondly, there should be a *user model*. This user model has an important position in AEH – the automatic modelling of the user through explicit or implicit measures is used to inform any reasoning about adaptation. A number of models such as the user model, group model, domain model, narrative model, and cognitive models can be represented in AH systems. Finally, an AH system should be able to *adapt* using these models – the applied technology of adaptation comprises of pedagogical theory, some form of user model, and decision-making computational process. Although AEH technologies have the capability to adapt to the learner and alter the content and presentation of the web page, to date there are few AEH environments that support metacognition. Those that do, often do so by providing the learner opportunities to reflect on their progress. While there are

[21] AH comes in numerous forms, including recommender environments and filtering services, however educational AH systems are considered leaders in the domain (Brusilovsky, 01; De Bra, Stash, Smits et al., 07).
[22] The DOM (Document Object Model) is the API used to access hypertext pages that are presented in the browser. This means that elements on the page can be accessed and dynamically updated (e.g. different media such as text and images can be dynamically positioned on the page) and events on the page can be tracked and responded to (e.g. a learner can press a button to request more info or scripts can trigger new material after some time has elapsed).

web based ITS environments that directly model metacognition (either through algorithms to infer regulatory actions or through measurements of learner's FOK) these are stand alone environments, meaning that metacognitive modelling and support is not available a service for other environments. While there has been progress in the area of metacognitive supports, and these achievements and approaches will be discussed in greater depth later in this chapter, this is still an important area of inquiry that requires more work. The importance and goals of metacognitive supports are now examined.

3.2.3 Metacognition in Technology Enhanced Learning

Metacognition is of particular importance to support because it is at the heart of self-regulated learning and is considered to be antecedent to positive lifelong learning (Flavell, 79; Tobias & Everson, 02; Brown, 87; Paris & Winograd, 90; Schraw & Dennison, 94; Whitebread et al., 09). The ability to understand your own abilities, strategies and knowledge is central to constructivist learning that enables the learner to become adaptive, autonomous, and respond to their learning environment. As learners attempt to achieve their goals – this might be to solve a problem or complete a task - they actively monitor their behaviour, and their cognitive and metacognitive processes, and constantly evaluate their progress. Subsequently, learners regulate their responses to the task, for example, by changing their cognitive strategy. Greater metacognitive knowledge results in a more flexible cognitive strategy repertoire (Schraw & Dennison, 94; Butcher & Aleven, 99). Learners who apply effective metacognition and self-regulation during learning activate more suitable schemata for the task at hand, but also activate schemata responsible for monitoring which consequently regulates their own performance at that task (Schunk, 96; Schraw et al., 06; Schunk & Zimmerman, 98, 00; Graesser & McNamara, 10).

Educators are viewed as metacognitive professionals who can scaffold metacognitive strategies along with traditional supports for domain learning. The support of metacognition during learning with TEL environments has proven beneficial to learners' self-evaluations and learning outcomes (Duffy et al., 09; Wilson & Bai, 10). In emulating the role traditionally provided by educators, TEL environments need not only promote the acquisition of knowledge, but can also foster learning skills and metacognition, enabling the learner to become self-regulated and autonomous (Kay,

11; Kinnebrew et al., 11; Azevedo, Moos, Johnson et al., 10; Graesser & McNamara, 10). In this sense, TEL environments that support metacognitive ability, as shown in Figure 3.1 below, can be described as having four goals (Koedinger et al., 09).

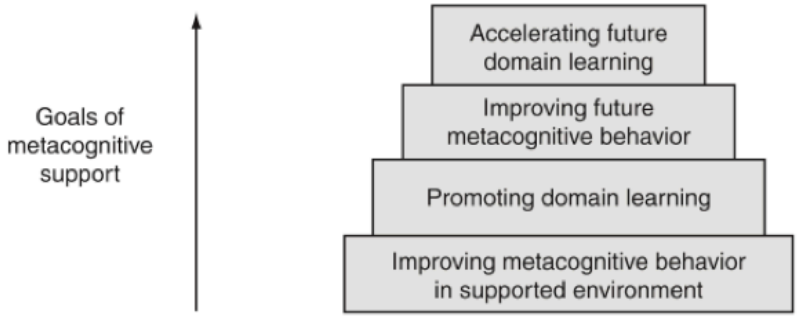


Figure 3.1 - Goals of Metacognitive Tutoring (from Koedinger et al., 09)

The first goal is to improve the behaviour within the context of the learning environment. The motivation behind this is to attain the second goal – to promote domain learning, which should lead to better student performance. The third goal is that these metacognitive strategies are internalised, so that they can transfer them to learning beyond the learning environment. The final goal is that this transfer[23] will lead to better learning in the future overall, that is faster and more complete.

Azevedo and his colleagues (Azevedo, Witherspoon, Chauncey, et al. 09) have identified *six characteristics* that should be present in a learning system for it to be considered a *metacognitive tool*:

1. The *learner should be required to make instructional decisions that can help them achieve their learning goals*. This might include planning, seeking, collecting, organising, and sequencing instruction, attending to and modifying their approach to meet their goals.
2. It is *embedded in a particular learning context*. This means that the learner needs to make decisions regarding the resources, or feedback that can lead to more successful learning outcomes.
3. It should *model, prompt, and support the learner's self-regulatory processes*. This can include cognitive, metacognitive, affective, and behavioural aspects of the learner[24].

[23] Positive transfer can result in increased performance and reduce the amount of cognitive load required from learners if they can activate previously encoded strategies or knowledge. This means that greater metacognitive knowledge can result in a more flexible cognitive strategy repertoire (Schraw & Dennison, 94; Butcher & Aleven, 99).

[24] An example of each of these is as follows: Cognitive competencies include activating prior knowledge, creating goals or sub-goals, and applying learning strategies. Metacognitive traits include feeling of knowing or judgment of learning. Affect refers to the learner's emotional responses such as frustration, flow, or surprise. Finally, behaviour can include engaging in help seeking or modifying the learning conditions.

4. It *models, prompts, and supports learners to engage or participate in using task, domain, or activity specific learning skills*. This includes skills that are complementary to the learning domain and have been identified as supportive of successful learning.
5. That it *resides in a specific learning context*. In this case, peers, tutors, or artificial agents have a role in supporting the learner by acting as external regulating agents.
6. It should be an *environment where the learner can practice metacognitive and self-regulatory processes*. These can be used prior to, during, and following learning. It means capturing a temporal model of the learner, and making inferences on the state of the learner at discrete stages of the learning process.

Table 3.1 - Azvedo's six characteristics of metacognitive tools

Not all TEL environments are required to implement each of these characteristics, rather the approach taken is chosen based on the goal and purpose of the tool. In developing a TEL environment with metacognitive supports, there are a number of questions to be considered (Knutov et al., 09; Brusilovsky, 96). Illustrated in Figure 3.2 below, adaptive system authors must consider the goals of the adaptation, user features, adaptation technologies, methods of adaptation, contextual accuracy, application area, and implementation techniques. In answering the research question[25], it is necessary to design a cognitive model for learner metacognition and describe an architectural approach to implement this model in a manner that is separate while still aligned with a TEL environment.

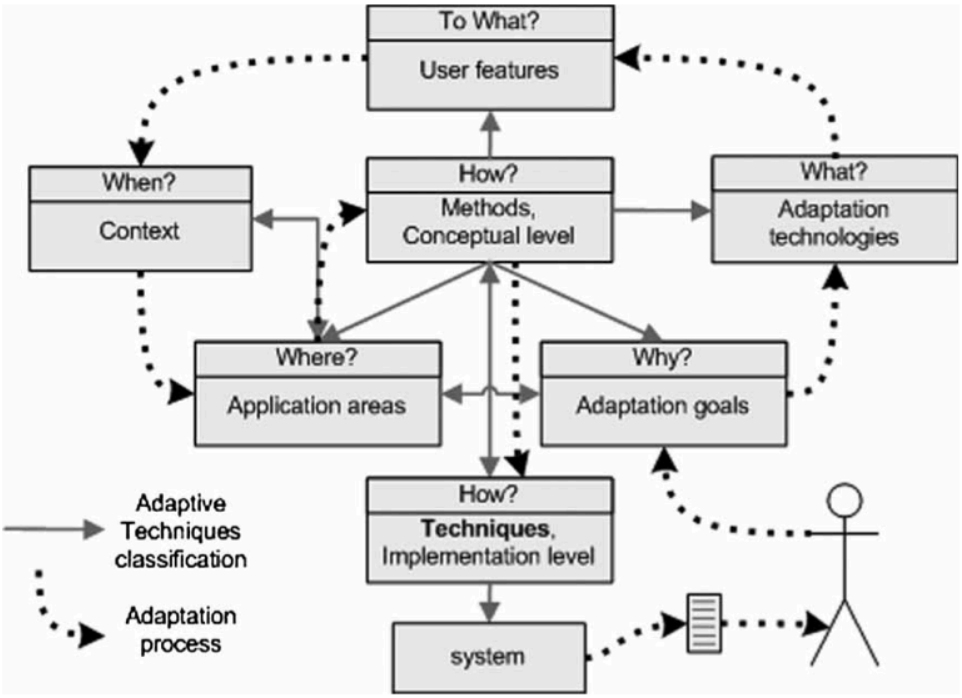


Figure 3.2 - Classification of AH methods and techniques (from Knutov et al., 09)

[25] *How and to what extent can the cognitive aspects of a learner be modelled to support learning with TEL?*

Thus, the *goal* of a model is to represent learner cognition, in a way that is logically separate when developed but is aligned both technically and pedagogically with a TEL environment. In this sense, the model should work alongside a learning environment while supporting complimentary skills to learning in that context. The *user features* that will be modelled and supported are the learners' regulatory metacognitive strategies. However, in order to contextualise the support and provide this support in the context of an application area it is first necessary to examine the implementation techniques, adaptation technologies, and methods of adaptation.

3.2.4 Design of TEL to Support Cognition and Metacognition

Learning environments draw from psychological and pedagogical learning theories. As discussed previously, learning can be considered a constructivist process, whereby the process of learning is active and involves the processing of information from our environment to derive meaning from experience, developing and fine-tuning our mental models of the world, making decisions, and responding to the learning environment (Gunstone, 94; Perkins, 91; Jonassen, 99; Harris & Graham, 94; Driscoll, 05). TEL environments are frequently cited as employing constructivist methods of instruction (Anderson, Boyle & Yost, 85; Koedinger, 01). This is because they provide cognitive and social-cognitive supports such as individual support, scaffolding and fading of supports towards enabling learners to becoming autonomous. This section refers back to the theories of learning presented in Chapter 2 and describes how adaptive TEL environments have implemented these theories in order to enable learners to engage in self-regulatory processes and active metacognition. In particular, it describes how TEL environments aim to emulate the traditional scaffolds provided by educators and tutors, the types of knowledge (declarative, procedural and metacognitive) that are modelled and fostered, the use of dialog and contextually represented feedback to interact with the learner and foster reflection, as well as personalised supports that can be implemented in technical supports (e.g. such as buffering cognitive load) to address individual differences (e.g. in cognitive and metacognitive ability). This section addresses how researchers and developers of TEL environments integrate psychological and pedagogical theories and is used as a basis for informing how a metacognitive model should be implemented as a service.

3.2.4.1 Emulating the Human Tutor

As learning is not considered to be an individual process[26], in *emulating the human tutor* and providing individualised support, TEL systems enable learners to develop knowledge and strategies beyond their immediate grasp. Human tutoring is believed to be the most effective form of instruction, whereby tutors *scaffold*[27] learners in order to achieve their learning potential whilst being sympathetic to their cognitive load (Vygotsky 62, 78; Eberle, 92; Berger & Luckman, 67). TEL environments can support learners to work within their Zone of Proximal Development (ZPD). This type of TEL scaffolding has been successfully employed to help bridge the gap between what learners want to achieve and what they are able to achieve themselves without assistance (Azevedo & Hadwin, 05). TEL environments have repeatedly demonstrated their ability to effectively scaffold learners in well-structured tasks such as maths, based on their ability to monitor and scaffold the learners individual progress (Azevedo & Hadwin, 05; Anderson et al., 95; Aleven & Koedinger, 02), however they can also be used to support learning about learning through metacognitive and SRL scaffolds (Azevedo & Hadwin, 05; Biswas et al., 05; Chase et al., 09; Azevedo, Witherspoon, Chauncey, et al. 09; Aviram, Ronen, Somekh et al., 08; McNamara et al., 07; Vizcaino, 05; du Boulay, 11). This can mean diagnosis and modelling of the learners status, calibrating personalised support, and fading of this support over time (Bruner, 75; Dickson et al., 93; Azevedo & Hadwin, 05) or by simply having the student engage in self-evaluation (Bednall & Kehoe, 11; Chi et al., 11; Azevedo & Hadwin, 05) to enable learner to develop an autonomous and self-regulated competence of skills

3.2.4.2 Declarative, Procedural and Metacognitive Knowledge Support

TEL environments support declarative, procedural and metacognitive knowledge (Anderson et al., 95; Koedinger, 01; Ritter et al., 07; Azevedo, Witherspoon, Chauncey, et al. 09; Puntambekar & du Boulay, 99; Roll et al., 06; Kay et al., 07). As discussed previously, knowledge[28] is the set of understanding or body of information possessed by an individual that is innately available or experientially acquired. For instance, the

[26] Learning is not just an individual process - we can make meaning from the educators and peers around us.
[27] As we have seen in Chapter 2, scaffolds are the tools, strategies, and supports offered by educators and TEL environments during learning to enable learners to acquire knowledge and develop autonomy (Azevedo & Hadwin, 05; Graesser, Wiemer-Hastings et al., 00).
[28] Knowledge can be described as declarative (factual), procedural knowledge (strategic) and metacognitive (knowledge about cognition and regulation of cognition) (Zimmerman, 89; Pressley, 87; Graesser et al., 10; Zimmerman, 89; Chomsky, 84; Brown, 87; Schraw & Dennison, 94).

ACT-R model used in Cognitive Tutors describes the type of knowledge stored in memory as both procedural and declarative (Anderson et al., 95; Koedinger, 01; Ritter et al., 07) whereas the MIRA environment models metacognitive ability by measuring learners' abilities to self-evaluate their progress (Gama, 04). Measures of learner knowledge are quantified in user models within these systems to represent levels of domain knowledge (Brusilovsky et al., 10; Conlan & Wade, 04), strategy development (Aleven et al., 09; Koedinger, 01), and metacognitive/self-regulatory functions (Avezedo et al., 10; Roll et al., 06; Kay et al., 07). Development of these competencies is antecedent of positive lifelong learning (Finley, Tullis & Benjamin, 10), and numerous studies have reported significant positive outcomes for the learner (e.g. Azevedo & Witherspoon, 09; Colineau & Paris, 10; Bednall & Kehoe, 11; Samsonovich et al., 10; Koedinger et al., 09).

3.2.4.3 Decomposition of Strategies and Knowledge into Components

The *decomposition of complex tasks and knowledge into components* is an instructional strategy that is used in TEL environments to represent strategies and skills as a hierarchy of sub-component skills (VanLehn, 06; Azevedo, Witherspoon, Chauncey, et al. 09; Cannela et al., 10). This is particularly used by ITS, whereby these models represent the expected path that the learner will take when engaged with their system[29]. Alternatively, in AEH the curriculum is broken up into discrete learning objects that are combined (e.g. in a single page, or as a series of links, or optional popups).

TEL environments that foster strategies and practical learning enable learners to master lower level skills first before integrating them into solving more complex tasks. The activities (procedural knowledge) that encompass a particular skill are often broken into their component parts as production rules (Heffernan & Koedinger, 02; Koedinger et al., 97). In essence, this means representing the optional paths a learner might take when engaged with the ITS. For example, Anderson's Adaptive Control of Thought-Reflection (ACT-R) model (Anderson, 83) of higher-level

[29] For example, these include the use of *production rules* and *model tracing* in Cognitive Tutors (Heffernan & Koedinger, 02); *curriculum scripts* (Graesser et al., 09); *example-tracing approaches*[29] (Aleven et al., 09; Razzaq et al., 09; Koedinger, Aleven & Heffernan, 03); *constraint-based modelling* (Mitrovic, Koedinger, Martin, 03; Mitrovic, Martin, Suraweera, 07; Ohlsson & Mitrovic, 07; Suraweera & Mitrovic, 02); *case-based reasoning* (Aamodt & Plaza, 94; Watson & Marir, 94; Kolodner, Cox & Gonzalez-Calero, 05; Graesser, Conley & Olney, 10); other *statistical modelling* approaches (Kinnebrew et al., 11, Schwartz et al., 09; Mettler et al., 11); *and algorithmic* and *rule-based reasoning* (Conlan et al., 02, Conlan & Wade, 04; Kabassi & Virvou, 06).

cognition is a constructivist approach to modelling skills in Cognitive Tutors[30]. *Model tracing* is an AI technique often used in ITS, in particular the Cognitive Tutors (Aleven et al., 06, Koedinger, 01), to compare the expected activity or '*procedure model*' to the learners' actions. This approach takes a componential analysis of learning, whereby the instructional developer must write production rules for each cognitive action (Anderson et al., 95), which results in a high level of support for very specific learning curriculum. A variety of other techniques have been employed in order to assess, trace, model, and support learner cognition including constraint-based modelling (Mitrovic, Koedinger, Martin, 03; Mitrovic, Martin, Suraweera, 07), case-based reasoning (Ohlsson & Mitrovic, 07), task analysis (Lesgold et al., 92), and example-tracing (Koedinger, Aleven & Heffernan, 03; Aleven et al., 09). The system needs to be able to match the student behaviour to the production rules in order to determine how to support them next. This type of approach is limited to domains where the skill can be described as a set of inferential chains, or process rules (Mitrovic, Koedinger, Martin, 03) but because the system can track the learner's progress towards a particular goal, this allows for just-in time and contextualised support to be delivered.

3.2.4.4 Supports in the TEL Environment

TEL environments often attempt to imitate the traditional classroom experience by providing contextually represented feedback (e.g. help on a particular math problem the learner is trying to solve) as well as offering general supports (e.g. study tips). This can achieved through a number of approaches such as reproducing interactive dialog patterns (Graesser, D'Mello & Person, 09) or altering the facial expressions on an avatar (Johnson et al., 03). Learners engage with the tutor by answering or asking questions, either through a menu system (Razzaq et al, 09), or in a chat window (D'Mello & Graesser, 10). Other systems highlight the part of the task or problem where the learner has done well or has made an error, and can suggest how to alter it (VanLehn et al., 05). They can also hint at the next step or even display the next step in the task. Feedback is often presented as a notification or popup on the learning system (Medicino et al., 09; Saadawi et al., 11) alongside the traditional learning material, or by providing visual overviews where the learner can inspect their

[30] ACT-R has been implemented in cognitive tutoring systems such as the LISP tutor (Anderson, Farrell & Sauers, 84), Geometry Tutor (Anderson, Boyle & Yost, 85), Geometry, Bridge to Algebra, Algebra I, Algebra 2, Excel, Ms. Lindquist algebra tutor (Heffernan & Koedinger, 02), the PUMP (Pittsburgh Urban Mathematics Project) Algebra Tutor (PAT) (Koedinger, Anderson, Hadley, & Mark, 97; Koedinger, 00), and Sherlock (Lesgold et al., 92).

progress or comparisons to an expert solution (Gott et al., 96; Gama, 04; Luckin & Boulay, 99).

TEL supports can be in the form of pre-stocked questions, pumps, prompts, and hints, as well as dynamic support (e.g. dynamic text or dialog interactions as well as visual representations of the learners progress) that is tailored to the student and context, or pedagogical agents that guide students in their thinking through simulated dialog (Azevedo & Hadwin, 05; Azevedo, Witherspoon et al., 09). Dialog can play an important part of self-reflection and of metacognitive awareness and development. Traditionally, this may take the form of discussion with peers, educators, or an internal dialog as part of the self-reflection process. There are several dialog-based tutors that have reported successful results in the literature. Learners can engage with tutor systems by answering or asking questions, either through a menu system (Razzaq et al., 09), or in a chat window (D'Mello & Graesser, 10). These scaffolds can include extra conceptual knowledge about the task, salient feedback, or identify how the learner can proceed to the next stage (Anderson et al., 95). Alternatively, the learner might be presented with an alternative rephrasing of the problem (Heffernan & Koedinger, 02), which will allow them view the problem from a different perspective.

3.2.4.5 Dealing with Individual Differences

To facilitate individual differences in the learner's cognitive and metacognitive abilities, a wide range of adaptive TEL environments have been developed in order provide intelligent support. TEL research has moved towards personalisation and adaptation in response to learners' unique dispositions. Over the course of our cognitive development we develop individual and idiosyncratic knowledge and strategy repertoires – our mental models, how we think, and interact with the learning environment varies from person to person (von Glasersfeld, 90; Tarricone, 11; Brown, 87). Often, there are *differences reported between novice and expert learners*. For instance, expert readers possess greater metacognitive knowledge about reading strategies, meaning that they are aware of their strategies and can employ them in the right context. *Cognitive load* is particularly limited in novice learners, however this can be buffered through scaffolds and learning supports. Knowledge and abilities strengthen with practice and use, which frees up our cognitive load

resources for more complex or novel tasks[31]. (Sweller, 04; Piaget & Inhelder, 73; Zimmerman, 89; Siegler, 82; Dienes & Perner, 99; Anderson, 83; Ritter et, 07). As they begin to demonstrate task mastery when they acquire more complex mental models, the responsibility of the learning can be given to the learner through fading of supports (Sweller, 04; Chandler & Sweller, 91; Bendall & Kehoe, 11; Ohlsson & Mitrovic, 07). Scaffolding support given to novice learners enables them to internalise new or difficult material and strategies so that they can apply them independently (Pressley & Gaskins, 06; Langer & Applebee, 86). In tutoring environments, support can be provided as needed - for example, extra examples are given to learners who struggle on a learning task. In AEH environments, learners are often categorised by stereotype in order to inform reasoning engines for later personalisation (Brusilovsky, 04; Conlan & Wade, 04; D'Mello & Graesser, 2010; Kinnebrew, Biswas, & Sulcer, 2011). Cognitive support is dependent on the category of learner – for example, numerous AEH systems personalise the course dependent on the learner's prevalent cognitive style (e.g. some learners may prefer illustrations whereas other learners may prefer written examples). Individual differences may be assessed on the fly (e.g. through comparison of the learners progress to the expected models), or at the beginning of the course (e.g. a quiz may be administered to the learner when they register with the learning environment).

3.2.5 Conclusion

TEL environments have the capability to not only model and support declarative and procedural aspects of learner cognition but also deal with their metacognitive competencies. Instructional design strategies that originated in the traditional educational setting have been implemented in technical models and systems in order to compensate for the lack of social and tutor interaction. These environments have been developed to take account of cognitive theories, such as the individual differences in how we process information and the level of cognitive load available to novice learners, as well as social cognitive learning theories of learning such as the promotion of reflective experiences and scaffolding of supports towards enabling learners to become self-regulated, metacognitively aware and autonomous learners. In particular, metacognition and regulatory strategies are important for successful

[31] Since, learning is a process of encoding, strengthening, and proceduralising knowledge this means that new knowledge is weak until it is strengthened through reuse and practice. Our ability to understand and respond to our environment becomes more able (and more complex) over time as we learn how to better process information, and build a rich knowledge and strategy repertoire.

learning. While cognitive processes can be modelled through model tracing, constraint modelling and other algorithms, these approaches are limited to domains where inferential chains can be created and are tied to one TEL environment. In designing a cognitive model of learner metacognition that can be implemented as a separate service, it is therefore important that it work with a separate TEL environment in a manner that is as loosely coupled as possible to allow for reuse. It is also important that a method to quantify metacognition is provided, while being cognizant in the implementation of this model that suitable instructional design decisions are taken. The next section examines the nature of adaptation and user modelling in TEL environments in order to describe which features of these models can be harnessed for such a model and to describe how modelling approaches are currently being distributed over the web as services.

3.3 User Modelling and Adaptation

Adaptation in TEL refers to the dynamic nature of content, support, and presentation in the learning environment, which is altered to suit each user or learner. This can be in the form of course feedback, support, hints, content delivery, or content annotation. A number of *models* are used to represent aspects that can influence the learning experience, such as a learner model, domain model, content model, narrative model, and pedagogical model. User models are sets of structured stores of information that represent the competencies and tasks carried out by the learner. In particular, the changing nature of learners' actions, responses, and characteristics (such as knowledge, skills, self-regulation, and metacognition) are modelled (Cannela et al., 10; Russo et al., 10; Conlan & Wade, 04; Brusilovsky, 04; Azevedo, Witherspoon, Chauncey, et al. 09). This information is assessed and traced in order to reason about the state of the learner and provide suitable personalised content or support. The development and integration of successful models requires the combination of technological methods with pedagogical and psychological approaches. A discussion of these AI, statistical, and algorithmic reasoning processes is included in Appendix A. This section examines the user modelling and adaptation approaches used in TEL environments, outlining the anatomy of these models, and how they are used to inform subsequent interactions with the learner. The tight coupling of metacognitive supports and TEL environments needs to be overcome, thus this section examines how traditional modelling services (to date, these currently focus on constructs such

as learner knowledge rather than metacognition) have been established as separate services. The separation of the models and their distribution as a service has implications for lifelong learning, because these models can then be reused across multiple environments.

3.3.1 The User Modelling Adaptation Loop

Adaptive systems, as illustrated in Figure 3.3 below, use a *user model* to represent information about the user and subsequently inform the decision making process.

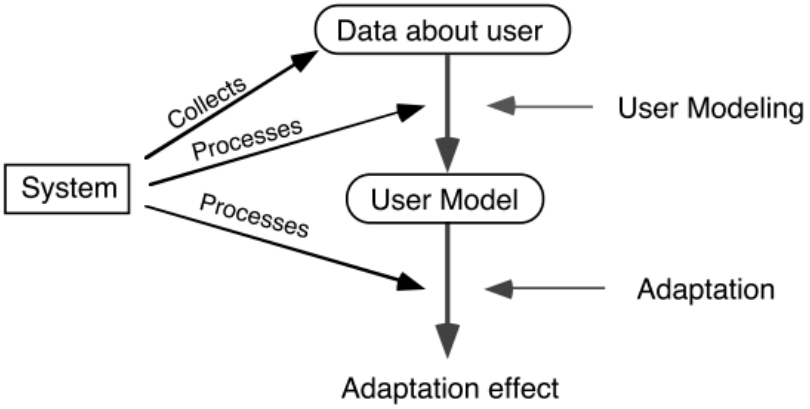


Figure 1. Classic loop "user modeling - adaptation" in adaptive systems

Figure 3.3 - "User Modelling - Adaptation" Loop (from Brusilovsky, 96)

This user model can include explicit log data describing the users path through the system (e.g. curriculum visited), time on page, interactions with controls, self-report measures, and eye-tracking (Azevedo, Moos, et al., 10; Azevedo, Witherspoon, & Graesser, 09; Conlan & Wade, 04; Bull & Gardner, 10; Luckin & Hammerton, 02; Brusilovsky & Sosnovsky, 05). These metrics are explicitly gathered about the learner or implicitly using inference rules or algorithms. The inference of a number of assumptions or rules about particular traits is key to the construction of a learner model. These are represented as a set of information structures designed to infer assumptions about knowledge or skills, cognitive abilities, objectives, motivation, interests, learning style, preferences, tasks and abilities (Brusilovsky, 01; Ruiz et al., 08). This means that adaptive environments can capture a temporal view of learners' progress throughout the course of the learning as well as modelling static aspects of cognition. Adaptation can be decomposed into two distinct phases, as shown in Figure 3.4 below - interaction assessment and adaptation decision-making (Brusilovsky, 01).

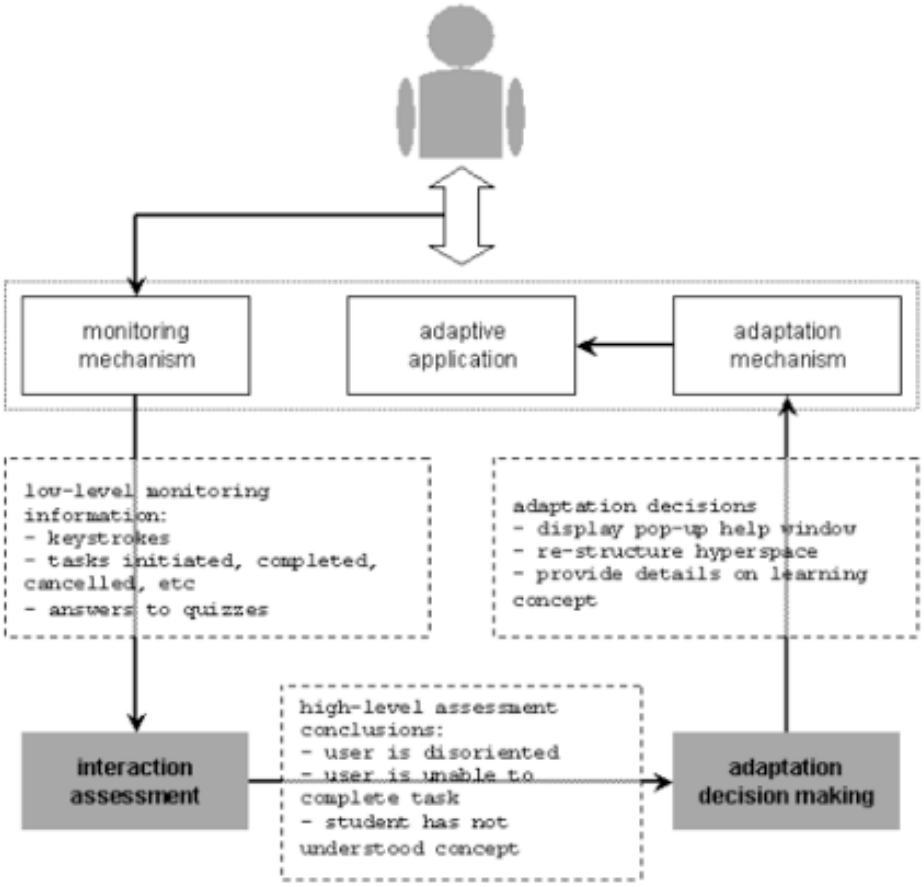


Fig. 1. Adaptation Decomposed. We consider that adaptation is characterized by (the interaction of) two high-level phases: *interaction assessment* and *adaptation decision making*

Figure 3.4 - Adaptation Decomposed (from Brusilovsky et al., 01)

The *interaction assessment layer* detects and reasons about the learner characteristics by using implicit and explicit triggers. The results are then stored in the user model. The second stage of adaptation is at the *adaptation decision-making layer*. Reasoning is carried out in order to make a decision on what is a valid and meaningful way to adapt the environment.

Adaptive techniques are incorporated in the implementation of TEL environments, and are represented as a set of AI functions or algorithms[32]. ITS models often use AI methods to model and deploy the expected actions, self-regulatory and metacognitive processes (Azevedo, Moos, et al., 10; Graesser & McNamara, 10). ITS generally includes a learner model that represents the ideal path through the system (Anderson

[32] These include the use of production rules and model tracing in Cognitive Tutors (Heffernan & Koedinger, 02); curriculum scripts (Graesser et al., 09); example-tracing approaches (Aleven et al., 09; Razzaq et al., 09; Koedinger, Aleven & Heffernan, 03); constraint-based modelling (Mitrovic, Koedinger, Martin, 03; Mitrovic, Martin, Suraweera, 07; Ohlsson & Mitrovic, 07; Suraweera & Mitrovic, 02); case-based reasoning (Aamodt & Plaza, 94; Watson & Marir, 94; Kolodner, Cox & Gonzalez-Calero, 05; Graesser, Conley & Olney, 10); other statistical modelling approaches (Kinnebrew et al., 11, Schwartz et al., 09; Mettler et al., 11); and algorithmic and rule-based reasoning (Conlan et al., 02, Conlan & Wade, 04; Kabassi & Virvou, 06).

et al., 95; Ritter et al., 07), common misconceptions (Graesser, D'Mello & Person, 09), or the constraints that a learner must not violate (Mitrovic, Martin, Suraweera, 07). This means comparing learners' recent actions to these models in order to inform the adaptation reasoning. For example, the Bayesian algorithm user modelling approach used in ITS systems such as Help-Seeking Tutor (Aleven et al., 06; Koedinger et al., 09) has similarly been used to model the learner's knowledge in AEH (Brusilovsky & Millán, 07).

In contrast, AEH environments often make use of algorithmic and rule-based algorithms to generate content on the web page dynamically. When the learner registers with a system a profiling quiz is often administered in order to categorise the learner into a stereotype model. These stereotype models are persisted in the environment and are used to inform reasoning engines (which implement algorithms and rule-based reasoning (Conlan et al., 02, Conlan & Wade, 04; Kabassi & Virvou, 06)) for later personalisation (Kay, 94). For example, learning objects can be annotated with metadata (e.g. With IEEE LOM standard) in order to characterise their content and pedagogical design (Santos, et al., 04). These fragments of content are marked up with metadata, which describes the features of the resource and their suitability for different conditions (e.g. metacognitive supports can be characterised as supporting the planning or evaluation phases). This separation of models, and adoption of standards based approaches means that it is possible to categorise content and pedagogical adaptive logic, in order to enable the reusability of content and instructional design (Conlan et al., 03; Dagger, et al., 03). By separating the content from the sequencing logic into separate models there is greater flexibility in how the course material can be adapted[33]. AEH adaptation may be carried out on the content (Kuntov et al., 09; De Bra et al., 99), navigation (Brusilovsky, 96), or links provided (De Bra et al., 99). These approaches can be used to inform the user of their progress and promote self-reflection (Brusilovsky et al., 09), highlight the most suitable links to resources, or display alternative or annotated material for certain categorise of learner (Graf & Ives, 10; Brusilovsky, 07; Brusilovsky et al., 10). The goal

[33] Conversely, these types of resources can be made available on the open web. As such, open corpus content has the potential to be a valuable source of educational material. For example, Information Retrieval (IR) educational systems have been developed in order to provide users with the most appropriate links to information that is relevant to their needs. Providing such systems with the intelligence to retrieve the most appropriate learning resources is a challenging process (Hampson et al., 11). Effective personalisation is dependent on the harvesting of information about users and the identification of the most appropriate methods to interpret and analyse this data to ensure the data used from the user profiles is most suited to the purpose of adaptation (Settouti, et al., 09).

is to reduce the cognitive load (Tarpin-Bernard & Habieb-Mammar, 05), to deliver personalised content that suits an individual's learning progress or cognitive and metacognitive styles (Graf & Ives, 10; Cannella et al., 10).

3.3.2 User Modelling and Adaptation Characteristics

There are a range of approaches to user modelling and adaptation that vary in their support provided and the dimensions along which they are implemented. This includes the use of dynamic and static user models, models that are updated with explicit or implicit measures, adaptation that is carried out on the fly or at the beginning of the course, timing of the support given, and the generalisability or specificity of the support given to the learning domain.

3.3.2.1 Dynamic and Static User Models

The user model can be categorised as either *dynamic* or *static*. User models represent the inferred state of the learner or expected state of the learner. There are typically a number of static models that are generated before the rollout of the learning system that are used for reasoning or adaptive decision-making. This can include a model of the expected responses or constraints, descriptions of the learning objects, or narrative flow. Dynamic models are detected directly or through inference of the learner's actions in the learning environment and change over time (e.g. the learners knowledge about a domain can increase through interactions with the environment resulting in less supports for introductory material).

3.3.2.2 Explicit and Implicit Mechanisms for updating User Models

User models are initialised or updated with *explicit* or *implicit* triggers. Metrics that are updated explicitly include log data or direct responses from learners to questions, whereas implicit metrics might include the affective state of the learner via analysis of their discourse and ITS agent. These two triggers may be combined in order to create a more holistic view of the learner. This could mean harvesting the data on the user by monitoring their use of the system and also by allowing the user to contribute some of their own preferences to the user profile. Psychometric inventories provide a mechanism with which to explicitly quantify cognitive functioning. For instance, the MAI has been validated and ratified as an inventory that can describe the knowledge and regulatory components of metacognition (Schraw & Dennison, 94; Young & Fry,

08; Yildiz et al., 09). This has been used in the TutorJ (Cannela et al., 10; Russo et al., 10) environment to generate an explicit user model of the learner prior to their engagement with the learning environment and inform which personalised supports are provided.

3.3.2.3 Adaptation On-The-Fly or Pre-Setup

The point at which personalisation is carried out varies: it can be done *on the fly* or *at the start* of the course. On the fly adaptation is done *just in time* in response to the learner activities. This is typical of feedback given by tutoring systems, which alert the user at each step in a task. For example, Cognitive Tutors (Anderson et al., 95) deliver support at each step during a problem whereas AutoTutor responds to free-text conversation with the learner (Graesser et al., 05). Alternatively a learner can complete a survey on registration in order for a personalised course to be generated. When the learner registers with a system a profiling quiz is often administered in order to categorise the learner into a stereotype model. These stereotype models are persisted in the TEL environment and are used to inform reasoning engines for personalisation (Kay, 94; Conlan & Wade, 04).

3.3.2.4 Timing of the Support

The point at which the supports and feedback are provided can also vary – supports may be provided *during the learning task*, however supports are often also provided *outside of the task* itself (before or after the learning task) (VanLehn, 08). Metacognitive, reflective, and self-regulatory processes can occur at any time before, after, or during a learning task (Zimmerman, 94; Bétrancourt et al., 09; Driscoll, 05). The ability to engage in critical reflection on cognitive and metacognitive processes is considered to be one of the key strategies in advanced stages of cognitive development (Piaget, 76) and positive feedback can motivate learners to set higher goals in proceeding tasks (Schnuck & Zimmerman, 94; Bandura, 91). Before the learner engages in a task, they can be prompted to plan and set goals for their learning and reflect on past performances. After completing of the task, learners may engage in reflection and self-evaluation in order to improve their approach in future learning tasks. Reflection can also be supported after a delay – this reflective follow-up (Katz et al., 03) can be implemented by indicators summarising the activities undertaken by the learner, allowing them to step through the way they solved a

problem, or view sample solutions (Bétrancourt et al., 09; Katz et al., 98). However, many TEL environments are intended for novices who do not have the ability to complete a task, so these systems (e.g., Anderson, Corbett, Koedinger, & Pelletier, 95) give feedback on a step-by-step basis to prevent long, unproductive engagement with the environment (VanLehn, 08).

3.3.2.5 Type of Support Target

Support that is provided can be categorised as being learning *task specific, domain specific,* and *generalised.* Tutoring environments that support learners on tasks often highlight the part of the task or problem where the learner has done well or has made an error and can suggest how to alter it (VanLehn, 06) or hint at the next step or even display the next step in the task (Mitrovic, 03). These supports are designed to explicitly support the task at hand. Metacognitive supports at this level can require the learner to reflect on their progress and assess their perceived success/weaknesses. Domain level and generalised supports are complimentary scaffolds that support the learner when learning. This may be by fostering learning strategies and metacognition that are useful during a task (e.g. help-seeking strategies that are useful when completing a geometry equation (Koedinger et al., 09)) or by providing general supports that are not specific to a domain (e.g. general prompts to engage in self-reflection (Chi, et al., 11)).

3.3.3 Distribution of Adaptive and Modelling Services

TEL environments have now been made available over the Internet using the Service Oriented Architecture (SOA) or Software as a Service (SaaS) architectural pattern (Mitrovic et al., 03; VanLehn et al., 05; McNamara et al., 07; Teachable Agents Group, 11). This has enabled widespread delivery of powerful modelling and decision-making tutors as services (McNamara et al., 07; Teachable Agents Group, 11; VanLehn et al., 05). Although ITS can be delivered over the web, they are still usually developed as centralised applications. This means that they are stand-alone and their component reasoning or modelling functionality is not available for use with other services. Another criticism is that the authoring of sample solutions or constraints is very specific to a task or strategy. This means they can be very precise and contextually aware, however they require a great deal of time and skill to implement (Anderson et al., 95; Ritter, Harris, Nixon, et al., 09) and are limited in their reuse.

The *decomposition of services* over a SOA means that models, adaptive decision making engines, and learning resources and services can all be owned and managed independently. This approach is commonly taken to distribute traditional educational and web-enabled systems. This can take the form of a client-server model whereby a centralised server carries out the decision-making processes and the session data is persisted using logic on the server[34]. With the logical separation of facets of adaptive educational courses, services that are complementary to each other can be delivered over a single platform. This is a feature that has been harnessed in AEH environments and environments that combine ITS with AEH features. A number of projects have made use of the distributed approach including KnowledgeTree (Brusilovsky, 04; Brusilovksy & Sosnovsky, 05a; Brusilovksy & Sosnovsky, 05b), iClass (Dagger, Conlan & Wade, 05; O'Keefe et al., 06; Brady et al., 05), ELENA (Dolg et al., 03), aLFanet (Santos, Barrera, et al., 04; Santos, Boticario, et al., 04), and SQL-Tutor which has been integrated with ADAPT^2 to provide a tutoring environment through an online learning portal (Sosnovsky et al., 09).

The active Learning For Adaptive interNET architecture (*aLFanet*) (Santos, Barrera, et al., 04; Santos, Boticario, et al., 04) system combines a number of different types of adaptation techniques such as adaptive learning elements, adaptation of the presentation of the user interface, adaptation based on learner interactions and reports on the course execution for the educator. Where possible, a standards-based approach was taken to describe each of these components in order to facilitate reuse. For example, Learning Objects (LO) were annotated with metadata (IEEE LOM standard) in order to characterise their content and pedagogical design and are encoded using the IMS Learning Design Specification (Santos, Boticario, et al., 04). ALFanet has been integrated with open-source services, and has the potential for components to be distributed.

iClass (Dagger, Conlan & Wade, 05; O'Keefe et al., 06; Brady et al., 05) is comprised of a number of discrete services such as a learner profiler and LO generator, which work

[34] Personalisation is carried out either on the *server* or *client* side. On the client side, the Document Object Model (DOM) can be accessed in order to dynamically hide or show content, links may be removed or annotated, or style sheets can alter the appearance of elements on the page. The other main feature is the decomposition of parts of the learning services over a network. Computational process can be carried out on the server-side in order to deliver personalised content to the client. This means that the learner's progress is persisted to a database and content can be amended, annotated, and updated over time.

together to deliver a personalised learning experience. The iClass project has delivered an AH learning environment using an open architecture. It incorporates a number of services that work together to provide a cohesive personalised learning experience. These services are incorporated using a LMS, which means that the learner can also access other LMS features such as collaboration tools or online quizzes. The components for personalisation in iClass include a *profiler* for profiling the learner preferences; *monitor* for monitoring the knowledge state; a *selector* for reasoning about the choice of learning concepts; a *LO generator* for creating tailored chunks of learning material; and a *presenter* for presenting the personalised learning experience (Dagger, Conlan & Wade, 05; Brady et al., 05; O'Keefe et al., 06). Resources are tagged with standard specifications that allow them to be interoperated with the LMS. This means that assets can be shared across multiple platforms and learning environments (Aviram, Sarid, Hagani et al., 08). The adaptive selection and generation of learning material is controlled through the Adaptive Engine 3 (AE3), which originated in APeLS[35] (Adaptive Personalised eLearning Service) (Conlan & Wade, 04; Conlan et al., 03; Conlan et al., 02). The services have been implemented with an interface designed to allow integration with a LMS to deliver personalised course material.

KnowledgeTree (Brusilovsky, 04) is a distributed architecture that combines a number of services. These services are integrated using a LMS in order to give the learner the experience of a cohesive service. There are four categories of servers supported in the KnowledgeTree architecture – *activity* servers which host reusable LOs and services, *value adding* servers which carry out content or link annotation, LMS *learning portals* for integration of the services, and learner *models* (Brusilovsky, 04). For example, services incorporated into KnowledgeTree include - QuizPACK (Brusilovksy & Sosnovsky, 05a; Brusilovksy & Sosnovsky, 05b) an adaptive service for delivering self-assessment quizzes, CUMULATE (Brusilovsky, Sosnovsky & Shcerbinina, 05) a centralised user modelling server, and WADEIn (Brusilovsky & Nijhavan, 02) a service for adaptive demonstrations and exercises. The main difficulty

[35] APeLS adapts using a *multi-model meta-data driven* approach (Conlan et al., 03). This means that it incorporates a number of models such as the user model, content or domain model, and narrative model. This separation of models places emphasis on the categorisation of content and pedagogical adaptive logic, in order to enable the reusability of content and instructional design (Conlan et al., 03; Dagger, Conlan & Wade, 03). By separating the content from the sequencing logic into separate models there is greater flexibility in how the course material can be adapted. Descriptive metadata aids in reuse of both the models and content. Fragments of content are marked up with metadata, which describes the features of the resource and their suitability for different conditions.

in combining learning services is in achieving agreement between vendors because it is necessary to ensure common communication protocols and specifications are adhered to (Dagger, Conlan & Wade, 05). This either requires the development of bespoke learning resources or services that can read open content. The generic user modelling approach exemplified in KnowledgeTree has allowed the modelling functionality to be centralised, so that it can interoperate with multiple adaptive systems. The CUMULATE server (Brusilovsky, Sosnovsky & Shcherbinina, 05; Sosnovsky et al., 09) maintains user information and activity and infers the user knowledge model.

ADAPT² (Advanced Distributed Architecture for Personalised Teaching & Training) (Sosnovsky et al., 09; Brusilovsky, Sosnovsky & Yudelson, 05; Brusilovsky et al., 10) extends the KnowledgeTree portal to accommodate a greater variety of adaptive components using ontology-based interoperability. SQL-Tutor (Mitrovic & Ohlsson, 99; Mitrovic, 03; Mitrovic & Martin, 07), which was originally delivered as a web-base ITS has been incorporated using the ADAPT² (Sosnovsky et al., 09) architecture. This means that the course can be delivered using the KnowledgeTree portal and that learner progress is modelled in the CUMULATE server (Sosnovsky et al., 09). Since the SQL-Tutor was originally developed as a stand-alone system, a *mapping module* was necessary to map the constraints to a user modelling ontology.

Personis (Kay, Kummerfeld & Lauder, 06) similarly performs centralised domain and user modelling. The central user model is updated according to XML-RPC messages that are sent to the server. This architecture incorporates tools to allow the user to explore their learner model, meaning that the model can be used as an OLM. A *resolver* component is included in Personis, to provide runtime inference of this data (Kay, Kummerfeld & Lauder, 06). Thus, depending on the requirements of the services that are connected to Personis, they would each need a bespoke resolver in order to process the user model data.

3.3.4 Conclusion

Adaptation in TEL environments requires the use of one or several models to represent constructs such as knowledge, cognitive competencies, as well as describing the content or domain. Modelling and adaptation may be carried out

through the use of dynamic and static user models, models that are updated with explicit or implicit measures, adaptation that is carried out on the fly or at the beginning of the course, varying timing of how the support given and the generalisability or specificity of the support given to the learning domain. In developing a model of learner cognition, an initial survey can be taken in order to provide a baseline model with which to reason about how to best support the learner. As responses to these supports may vary from learner to learner, a dynamic model can be used to track the learner over time. The timing and specificity of these supports is also of importance. From an examination of the distribution and implementation of modelling over distributed services, it becomes evident that there needs to be a common communication agreement between services to ensure interoperability. If these needs are met, models and service components can then be transported and reused in other contexts. For instance, the Adaptive Engine (AE) in APeLS (Conlan & Wade, 04; Conlan et al., 03; Conlan et al., 02) is an algorithmic rule-based reasoning service which has not only been used to deliver a SQL course, but is also used successfully in the *iClass* system (Dagger, Conlan & Wade, 05; Aviram, Ronen, Somekh et al., 08; Brady et al., 05)). Another benefit afforded by SOA decomposition is the centralised user model (e.g. CUMULATE (Sosnovsky et al., 09) and Personis (Kay, Kummerfeld & Lauder, 06)). Harnessing standards (e.g. IEEE LOM used by aLFanet (Santos, Barrera, et al., 04; Santos, Boticario, et al., 04) and APeLS (Conlan & Wade, 04)) means that services and user models could be reused across multiple learning environments (e.g. Brusilovsky, 04; Sosnovsky et al., 09). Next, this chapter examines the instructional strategies, user modelling, and adaption techniques and characteristics of TEL environments that support metacognition. This provides an analysis of how and to what extent aspects of learner metacognition are currently modelled and supported.

3.4 Metacognition in TEL Environments

There are a number of instructional approaches with which to model and support learner metacognition. While many environments aim to support metacognition, they do not necessarily model or represent learner metacognition metrics. For example, through Open Learner Models (OLMs) to enable reflection (e.g. Mitrovic & Martin, 07; Bull & Kay, 08), fostering interactive metacognition by putting the learner into the role of the tutor (e.g. Betty's Brain teachable agent (Biswas et al., 05; Chase et al., 09;

Kinnebrew et al., 11; Schwartz et al., 09)), providing adaptive support for self-regulation through conversational agents (e.g. MetaTutor Azevedo, Witherspoon, Chauncey, et al. 09), and fostering the learner's help-seeking behaviours (e.g. Help-seeking tutor (Aleven et al., 06; Koedinger et al., 09). A number of environments explicitly model learner metacognition in order to promote complimentary strategies. For example, explicit modelling of learners' metacognition before engaging with the environment in order to prompt self-regulatory strategies (Cannela et al., 10; Russo et al., 10) and engaging learners in self-assessment by comparing how well they thought they solved a problem to the actual results (Gama, 04). There are also a number of TEL environments that report to implicitly support metacognition or SRL, however this is not the goal of the learning environment. These implicit supports are provided in environments that are aimed at fostering declarative and procedural knowledge rather than cognitive and metacognitive skills (e.g. McNamaer et al., 07; Halpern, 02).

Table 3.2 below provides a visual overview of TEL environments that include metacognitive modelling or support. It provides the *system* name, its *domain,* and a description of the *metacognitive supports* provided in the environment. The *MC (metacognitive) goal level* examines how it has achieved the goals of the metacognitive supports (as described previously in Figure 3.1). It also describes the *user model characteristics, adaptation* and *support timing,* and *target of the support* by referring back to the user modelling and adaptation characteristics outlined in the previous section. It also categorises the *approach* taken to support metacognition – these descriptions refer to the categories with which these metacognitive environments will be examined in greater depth in this section. In particular, this section examines environments that explicitly model or support metacognition. A number of *observations* are also made about the approach taken and outcomes reported about these environments in order to highlight the issues or strengths reported.

System	*Domain*	*MC Support*	*MC Goal Level*	*User Model Characteristic*	*Adaptation Timing*	*Timing of Support*	*Target of Support*	*Approach*	*Comments*
Betty's Brain (Biswas et al., 05; Chase et al., 09; Kinnebrew et al., 11)	Science	MC skills (planning, self-evaluation) through learning by teaching	Learning gains	Dynamic matching of student activities to SRL model	On the fly	During	Domain specific	Interactive MC	Protégé effect in teaching simulated student Specific agent to support MC and SRL strategies
CALMsystem (Kerly, et al., 07, Kerly, et al., 08)	Science	Reflection on difference between the learners self-belief, their confidence in abilities, and the systems assessment of their abilities	MC improvements in self-assessment, particularly for those who had access to both OLM and chat	Dynamic model of learning knowledge and learner confidence. Learners explicitly indicate confidence during task	On the fly (Presented summary after learning)	Immediate, after each question answered	Task belief compared to knowledge	OLM	Interaction with chatbot allowed for disambiguation between learners assessments and their actual abilities.
Ecolab II (Luckin & Boulay, 99; Luckin & Hammerton, 02)	Science (Food chains)	Reflection for monitoring and regulation (Also support for help-seeking and task selection)	Increase in MC strategies during learning, particularly for weaker students Learning gains – again particularly for weaker students	Dynamic modelling of knowledge, degree of challenge attempted, help-seeking	On the fly (Presented summary after learning)	Prompts during learning task OLM available after initial learning task	Summary of tasks completed	OLM (Also prompts for better help-seeking/task selection during task)	Comparison of degree of challenge compared to results achieved similar to learner MC FOK ability

HabiPro (Vizcaino, 05; du Boulay, 11)	Program ming	Interactive MC, support to verbalise thoughts (regulate approach as a group)	More problems solved	Comparison of learner interactions in chat interface to improve collaboration	On the fly	During	Domain specific	Interactive MC	Simulate peer was used to keep learners on track
Help-Seeking Tutor (Aleven et al., 06; Koedinger et al., 09) (In Geometry Tutor)	Geometry	Help-seeking, self-evaluation for monitoring and regulation	Learning gain where learners followed help-seeking, No increase in MC (help-seeking abilities) after	Static model of ideal help-seeking behaviour compared to dynamic UM	On the fly	During	Task specific	Help-Seeking MC	Prioritising algorithm to decide whether cognitive or metacognitive supports should be provided Learners reported they were not motivated by the advice
iClass (Aviram, Ronen, Somekh et al., 08)	Physics	Planning and goal setting support. Reflection tools for monitoring and regulation.	Improvements in learning and MC (planning and self-assessment)	Dynamic modelling of learner knowledge	Supports on the fly	Before, during, and afterwards	General supports with task specific tips	Reflection before and after	Control given to learner to set goals and design workspace to encourage autonomy (with support to ensure learners are on the right path)
iSTART (McNamara et al., 07)	Reading strategies	Reading strategies and self-assessment	Improvements in strategy use and comprehension No post MC evaluations	Modelling of learners reading strategies MC modelled as accuracy with which identify reading strategy	Dynamic interaction	Initial MC supports prior to practicing self-explanations	Domain specific	Self-assessment	MC measurements possible by comparing self-evaluation to results Demonstration and practice provided to learners

MetaTutor (Azevedo, Witherspoon, Chauncey, et al. 09)	Biology	Support for 3 phases of SRL (plan, MC monitoring, implement strategies)	MC changed during learning task Some improvements in learning gains MC improvements immediately after learning task	MC and SRL inferred from learners actions or by learner selecting from palette	On the fly	During task	Domain level supports (Recording of learners used to determine when SRL processes were deployed)	MC through dialog	Multiple pedagogical agents to support 3 phases of SR Designed to foster future MC abilities
MIRA (Gama, 04)	Algebra	Reflection, self-assessment, and subsequent monitoring and regulation	Change in MC behaviour during task Improvements in learning outcome No lasting MC improvements	Modelling of learning knowledge and metacognitive knowledge	Supports inviting learners to reflect pre, reflection on dynamic model	After learning task	General supports	Reflection before and after learning task	Direct modelling of MC in MIRA – however simple model on knowledge monitoring ability
MIST (Puntambekar & du Boulay, 99; du Boulay, 11)	Reading from academic text	MC awareness, goal setting, planning, self-evaluation, and subsequent regulation	Better MC engagement during learning task from those who had higher prior ability (learning and study skills)	Dynamic modelling of progress on achieving learning goal	Pre generated supports with support on the fly	Before, during, after	Domain specific	Interactive MC	Strategy bank was developed for the domain prior to the learning task, this is combined with feedback on individual progress
OLMlets (Bull & Gardner, 10)	Engineering	Reflection for monitoring and regulation	Students found the OLM useful	Dynamic model of learning knowledge used to provide overview of abilities	On the fly (Presented summary after learning)	Available after initial learning task	Summary of tasks completed	OLM	Implemented in a manner that means OLM can be reused across multiple domains (if agreed API used) Further empirical studies needed. Correct and incorrect understanding modelled

QuizGuide (Brusilovsky & Sosnovsky, 05; Brusilovsky et al., 09)	SQL	Reflection on progress, curriculum visited	No learning gains	Dynamic modelling of learner progress to annotate links	Visual cues updated on the fly	Immediate	Specific to task completed	OLM	Large motivational effect from annotated links and visual cues These types of visual cues can be used in multiple domains
Reflect (Kay et al., 07)	C and UNIX	Self-explanation and evaluation of sample solutions	Weaker students tended to over-rate their solutions, whereas stronger students were more accurate	Dynamic modelling of learner self-assessment capabilities	Dynamic interaction based on progress UM	Reflection during question answering	Domain specific	Self-assessment	Sample answers given where students can chose if they are rotten to excellent Self-reflection improved motivation
SE Coach (Conati & Vanlehn, 99; 00)	Physics & self-explanations	Self-explanation	Improvements, particularly at early stages of learning and for weaker students	Dynamic modelling of learner knowledge and self-explanation abilities	Dynamic interaction	During the learning tasks	Domain specific	Self-assessment	As learners become proficient in self-explanation do not need complex scaffolds – prompting suffices Labour intensive process creating self-explanation model for specific domains.
Sherlock 2 (Lesgold et al., 92)	Aviation	Reflection for regulation and self-evaluation	Changes in MC behaviour with learning improvements	Modelling of learning knowledge and metacognitive knowledge	Supports inviting learners to reflect pre-built, reflection on dynamic model	After learning task	Domain related reflection (with task specific scaffolds)	Reflection after task (with OLM to track goals)	Troubleshooting skills transferred to multiple tasks

SlideTutor (Saadawi et al., 11)	Science (Pathology)	MC supports from the MAI (e.g. planning, information management) Reflection OLM	MC in learning - OK Learning gain -No	Dynamic UM compares problem-solving steps to expert model. Learner MC not modelled.	No adaptation	OLM after the task Reflection immediate but faded (with MAI prompt)	General MAI Task specific feedback	MC through dialog (with extra OLM and reflection support)	Although there was an increase in learning gain, the environment, MC was not explicitly modelled. The general supports from the MAI may be reusable in other environments.
SQL-Tutor OLM (Mitrovic & Martin, 07).	SQL	Reflection for monitoring and regulation	Learning gains for weaker students	Dynamic model of learning knowledge used to provide overview of abilities	On the fly (Presented summary after learning)	Available after initial learning task	Summary of tasks completed	OLM	Correct and incorrect understanding modelled Positive feedback on progress indicators
Triple-A-Challenge Gameshow (Chase el al., 09)	Science	MC skills (planning, self-evaluation) through learning by teaching, with social interactions	Learning gains, particularly in weaker students	Concept maps of peers dynamically generated to for social-cognitive learning	On the fly	During	Domain specific	Interactive MC	Greater motivation where learners could view the concept maps of other students in their group
TutorJ (Cannella et al., 10; Russo et al., 10)	Reading Wikipedia articles	MC supports though dialog to support SRL Hinting learning path and content	Aim to improve learning with SRL abilities No evaluation	Dynamic knowledge UM Static MC UM prior to course Dynamic MC model during	On the fly	During learning	Task Specific	MC through dialog support (with hints on content /annotation)	Empirical studies needed. May be a good approach to explicitly quantification of learner MC.

Table 3.2 - TEL Environments that Model or Support Metacognition

3.4.1 Scaffolding Metacognition through Dialog

Dialog can play an important part of metacognitive awareness and development. Traditionally, this may take the form of discussion with peers, educators, or an internal dialog as part of the self-reflection process. Dialog scaffolds can be in the form of pre-stocked pumps, prompts and questions, dynamic support that is tailored to the student and context, menu driven dialog, and pedagogical agents that guide learners in their thinking using natural dialog techniques (Azevedo & Hadwin, 05; Graesser, D'Mello & Person, 09; Azevedo, Witherspoon, Chauncey, et al., 09; Graesser & McNamara, 10; Kerly et al., 07).

Research reports that even prompting students to self-explain can increase learning gains (Chi et al., 11). Chi (2011) provided no training, suggesting that learners already had the ability to self-explain. The learner can have metacognitive knowledge, but not apply it. This might be because they have incorrect goals, or cannot effectively monitor or assess their progress. A number of non-adaptive TEL environments explicitly support metacognition through dialog and prompts. For instance Bendall and Kehoe (2011) undertook a series of web-based learning experiments with SRL prompts. In one experiment, participants were prompted on a large range of study strategies. This group performed significantly better than a control in a subsequent examination (Bednall & Kehoe, 11). The support was in the form of a supplementary study tips page that described a list of study strategies. When they were prompted on just two strategies – elaboration and summarisation, there was no improvement, however participants reported greater ease of learning. Thus, it appears to be necessary to encourage a broad range of strategies to enhance the learning experience. Similarly, *SlideTutor* (Saadawi et al., 11) is a non-adaptive TEL environment that delivers static metacognitive prompts along side domain material and other metacognitive scaffolds. The items on the MAI were used in SlideTutor to create static prompts to encourage learners to engage in regulatory strategies such as planning (e.g. setting goals) and information management strategies (e.g. slowing down when encountering important information). Although this approach resulted in significant improvements in learners' abilities to distinguish correct and incorrect

responses[36], there was no increase in learning gains or evaluation of metacognition after the learning task.

TutorJ (Cannella et al., 10; Russo et al., 10) was designed to stereotype learners using the MSLQ or MAI. The cognitive architecture of TutorJ requires learners to first complete a questionnaire (the MSLQ inventory) in order to define their strengths and weaknesses. A deterministic (algorithmic) and statistical model (Markov process) is used to provide both cognitive and metacognitive supports. The cognitive supports are in the form of dialog interactions with the learner as they engage in a learning task that requires them to use Wikipedia. Metacognitive supports are provided with the goal of enabling better self-regulation of learning. For example, after the learner defines the topic that they are studying, the environment will create metacognitive actions such as providing learning paths through a series of links, listing possible topics that are useful for the learning task, or providing summaries of content, alongside dialog strategies (through a chatbot) to support the self-regulation skills in these situations. While this work is in the early stages, it is an interesting approach as the TutorJ framework has been modified to quantify both cognitive and metacognitive aspects of the learner. However, the implementation of this version of TutorJ has yet to be evaluated to assess whether it can achieve metacognitive and learning benefits.

MetaTutor (Azevedo, Witherspoon, Chauncey, et al. 09; Azevedo, Witherspoon, Graesser, et al. 09; Azevedo, Moos et al., 10; Azevedo, Johnson, Burkett et al., 10), illustrated in Figure 3.5 below, is an adaptive web-based environment, which incorporates *pedagogical agents* who interact in natural language for tutoring biology (e.g. the body, circulatory, digestive, and nervous systems). SRL is represented as three phases in MetaTutor. These include *planning*, *metacognitive monitoring*, and *implementing strategies* for learning, and methods of handling task difficulties and demands (Azevedo, Witherspoon, Chauncey, et al. 09). Measures of the skill are assessed based on the learner's actions, decisions, ratings, and verbal inputs. This means that MetaTutor can only detect a few learning strategies, through the use of algorithms designed to infer them from the learner's actions. Each of the three phases

[36] This was measured using FOK (Feeling of Knowing) measurement, i.e. how sure or unsure of the identified feature with no relevance to whether it is correct or incorrect. This was compared to the overall degree to which the learners' confidence matched their performance.

has a distinct pedagogical agent, which communicates with the learner using a dialog box.

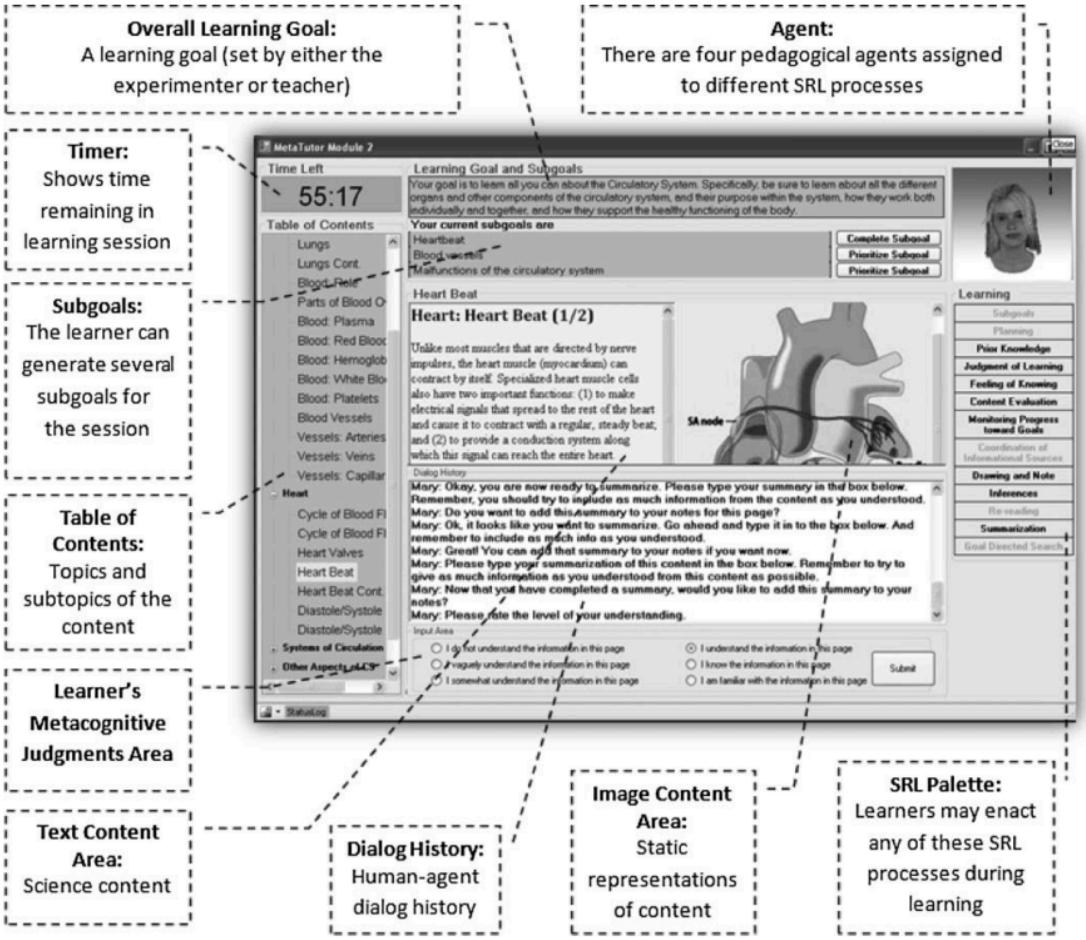


FIGURE 3 Screenshot and interface elements of MetaTutor.

Figure 3.5 - MetaTutor (from Azevedo, Moos, Johnson et al., 10)

The agent provides feedback on the learner's progress in their task, as well as prompting the learner to engage in planning, metacognitive monitoring, or strategy use. Although MetaTutor can assess these actions, it cannot assess the quality of the behaviour. For example, the learner might take notes, but the quality of these notes is not assessed. However, incorporation of a number of indicators can result in greater accuracy, such as triggering tutor dialog if the learner quickly opens and closes a page to ask if they understand the content (Azevedo, Moos, Johnson et al., 10)[37]. As part of the tutoring environment, learners can watch videos of actors demonstrating the SRL process. The SRL processes are listed in a window in the environment. The learner

[37] A more recent version of MetaTutor has been developed to include an eye tracker. Current work is being carried out on developing a database of reliable eye-tracking signatures for individual cognitive and metacognitive processes (Azevedo, Moos, Johnson et al., 10).

can select the process that they feel they are about to use. The goal is to increase metacognitive awareness, and let the system model the learners SRL.

Results from a MetaTutor (Azevedo, Witherspoon, Graesser, et al. 09; Azevedo, Johnson, Burkett et al., 10) revealed that learners (high school and college students) who underwent SRL training scored higher on the SRL quiz than the control. In particular, those in the SRL training condition deployed more regulatory processes, had more prior knowledge activation; more recycling of goals in working memory; monitored their understanding by using judgments of learning; monitored their progress towards their goals; and used knowledge elaboration to help them learn. There were mixed results for the learning outcomes – in one section of the course there was no significant improvement, whereas in two other tests there were notable improvements (Azevedo, Witherspoon, Graesser, et al. 09). By prompting students to activate their prior knowledge at the beginning of each sub-goal, there were demonstrated learning benefits. Also, learners read fewer materials, navigated through fewer pages, and spent longer on the pages they were on (Azevedo, Johnson, Burkett et al., 10). These results are promising, as they indicate that SRL training can be effective in improving a learners SRL strategy repertoire.

3.4.2 Reflection and Open Learner Models

Learning environments can support learner reflection through *Open Learner Models* (OLM) (Mitrovic & Martin, 07; Bull & Kay, 08; Kerley et al., 07). Traditionally ITSs track a learner's progress, learning gain, or cognitive competencies. The OLM takes advantage of this in order to display an overview of the data to the learner. The premise is that making the learner model available triggers reflection (Bull & Kay, 08; Kerley et al., 07). Reflection on learning and self-assessment require metacognitive awareness. This can encourage the learner to monitor the model and self-assess their progress in order to plan better (Bull & Kay, 08; Kay, 08; Kerley et al., 07). A number of other ITS have incorporated OLMs to prompt monitoring and regulation of learning, including SQL-Tutor OLM (Mitrovic, 03; Mitrovic & Martin, 07), OLMets (Bull & Gardner, 10), Ecolab II (Luckin & Boulay, 99; Luckin & Hammerton, 02), CALMsystem (Kerly et al., 07; Kerly et al., 08), and QuizGuide (Brusilovsky & Sosnovsky, 05; Brusilovsky et al., 09).

A notable example of a system that has reported the benefits of an OLM is *SQL-Tutor* (Mitrovic, 03; Mitrovic & Martin, 07). SQL-Tutor was extended under the hypothesis that allowing students access their learner model would benefit their learning and self-assessment skills (Mitrovic & Martin, 07). The original system was capable of comparing the students' solutions to the correct one and to domain knowledge represented by more than 500 constraints. Rather than visualise the students' activities against all of the constraints, a limited overview was created to resemble six clauses of the *select* statement: select, from, where, group by, having, and order by. The summary, illustrated in Figure 3.6, lets the learner view their progress, as assessed by the system.

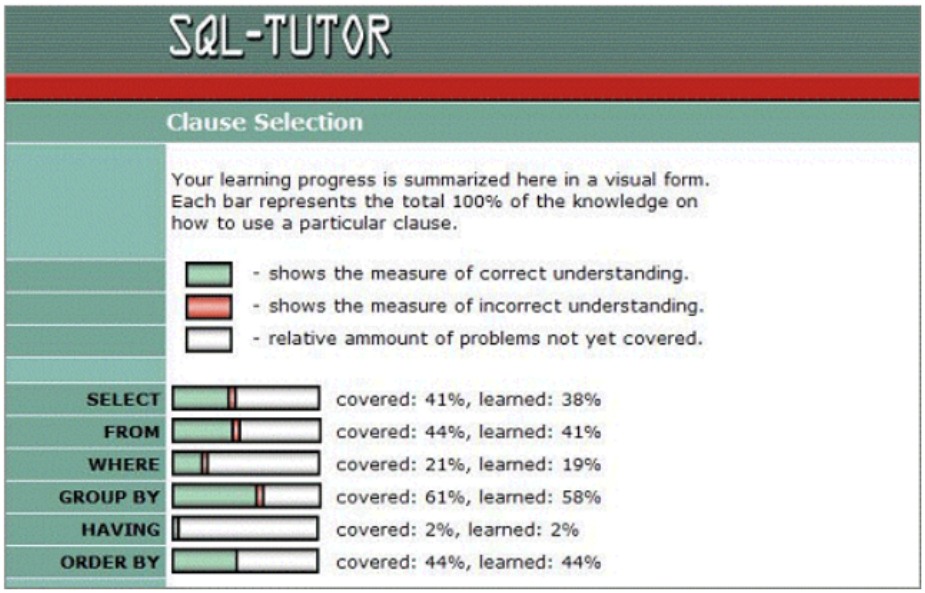


Figure 3.6 - SQL-Tutor Open Learner Model (from Bull & Kay, 08)

This approach reported learning benefits for database students, compared to those who did not use the system, that were significant for the weaker students but were not significant for the more able students; as well as positive feedback for the progress indicator (Mitrovic & Martin, 07). This indicates that the OLM has assisted learners in regulating their learning, which is a metacognitive skill for managing their learning (Bull & Kay, 08).

OLMlets (Bull & Gardner, 10) is of note, because it was developed to work alongside a number of courses. It has been deployed for several third level courses, such as electronic and computer engineering modules. Learners answer questions about their course material, so that the OLMlets system can create a visual overview of their ability or highlight their mistakes. OLMlets also lets the learner compare their

progress against the standard. Instructors author the expected level of knowledge for each stage of the course (lecture, day, week, etc.), and the learner can compare their progress against the expected level. OLMets promotes formative assessment and self-reflection during their progress through a course, supporting self-evaluation and planning. OLMets can be delivered independently as a separate service; however it is tightly integrated with the course material. Conceptually however, this is a separate service that has a discrete and different goal than the learning environment. It encourages independent learning and self-reflection by using a skill-meter that presents a graphical overview of the learner's knowledge in certain areas and by highlighting problem areas.

Ecolab II (Luckin & Boulay, 99; Luckin & Hammerton, 02) supports domain learning (concepts of food chains to 10-11 year olds) with metacognitive scaffolding strategies to support help seeking and task selection. The Ecolab II interface displays a visual map for students to show which parts of the curriculum they have visited, the levels of help that they requested, and the degree of challenge attempted (Luckin & Hammerton, 02). During the learning task, the environment prompts the learner about their strategy use. For example, by advising them to seek more challenging tasks or to make better use of the help facilities (de Boulay, 11). During an evaluation of Ecolab II to assess the results of the metacognitive scaffolding, learning gain was reported in both cohorts, with low ability students reporting the greatest gains. In particular, low ability students who were given metacognitive scaffolding engaged in more effective learning behaviour, including making more use of the help system (Luckin & Hammerton, 02).

The *CALMsystem* is a Conversational Agent for Learner Modelling, which supports metacognitive reflection using an OLM as well as incorporating a *conversational agent* (Kerly et al., 07; Kerly et al., 08). The OLM visualisation is illustrated in Figure 3.7. The learner can compare the systems assessment of their abilities to what it perceives as the learner's self-belief. This communication is used to query the user model, ask the system to explain its belief, justify their own beliefs to the system and thus amend the user model if necessary.

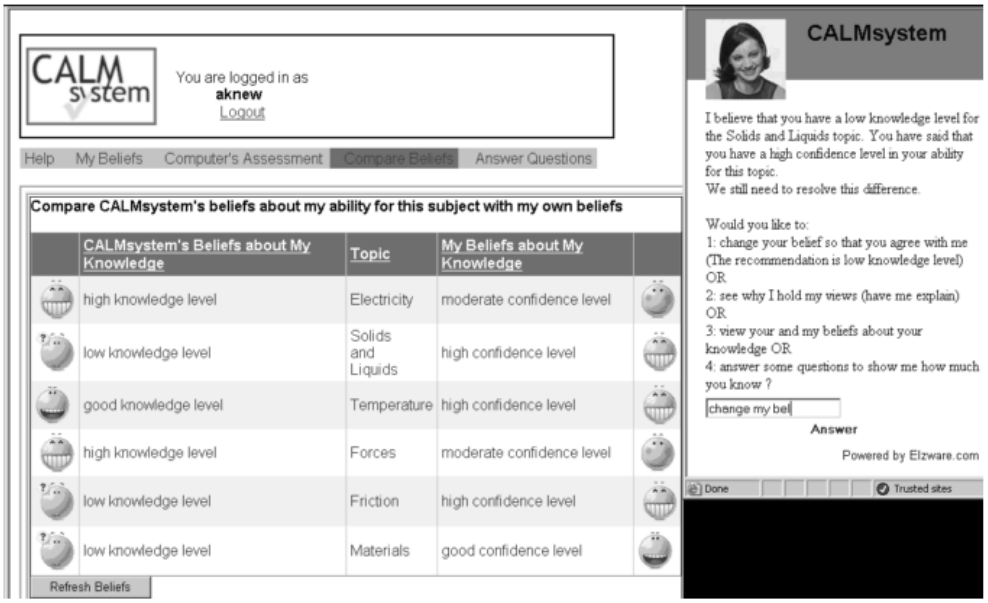


Figure 1 The CALMsystem user interface showing system and user beliefs about the user's knowledge on six topics, and the system chatbot.

Figure 3.7 - CALMsystem (from Kerly et al., 07) On the right hand side, the learner can interact with a pedagogical agent (a *chatbot*) using natural language using a chat window.

For example, in Figure 3.7 above, the system has asked the learner to resolve the difference between their ability and results. The learner can then respond with one of four options, including change their belief, have the system explain, view the system and learner belief model, or answer a question to show how much they know. Evaluations reported improvements in self-assessment accuracy for students (8-9 years old) who could view their learner model and significant improvements for those who could also use the chat system (Kerly, et al., 07). There were more positive results reported from learners who engaged with the system to discuss their model, probably because this discussion prompted deeper processing.

One of the learning services that are available in KnowledgeTree and Exploratorium (Brusilovsky et al., 10) is *QuizGuide* (Brusilovsky & Sosnovsky, 05; Brusilovsky et al., 09). Illustrated in Figure 3.8 below, QuizGuide provides personalised access to self-assessment quizzes, and annotates links with arrows/bullseyes to indicate their performance in components of the AEH course. While not a traditional OLM, this visual reification simply provides feedback about their progress, using a visual cue to indicate their ability. Here, access to the user model, resulted in non-significant improvements to the learning outcomes and significant motivational effects (Brusilovsky et al., 09).

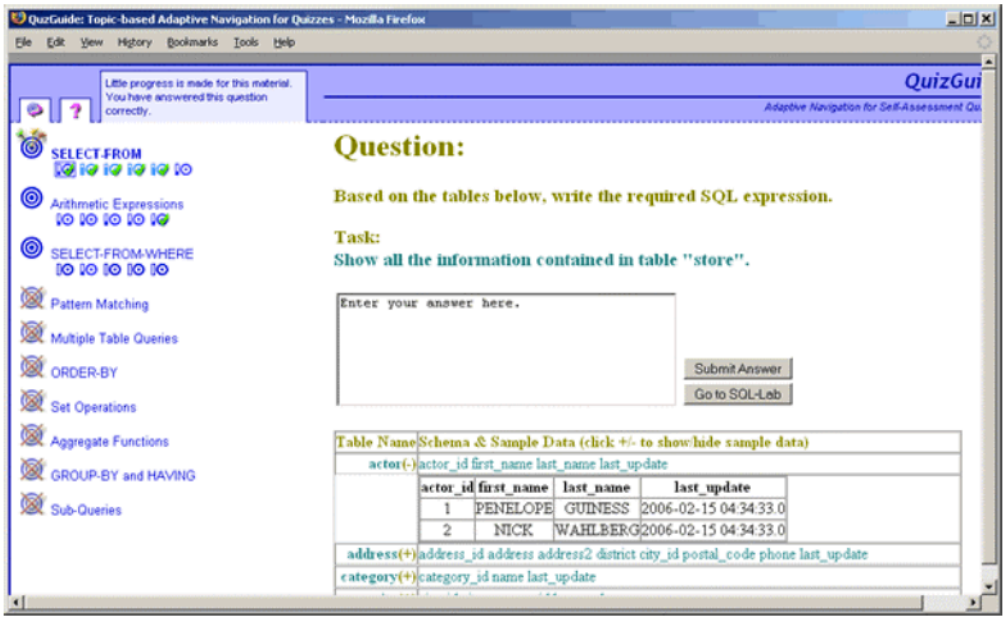


Figure 3.8 - QuizGuide (from Brusilovsky & Sosnovsky, 05)

3.4.3 Reflection Before and After the Learning Task

TEL environments can support reflective follow-up (Katz et al., 03) after a learning task (e.g. reviewing their performance and actions) or enable learners to engage in regulatory strategies prior to learning (e.g. planning and goal setting). In order to minimise the extra cognitive load on the learners of both thinking about problem solving while also trying to solve learning problems, TEL environments alternatively provide pre- and post-task reflection (Gama, 04).

iClass (Aviram, Ronen, Somekh et al., 08; Aviram, Sarid, Hagani et al., 08) aimed to support learner reflection before, during and after learning. Learners were encouraged to plan, monitor, and regulate their learning. Self-personalisation of the learning space was reported to encourage the learner to engage in mindfulness and meaningfulness. Mindfulness in setting goals and planning is required for deep understanding of the task or problem to be solved (Aviram, Ronen, Somekh et al., 08). This enables learners to clarify to themselves what steps need to be taken to solve a problem and develop as an independent learner. Learners' cognitive knowledge is modelled using a knowledge-spaced mathematical approach[38]. Values of the learners current abilities can be used within the class system to recommend the next learning goal, or set of options from which the learner should choose (Aviram, Sarid, Hagani et

[38] In this approach, links between packets of knowledge are described in interconnected nodes (dependencies, prerequisites, logical sequences etc.).

al., 08). Evaluations of iClass reported increases in motivation, independent learning, planning, and self-assessment ability (Aviram, Sarid, Hagani et al., 08).

The *MIRA* (Metacognitive Instruction using a Reflective Approach) (Gama, 04) environment implements a metacognition reflection model (called the Reflection Assistant (RA)) to support the following metacognitive skills: problem understanding and knowledge monitoring, selection of metacognitive strategies, and evaluation of learning experiences. MIRA is a domain specific environment that supports these skills in the context of the algebra domain. This means that it supports both the cognitive and metacognitive strategies for learners. Two aspects of the learner's knowledge monitoring ability were inferred from their interactions with the environment[39]: knowledge monitoring accuracy (KMA or their ability to predict performance) and knowledge monitoring bias (KMB or their tendency to be biased when monitoring their ability). MIRA provided pre- and post-task reflection by employing five strategies for metacognitive reflective (Gama, 04):

1. Invite the student to view a graphical and textual account of their assessment of how well they understood and thought they would be able to tackle previous problems against their actual performance.
2. Invite the student to view any tendency in past problems towards optimism or pessimism in their knowledge monitoring judgements.
3. Invite the student to make an assessment of their understanding of the current problem and their ability to solve it.
4. Invite the student to choose which metacognitive strategies to apply to the current problem e.g. monitoring progress and controlling errors or revisiting solution paths.
5. Invite the student to review progress on the most recent problem including use of resources, outcome, and time spent.

Evaluations of MIRA reported that learners required more time to undertake the reflective activities, which meant that the experimental group solved fewer problems than the control group, however they reported significantly better learning outcomes. There were no lasting changes in their KMA score after the environments, suggesting that they did not internalise better self-assessment strategies.

[39] Knowledge Monitoring Accuracy (KMA) refers to how skilful a student is at predicting how she will perform on a learning task; it reflects their awareness of the knowledge she possesses. Knowledge Monitoring Bias (KMB) provides a statistical measure of any tendency or bias in the learner's knowledge monitoring ability (Gama, 04).

Sherlock 2 (Lesgold et al., 92) is a stand-alone pedagogical agent with a coached practice environment using structured dialog for complex troubleshooting in Air Force electronics. The dialog approach in Sherlock arose out of task-analysis research[40] (Gott et al., 96; Katz et al., 98; Lesgold et al., 92). In Sherlock, each troubleshooting job is represented as a hierarchy of sub-tasks, each of which has a corresponding solution (Lesgold et al., 92; VanLehn, 06). However, this approach has limitations because task analysis does not necessarily reveal the metacognitive or self-regulatory cognitive competencies that are prerequisite or complementary to the task. In order to support metacognition and reflection, a post problem review phase was included (called reflective follow-up or RFU) and a visual graph to keep track of the status of their troubleshooting goals (Katz et al., 98). During reflective follow-up, learners can step though their solution, review a simulated expert solution, review the learning objectives, ask questions about their approach, and receive suggestions for how to better approach the next problem. The reflection in Sherlock enables students to evaluate their strategies and compare their solution to that of an expert. In evaluations, learners improved in their troubleshooting skills both during the problem solving as well as on a post-test. In particular, this support was particularly effective in improving learning outcomes on more difficult tasks (Gott et al., 96).

3.4.4 Metacognition through Self-Assessment

Self-assessment and self-evaluation are closely related to self-regulated learning (Paris & Paris, 01). This is because self-assessment is a necessary process in monitoring and regulating cognitive strategies in order to acquire new knowledge and expand expertise. Even prompting students to explain their actions by reflection on their progress towards their learning goals has been shown to increase learning gains even where no training is included (Chi, et al., 11). This suggests that learners already may have the ability to reflect on and improve their approach but they did not implement these useful strategies adequately. A number of TEL environments combine self-assessment interventions with other metacognitive supports. For instance, MetaTutor (Azevedo, Witherspoon, Chauncey, et al., 09) and SlideTutor (Saadawi et al., 11) combine a FOK assessment with concurrent metacognitive supports. However, it is important that designers of environments be cognizant of not

[40] This involved an analysis of in depth interviews with experts in the electronics domain. The interviews are used to model the process of learning and monitor the skills not only in performing a task, but also deciding how a task should be performed, and what support to provide.

overloading the learner. Requiring judgments of learning can produce split attention by dividing the cognitive resources of the learner (Bednall & Kehoe, 11). This extra cognitive load can be detrimental to learning outcomes (Bednall & Kehoe, 11), which is indicative of the importance of ensuring that extra support does not overburden the learner. In a web-based learning experiment designed to encourage self-feedback (Bednall & Kehoe, 11), prompts for student self-assessment significantly degraded performance[41].

The *iSTART* (Interactive Strategy Trainer for Active Reading and Thinking) environment (McNamara et al., 07) is a web-based ITS that trains students to self-explain science texts by using active reading strategies that facilitate and enhance comprehension (Graesser & McNamara, 10). These strategies include paraphrasing text, generating inferences, predicting what will happen next in the text, and monitoring their own comprehension (Graesser & McNamara, 10). Metacognitive skill is explicitly measured using the accuracy with which students can identify the correct strategy exhibited by the agent (Graesser & McNamara, 10). iSTART uses three modules for teaching the use self-explanation and reading strategies while reading challenging texts. In an *introduction* module, students watch a pedagogical agent explain the reading strategies to two student-agents. In a *demonstration* module, students are quizzed on the strategies as they communicate with the agent. In a *practice* module, students practice generating typed self-explanations and a conversational agent provides feedback on performance. Evaluations on iSTART reported significant improvements in strategy use and comprehension (Graesser, Conley & Olney, 10; Graesser & McNamara, 10).

The *SE Coach* (Conati & Vanlehn, 99; 00) (Self-Explanation Coach) framework provides three types of support – first it explicitly monitors and supports self-explanation, secondly it incorporates a model for assessment of self-explanation actions, and finally it fosters further self-explanation in order to promote better domain learning. The framework has been implemented within Andes, a system that tutors on physics through example studying and problem solving. Students can self-explain through a simple dialog interface, whereby they select text from a menu list. SE-Coach provides advice through assessment of a probabilistic student model,

[41] In this evaluation, participants were required to respond to JOL questions with yes/no or similar true/false questions, and then reread over the related sections.

students' domain knowledge, and the model of correct self-explanation to provide supports and improve the student's understanding. Results from evaluations showed that structured scaffolding (e.g. asking the learner to consider using a help feature to explain an item while also revealing the item to highlight it) of self-explanation was beneficial at the early stages of learning, particularly for less proficient students. As learners become more proficient in subject matter, simply prompting the learner resulted in successful self-explanation. A limitation of the approach taken in SE Coach is that the learners cannot explain in their own words (e.g. with natural dialog), which means that it may not be a truly accurate report. Also, generating the rule-based cognitive model to support the learner's self-explanation is very labour intensive and is not flexible enough to use in a variety of domains (Conati & Vanlehn, 00).

Reflect (Kay et al., 07) is an AEH service that directly supports self-reflection. Reflect is a learning support tool designed to improve learning C in the UNIX domain by enabling the learner to self-reflect. Similar to the constraint-based modelling approach used in pedagogical tutors, the learning objectives and common misconceptions for learning C in this context were identified. Learners' progress through the system was recorded and assessed against this model. This meant that the system could infer their performance. This model was made available to the students in order to make them aware of their progress and prompt self-reflection. In Reflect, a number of sample answers, ranging from 'rotten to excellent' are provided to the learner. They are then asked to provide their own solution. The probability that the learner has understood a learning objective is estimated and reported to the learner so that they can compare their own ability to assess the solutions. An analysis of over 260 participants reported that the stronger students were accurate at self-assessment and weaker students tended to over-rate their solutions. More importantly, students were motivated by the open model and functionality to self-assess solutions (Kay et al., 07).

3.4.5 Interactive Metacognition through Collaboration

Collaborative supports through reciprocal teaching enables social constructivist learning (Vygotsky, 78; Sjøberg, 07). By teaching an external agent and interacting with others, learners engage in interactive metacognition. This participatory design approach means that learners must verbalise (through internal dialog or explicit

dialog with human/computer peers) their cognitive strategies in order to explain or elaborate their approach to solving the learning task (Schwartz et al., 09). This approach is based on research that shows that teaching another person is an effective way to learn (Schwartz et al., 09). It is often easier for an individual to question, evaluate and monitor errors in another person than in themselves (Biswas, et al., 05).

MIST (Metacognition in Studying from Texts) (Puntambekar & du Boulay, 99; du Boulay, 11) enables this form of interactive metacognition through collaboration. The MIST interface provides triggers and questions for the learners on their reading strategies with no awareness of the content that the learners are engaged in. Learners indicate which point they are at during a reading task (by selecting a 'planning', 'reading', or 'after reading' button) and are presented with a list of cognitive reading strategies that may be suitable during that phase. Rather than support specific domain expertise, MIST supports learners in developing cognitive reading strategies, as well as proving tools to monitor their progress, and reflect on how well they have achieved their learning goals. Learners worked in pairs to enable collaborative reflection on the metacognitive skills used when learning from academic text. There were mixed results from evaluations on MIST, whereby learners who had higher learning and study skills prior to the experiment engaged more actively with the metacognitive supports than those with lower prior abilities (du Boulay, 11).

Similarly, the *HabiPro* (Vizcaino, 05; du Boulay, 11) environment was designed to enable teams of students working remotely to jointly work on a programming problem using a shared space and chat interface. The goal of the environment was to foster cooperative problem solving at the metacognitive level by enabling students to chat about co-constructing and submitting answers. A tutor within the system provides the learners with programming problems, responds to solution, and provides help. Unknown to the students, one of the '*student*' participants in the chat was a *simulated student.* This simulated student aimed to keep cooperation between the human students on track (e.g. keep the chat focused on programming, ensuring that they were all talking, and provide hints). An evaluation on the environment reported that students solved more problems when the simulated student was

present. The system was also successful in detecting when students were not contributing[42].

A Teachable Agent (TA) (Chin et al., 10; Schwartz et al., 09) enables '*learning by teaching'*, whereby the learner can track their agent's reasoning, and correct it if necessary. The teachable agents often report a protégé effect, whereby students are observed making a greater effort to learn for their TA than they do for themselves (Chase, Chin, Oppezzo, & Schwartz, 09). For instance, *Betty's Brain* (Biswas et al., 05; Chase et al., 09; Kinnebrew et al., 11; Schwartz et al., 09) is a TA whereby the student acts as a tutor and the system adapts to target their metacognitive needs. This environment, illustrated in Figure 3.9 below, uses two agents – Betty and Mr Davis. Betty is the tutee, who incorporates metacognitive and self-regulation strategies in order to alert the student on what processes are appropriate. Mr Davis acts as a mentor agent to provide feedback on Betty's performance, and make suggestions on what type of SRL strategy the learner could use next.

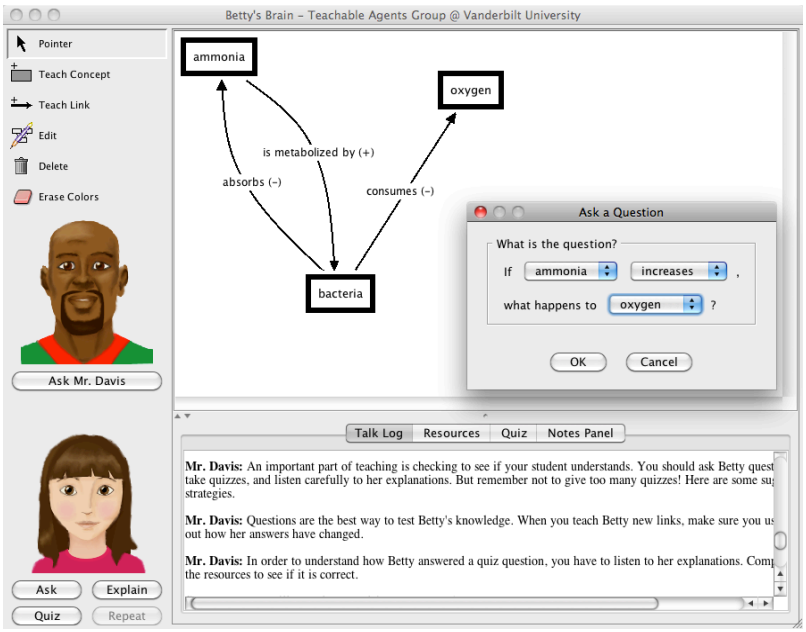


Figure 3.9 - Betty's Brain Teachable Agent (from Kinnebrew et al., 2011)

The learner monitors the agent's metacognitive reasoning, and is required to regulate their processes. The system monitors for patterns in the learner's interaction. Agent feedback is triggered based on these patterns and the system tries to support better learning strategies (Kinnebrew et al., 11). For example, the 'monitoring through

[42] For example, either through deficient knowledge, had adequate knowledge but were not motivated to engage, or hyperactive students did not give their peers time to contribute.

explanation' goal is triggered if the learner makes multiple requests for Betty to give an answer but does not request an explanation (Schwartz et al., 09).

In the *Triple-A-Challenge Gameshow* (Chase el al., 09), multiple teachable agents, each of which are initially taught by a student, compete in a game show. This was motivated by a version of Betty's Brain where students could see the concept maps of other students in their class. In this version of Betty, there were improvements in the student's ability to create complex concept maps. In the showroom students wager on whether their agents will answer correctly. In order to answer the questions in the game show, the agents reasoned over these questions by using rules that were based on what the students taught. Results from an evaluation of this system showed that the learners had greater motivation in learning when teaching their agents, that they felt as though the agent was sentient, and that there were learning gains reported in the tutoring condition, particularly in low achieving students (Chase el al., 09).

3.4.6 Scaffolding Help-Seeking Metacognition

Help-seeking behaviours, whereby learners ask for help rather than just asking for the correct answer, enable learners to become more independent (Newman, 02). Help-seeking is an adaptive skill that is recognised as an important metacognitive skill in SRL (Koedinger et al., 09; Roll et al., 06). As a result, TEL environments have started to incorporate functionality to support help-seeking behaviours because this type of learning can have a positive effect on independent mastery of skills (Koedinger et al., 09; Roll et al., 06). Help-seeking is indicative of having a learning goal, whereby students have a willingness to learn how to evaluate and regulate their cognitive strategies. This differs from traditional performance goals, whereby learners are more focused on getting good grades. In this case learners avoid asking for help to mask poor ability. In the classroom, educators can influence the students to see the benefits of learning goals, by giving them value and encouraging questioning. Learning goals are particularly important for lower achieving students who might otherwise ask for the answer or avoid questioning to hide their lack of understanding (Newman, 02).

For instance, Help-Seeking Tutor, illustrated in Figure 3.10 below, combines geometry education using the Geometry Cognitive Tutor alongside metacognitive

supports (Aleven et al., 06; Koedinger et al., 09). A Bayesian algorithm is used to represent the ideal help-seeking behaviour. As well as tracking the help-seeking behaviour, the cognitive tutor provides feedback on their geometry. The tutor keeps track of learners' knowledge growth over time using Bayesian algorithms to estimate their mastery of target skills. A prioritising algorithm decides whether the cognitive or metacognitive feedback is more appropriate (Koedinger et al., 09).

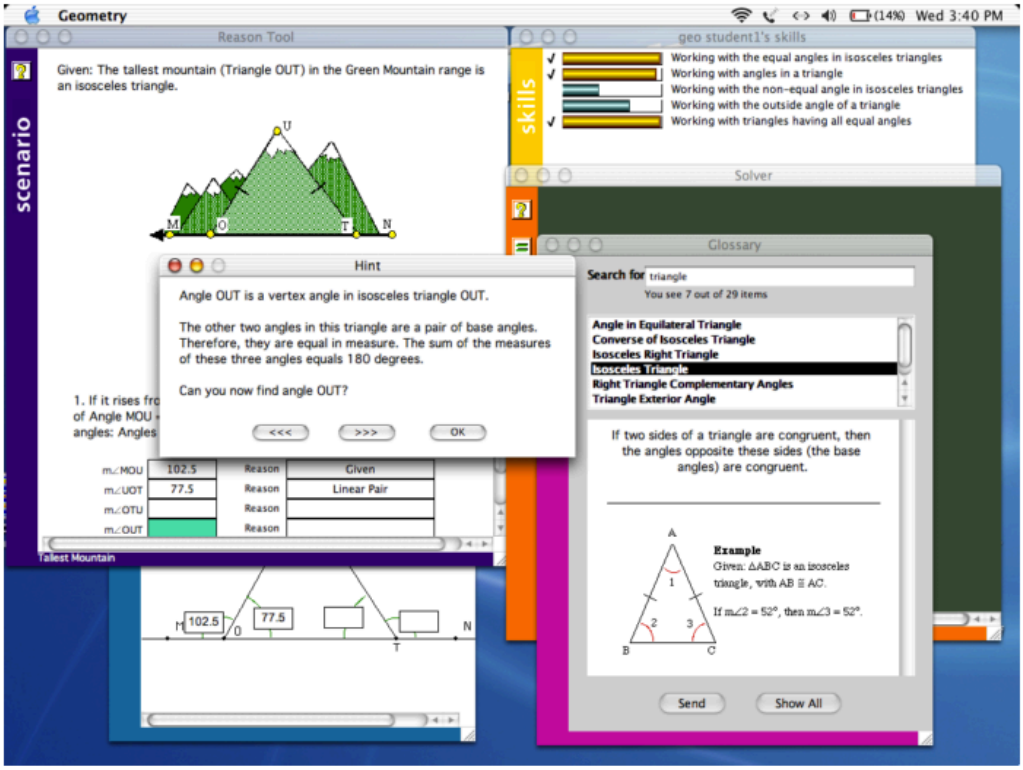


Fig.1.The Geometry Cognitive Tutor.

Figure 3.10 - The Geometry Cognitive with Help-Seeking Tutor (from Aleven et al., 06)

In evaluations, this approach achieved positive effects in some cases where learners followed advice, however they did not internalise the help-seeking principles for future use (Roll et al., 06). In other cases, the lack of improvement in learning gains is probably as a result of students choosing not to apply the help-seeking strategies. Qualitative reports from participants revealed that the students did not like the system commenting on their help-seeking behaviours, even if they agreed with the advice. Further work needs to be done on motivating students to want to engage in help-seeking behaviour. More reflection before or after a task might have been helpful to reinforce the help-seeking behaviour (Roll et al., 06).

3.4.7 Conclusion

Metacognitive supports in TEL can have four goals – firstly, to support metacognition within the learning environment in order to (secondly) improve the learning experience (e.g. increase in learning gain, engagement with material and motivation (Aviram, Sarid, Hagani, et al., 08)). The third and fourth goals are to improve future metacognitive behaviour and accelerate future domain learning respectively (Koedinger et al., 09). Open Learner Models (OLM), for instance, are reported to prompt reflection and subsequent regulation of the learner's approach towards their learning in order to address the first two goals. Some environments aim to address the third goal by improving further metacognitive behaviour (e.g. Help-Seeking Tutor (Aleven et al., 06; Koedinger et al., 09) and MIRA (Gama, 04)). A number of environments support metacognition directly but do not monitor metacognitive metrics (e.g. Reflect (Kay et al., 07)). However, it is possible to explicitly model the learner's metacognitive interactions (e.g. Help-Seeking Tutor (Koedinger et al., 09), MIRA (Gama, 04)). Numerous interaction assessment approaches have been used to generate these measures, including conversational and inferred cues, and responses to direct questions about the learner's cognitive state. The limitation with current approaches is that most do not model the components of metacognition (e.g. regulatory strategies which comprise of factors such as planning, evaluation, comprehension) and those environments that do address specific metacognitive components do so in a manner that is tightly coupled with the learning environment (e.g. algorithmic intelligence to infer when a learner is engaged in self-regulation in a geometry problem). Although the metacognition fostered in a TEL environment is not necessarily antecedent of better metacognition or learning outcomes in empirical evaluations, personalised metacognitive supports often improve how a learner engages with the material, and results in an increase in their motivation.

3.5 Discussion

Supporting the development of metacognition presents a significant challenge in TEL. Current systems that support the acquisition of these skills do so indirectly or are developed as bespoke solutions that cannot travel and grow with the learner. The challenge is to develop a cognitive modelling service that is logically separate from the learning environment that can communicate with and work in symbiosis with educational environments. This notion of symbiosis is important because the

cognitive strategies that are supported must compliment the domain learning that is undertaken in order to enrich the learning experience. Metacognition has been selected as a target for cognitive support, because it is an important component of self-regulated learning and is considered antecedent to positive lifelong learning. To return to the research question - how and to what extent can the cognitive aspects of a learner be modelled to support learning with TEL? First, it is necessary to *model* learner metacognition and then subsequently *support* metacognition in the learning environment. In supporting the learner (as illustrated in Figure 3.1 above), the goals are to change learner metacognition behaviour in the learning environment, to improve learning outcomes, and foster metacognition for future learning.

There are a number of questions to be considered when providing adaptive supports (as described in Figure 3.2 above). The *adaptation goals* of the model are to represent learner metacognition and cognition, in a way that is logically separate when developed but is aligned both technically and pedagogically with a TEL environment. In this sense, the model should work alongside a learning environment while supporting complimentary skills to learning in that context. The implications of instructional strategies and good pedagogical design also need to be considered – while not necessarily novel, these will form practical requirements for the implementation of a model that represents and supports learner cognition. These psychological and pedagogical theories and their realisation in TEL features are described in Table 3.3 below. The *observations* in this table have been used to inform how these questions are to be answered. This means scaffolding the learner by supporting their individual metacognitive abilities through instructional strategies harnessed by TEL environments (such dialog interactions).

The *user features* that will be modelled and supported are the learners' regulatory metacognitive strategies. There are a number of environments that explicitly measure metacognition, For instance requiring learners to make judgements on their ability to solve a problem means that it is possible to compare their beliefs to their actual results. However this approach is limited to learners' self-assessment abilities and does not measure specific regulatory strategies. While some environments model specific strategies, they are tied to the learning environment (algorithms and statistical analysis is used to infer which actions indicate a particular cognitive

strategy). An alternative approach would be to use psychometric inventories to first model the learner and then subsequently provide supports based on that model. However, to date, these inventories have not been used as a basis for structuring a dynamic model that would change over time. The separation of the modelling from the context of the learning environment means that there needs to be some mechanism with which to define when metacognitive supports should be supported or when the learner should be asked for more information about their regulatory strategies.

There is a gap to be bridged between the metacognitive service and the learning environment. This means dealing with the changing nature of the TEL environments in order to describe *when* to support the learner. These types of general descriptions of the cognitive strategies have been exemplified in systems that support learning as a series of phases (e.g. before, during and after or introduction, demonstration, and practice) with a range of strategies that are undertaken in each. As the model will be implemented to work with an AEH environment that requires learners to engage in academic reading (reading text, examining figures and examples) this means also modelling the cognitive tasks that a learner undertakes as they progress through the system. The clear limitation of this approach is that the metacognitive processes are not explicitly linked to specific tasks, however general and domain related supports have previously been shown to result in improved learning experiences.

Thus, three *user features* may be modelled – metacognition (trait), cognitive strategies (series of tasks that are undertaken), and learner progress through the environment. There are a number of approaches that could be suitable for describing *how* to support the learner – visual reification through OLMs enables self-reflection and subsequent monitoring and regulation of the learners' progress, however this will not provide sufficient feedback to update the learner model. Through prompting and questioning the learner directly, environments have been shown to prompt both reflection and changes in metacognitive behaviour while learning, but also provide information for the environment in order to infer the abilities of the learner. The items on the MAI have previously been used in non-adaptive environments to successfully change learners' behaviour and improve learning outcomes. The use of these inventories as both the basis for the model but also as subsequent simple

scaffolds offers a way to both monitor and support learner metacognition. Nonetheless, in order to contextualise these items, access to information on the current LO (a hypermedia page) metadata means that these items can be simply contextualised for the learner.

When considering *where – or what application area*, the metacognitive supports will be delivered as general supports that are delivered in a SQL course. This is because, as proof of concept, the APeLS AEH environment, which has been previously ratified as a learning environment, will work alongside a metacognitive service. This means that the two will be delivered as a mashup web application to deliver both metacognitive supports and domain learning within the same browser window. Finally, when considering *what adaption technologies* will be harnessed – as this is to be a model for use as a distributed service, this means that it should be a separate model (as has been achieved in the distribution of centralised user models) that represents these metrics over time and can be reasoned over (using an intelligent algorithm to decide which supports to provide the learner).

3.6 Conclusion

This chapter has presented an examination of the current mechanisms with which learning supports are provided in TEL environments, with reference to the pedagogical and psychological learning theories examined in Chapter 2. It has examined the characteristics of user modelling and adaptation, and strategies for providing metacognitive support. A feature list is presented in Table 3.3 below, which describes how theory has informed the design of TEL environments and can be harnessed in this research. The *learning theories* column refers to concepts and theories that underpin approaches to user modelling and adaptation in TEL. The '*features of TEL environments*' column provides a feature list to describe how these are realised in TEL environments. *Observations* are made about the implications of theory and TEL features in order to inform the research and practical requirements for the design of a metacognitive model that can be implemented as a service. Finally, the *keys* enable the reader to quickly reference these concepts in other chapters[43].

[43] Keys that begin with L refer to a learning or pedagogical construct, and originated in Chapter. Keys that begin with F refer to TEL features and are further discussed in the design chapter (Chapter 4) in the discussion of the influences of the literature.

3.6.1 Features of TEL Environments

Key	*Learning Theory*	*Key*	*Features of TEL Environments*	*Observation*
L13	***Metacognition is antecedent to positive lifelong*** learning. It is a ***component of self-regulated learning*** that can be described as comprising of ***knowledge of*** cognition and ***regulation of cognition***[44].	F1	***Metacognition in TEL is desirable and can be supported in three ways*** - no modelling of the learner, but supporting metacognition, modelling of learner cognition in order to prompt reflection and metacognition, and ***direct modelling and support metacognition***. TEL supports should provide environment where the learner can practice metacognitive and self-regulatory processes. These can be used prior to, during, and following learning. It means capturing a temporal model of the learner, and ***making inferences on the state of the learner at discrete stages*** of the learning process[45].	The ***goal*** in designing a new cognitive model is to ***both model and support*** metacognition.
L1	Learning is a ***constructivist process***, whereby the process of learning is active and involves the processing of information from our environment to derive meaning from experience, form hypotheses, make decisions and respond to the learning environment[46].	F2	TEL environments enable learners to ***engage in learning tasks***, scaffold goal-setting behaviours, and provide supports (which may be faded) in order to enable learners to become autonomous and self-regulated. Metacognition and SRL are complimentary constructs for active learners. For a TEL environment to support metacognition and SRL, the learner should be ***required to make***	Thus, a model of MC, in particular a ***model of regulatory strategies is desirable.***

[44] Flavell, 79; Tobias & Everson, 02;Brown, 87;Paris & Winograd, 90; Schraw & Dennison, 94; Whitebread et al., 09

[45] Azevedo, Witherspoon, Chauncey, et al. 09

[46] Gunstone, 94; Perkins, 91; Jonassen, 99; Harris & Graham, 94; Driscoll, 05

			instructional decision that can help them to achieve their learning goals [47] . This means supporting ***regulatory*** cognition – including planning, organising, attending to and modifying their approach, and self-evaluation.	
L14	***Educators are metacognitive professionals*** who can scaffold metacognitive strategies along with traditional supports for domain learning. The ***prompting of metacognitive reflection during learning has proven beneficial*** to their self-evaluations and learning outcomes[48].	F3	TEL environments have taken a number of approaches to take the ***role of the traditional educator in supporting the development of self-regulation and metacognition.*** In particular, approaches include reflection through dialog, visual OLMs, reflection at different phases (before, during and after), interactive metacognition through collaboration, and supporting help-seeking behaviours.	There is a ***range of strategies*** available to support metacognition – e.g. planning, information management, and self-evaluation. In providing modelling and support alongside and AEH environment, this means that the regulatory strategies can be supported using a number of mechanisms.
L8	Cognitive strategies and metacognition are particularly important when ***reading***. Successful readers use more cognitive strategies, use them more frequently, and have enhanced metacognitive awareness of their own use of strategies and what they know, which in turn leads to a greater reading ability and proficiency. Expert readers use targeted metacognitive strategies ***before, during and after reading to aid their comprehension and understanding***[49].	F4	***Enhanced metacognitive awareness is desirable for leaners in AEH environments who are expected to manage and direct their own reading strategies and goals***. Reading strategy support and reflection on the implementation of learning strategies can improve learning experience.	Metacognitive strategies are important, particular for ***learners engaged in academic reading and who are given more control over their learning***.

[47] Azevedo, Witherspoon, Chauncey, et al. 09
[48] Duffy et al., 09; Wilson & Bai, 10
[49] McNamara, 09; Illustre, 11; Pressly & Afflerbach, 95; Hamadan et al., 10

L11	***SRL*** is important to enable learners to become autonomous and self-directed. Learners who apply effective self-regulation during learning activate more suitable schemata for the task at hand, but also activate schemata responsible for monitoring which consequently regulates their own performance at that task[50].	F5	TEL environments can ***model, prompt, and support*** the learner's self-regulatory processes. This can include cognitive, metacognitive, affective, and behavioural aspects of the learner[51]. While metacognitive traits often include feeling of knowing and judgement of learning, these are simple metrics that do not represent a range of regulatory strategies.	Prompting and support of ***metacognition as a component of SRL is desirable***. The harnessing of TEL techniques – modelling, prompting, and support may be possible beyond simple metacognitive metrics (e.g. FOK) to instead support regulatory factors (e.g. planning, debugging, evaluation).
L16	***Psychometric*** inventories provide a mechanism with which to quantify cognitive functioning. The ***MAI*** in particular has been validated and ratified as an inventory that can describe the knowledge and regulatory components of metacognition[52].	F6	The ***quantification of cognitive and metacognitive competencies*** is possible through the use of inventories. While environments have used these as ***pre-test models*** to set up static models, the structure of these models has not been used to date to trace the learner over time. This can provide a useful structure with which to ***trace the leaner over time*** and to compare the user model to empirical evaluations in post-test evaluations.	***Regulatory strategies*** will be ***initially modelled*** (baseline model), ***traced*** (adaptation will be carried out according to individual metrics), and subsequently evaluated (the system user model will be compared to the learners post-test survey) by using the ***MAI***. The MAI is a ratified mechanism with which to measure a set of regulatory strategies.
L9	Learning is not just an individual process; we make meaning from the people and our peers. ***Tutoring*** is the most effective form of instruction, whereby ***tutors support and scaffold learners in order to achieve their learning potential whilst being sympathetic to their cognitive load***[53].	F7	TEL environments em***ulate the role of the tutor*** in providing supports, scaffolds, and promoting autonomy through dynamic assessment of capabilities, and the ***support of a range of knowledge*** (declarative, procedural and metacognitive) for a ***range of learners*** (individual differences).	The model of learner metacognition needs to model learner metacognition, but also ***work with a TEL environment***.

[50] Schunk, 96; Schraw et al., 06; Schunk & Zimmerman, 98, 00; Graesser & McNamara, 10

[51] Azevedo, Witherspoon, Chauncey, et al. 09

[52] Schraw & Dennison, 94; Young & Fry, 08; Yildiz et al., 09

[53] Vygotsky 62, 78; Eberle, 92; Berger & Luckman, 67

L10	Through the structure provided by scaffolding, learners are given ***personalised feedback*** and ***support*** towards independent and self-regulated competence of skills[54].	F8	***User modelling and adaptation techniques*** are used in TEL environments in order to provide structured and simple scaffolds (that may be faded over time). The goal of developing self-regulatory, metacognitive, and self-evaluation abilities is to enable learners to become autonomous.	***Modelling*** of the learner with a baseline model and subsequent dynamic model will be used to trace the learner's ***progress over time***. An algorithmic rule-based prioritising algorithm can be used to define ***which supports are useful*** (for the individual learner and for the current stage they are in)
L12	***Scaffolds*** can enable learners to make the progression from dependent to self-regulated learners. For example, enabling learners to ***engage in reflection and introspection*** facilitate the development of knowledge about their internal processes, which is fundamental to metacognition[55].	F9	Scaffolds are determined from user model and adaptation characteristics – in essence they vary in their ***level of support*** (general vs. task specific), ***timing*** (introduction, during, evaluation), ***implementation phase*** (pre determined or adaptation on the fly), ***assessment*** procedure (based on explicit measurements or from inferred metrics), and ***state of the user model*** (static pre-determined user models or dynamic models). The ***timing*** of these scaffolds is important. Cognitive strategies have been implemented in TEL environments in order to suit alternative phases of learning (e.g. reading strategies before, during and after or SRL strategies for planning, metacognitive monitoring, and implementing strategies).	In using items from the ***MAI*** as the basis of the user model, there needs to be a mechanism with which to ***update this model*** – although the values can be used to trigger self-reflection (e.g. through the use of an OLM) we need to get ***feedback from the learner***. This means either questioning them/prompting them or creating algorithms/rules to assess what strategies they are using the learning environment. Since the model will work with a AEH environment, the use of direct questions and prompts can be used to both trigger the learner, but also receive feedback. While learner metacognition may be modelled with an inventory, the timing with which they are prompted is of importance. Since the metacognitive supports are delivered as a separate service to the AEH environment, needs a ***bridge*** is needed to connect the learning tasks with the

[54] Bruner, 75; Dickson et al., 93
[55] Bruner, 90; Tarricone, 11

				metacognitive strategies. ***Identification of the sequence*** of ***cognitive tasks*** that the learner engages in allows for stepping through the phases of learning (e.g. planning at the introduction, self-assessment at the conclusion/summary).
L13	Positive transfer can result in increased performance and reduce the amount of cognitive load required from learners if they can ***activate previously encoded strategies or knowledge***. Greater metacognitive knowledge results in a more flexible cognitive strategy repertoire[56].	F10	Learning should be ***situated within a particular learning context***[57]. This means that the learner should be supported to make decisions regarding the resources or strategies that can lead to more successful learning outcomes. However, the goal of metacognitive supports is not always to change the metacognitive behaviour within the learning task, but can also be designed to support future metacognition. Supports can be in the form of general, domain specific, and task specific strategies.	When separating the modelling and support from the learning environment, this means supporting more general or domain related aspects of learning. Regulation of cognition comprises of general abilities that are reusable across multiple learning tasks. However, in order to ***contextualise supports***, harnessing of standards in describing LOs (the current web page) can be used to create simple dynamic prompts.
L2	Knowledge and abilities ***strengthen with practice and use***, which frees up our cognitive resources for more complex or novel tasks. Our ability to understand and respond to our environment becomes more able (and more complex) over time as we learn how to better process information, and build a rich knowledge and strategy repertoire[58].	F11	TEL environments ***enable learners to practice*** new cognitive and metacognitive strategies. The ***changing nature of cognition*** is modelled and measured with ***dynamic models*** of the learner through explicit and inferred assessment of their interactions. This allows environments to respond to the status of the learner.	A ***temporal***, and ***progressive*** model of metacognitive competencies is desirable.

[56] Schraw & Dennison, 94; Butcher & Aleven, 99
[57] Azevedo, Witherspoon, Chauncey, et al. 09
[58] Sweller, 04; Piaget & Inhelder, 73; Zimmerman, 89; Siegler, 82; Dienes & Perner, 99; Anderson, 83

L3	We possess ***unique and individual differences*** in our cognitive and metacognitive styles. Over the course of our cognitive development we develop individual and idiosyncratic knowledge and strategy repertoires – our mental models, how we think, and interact with the learning environment varies compared to the next person[59].	F12	User models in TEL environments enable intelligent adaptation and personalisation to suit the needs of ***the learner as an individual.***	A ***unique user model*** for each user that represents their individual abilities to regulate their cognition is desirable.
L4	There are ***differences between novice and expert learners.*** As individuals learn new procedures and become more expert they become progressively automatic. Expert readers possess metacognitive knowledge about reading strategies, meaning that they are aware of their strategies and can employ them in the right context. Scaffolding support given to novice learners enables them to internalised new or difficult material and strategies so that they can apply them independently[60].	F13	Learners ***begin their learning experiences with prior knowledge and abilities*** – both cognitive and metacognitive. In TEL, ***initial supports are often more rich*** (in order to trigger deeper processing and highlight to the students which strategies are important – learners often have learning and metacognitive strategies, but may simply may not implement them), whereas later supports can reduce to a prompt to trigger the strategy.	An ***initial baseline model*** of learner metacognition is desirable. Also, ***scaffolds should be in two forms –*** the first rich with the second being simple (e.g. a simple prompt). It is also interesting to investigate differences between weaker and stronger students in subsequent evaluations.
L5	***Cognitive load is limited***, but this can be ***buffered through scaffolds*** and learning supports. As students begin to demonstrate task mastery as they acquire more complex mental models, the responsibility of the learning should be given to the learner and less support provided[61].	F14	Cognitive load is supported in a number of ways, such as optional supports that are offered but not required. In some cases, where metacognitive supports were forced on the learner, the mixed attention resulted in negative effects to the learning experience.	It is important that any ***supports that are provide in the learning environment do not overshadow the learning task at hand*** – the SQL course should be given the highest priority.

[59] von Glasersfeld, 90; Tarricone, 11; Brown, 87
[60] Pressley & Gaskins, 06; Langer & Applebee, 86
[61] Sweller, 04; Chandler & Sweller, 91; Bendall & Kehoe, 11; Ohlsson & Mitrovic, 07

L6	***Schemata (mental models)*** are organised patterns of behaviour or mental representations that organise knowledge, skills and rules, and are used to understand and interact with the world. Schemata can provide the impetus for reflective thinking and enable learners to transfer strategies across domains according to cognitive constructivist theories[62].	F15	The use of triggers, or schema signals is useful, as this can ***activate prior information and capabilities*** that we have available to us but were not necessarily successfully activating.	Schema theory provides a ***useful mechanism with which to describe how our cognition is stored and processed in our mind***. Mental models represent information that is related to other information, has a changing nature, and is used to attend to and respond to our immediate environment.
L7	Knowledge is the set of understanding or body of information possessed by an individual that is innately available or experientially acquired. ***Knowledge can be described as declarative*** (factual), ***procedural*** knowledge (strategic) and ***metacognitive*** (knowledge about cognition and regulation of cognition)[63].	F16	TEL environments support two types of learning experiences –***tasks*** that comprise of a number of steps and activities along with ***conceptual knowledge*** or facts. Metacognitive abilities similarly comprise of knowledge and strategies.	In designing a model of learner metacognition that will work with a TEL environment (over hypermedia on the web) – there are two paths that can be taken – some environments enable learners to practice (e.g. by viewing a demo of SRL and then implementing the strategy), or by providing the learner with knowledge of their strategies (e.g. through prompts or questions). In developing supports for metacognition, it should be ***capable of selecting from a bank of supports*** – the first step being to trigger the learner in a way that does not overburden them.

Table 3.3 - Features and Observations of How Theory Can Influence the Development of TEL Environments

[62] Ibrahim et al., 03; Piaget 29; Anderson, 77; Anderson, 84; Bartlett, 32; Rumelhart 80; Derry, 96

[63] Zimmerman, 89; Pressley, 87; Graesser et al., 10; Zimmerman, 89; Chomsky, 84; Brown, 87; Schraw & Dennison, 94

Chapter 4 Design

This chapter outlines the design requirements for a technical approach to model learner metacognition for use in a support service that can work alongside a TEL environment. Here, there are two goals – the design of a cognitive model and an approach to integrate it with a TEL environment. Previously, Chapter 2 provided an examination of the psychological and pedagogical learning theories that play an important role in learning, cognition and metacognition and have influenced the development of a model to support metacognition in the context of a TEL environment. Chapter 3 subsequently provided an examination of the influences of cognitive science on TEL environments; user modelling and adaptation approaches that can influence the development of a novel reference model for modelling, assessing and fostering learner metacognition; and specific examination of TEL environments which model or explicitly support learner metacognition. These have influenced the requirements, design, and approach undertaken. As such, this chapter has four aims. This first is to outline the requirements of a system that supports good practice and tackles current challenges in modelling cognition. An overview is first provided of these requirements. Subsequent sections discuss each requirement in depth, outlining how they relate to the proposed model and implementation.

The second aim of this chapter is to define the ETTHOS (Emulating Traits and Tasks in Higher-Order Schemata) model of learner cognition. ETTHOS describes the components of a cognitive model that can be used when implementing a metacognitive modelling and support service that will work with an AEH environment (in particular, the test-bed for ETTHOS has been the Goby service which works alongside the APeLS AEH environment). The components of ETTHOS are then described. The trait component comprises of a static descriptive trait model, a baseline model, as well as a dynamic learner trait model. Traits comprise of a number of descriptive factors, each of which is measured with a number of observable items. The dynamic learner trait model is used to trace the learner's progress over time using items from the MAI. The task model similarly comprises of static and dynamic models – a descriptive and learner task model respectively. This task model describes

the activities and sub-activities undertaken by learners when engaged in academic reading. The development of the trait-task model, which maps between traits and tasks, is also discussed.

The third aim of this chapter is to describe an approach to implementing ETTHOS. The models in ETTHOS have been developed in a manner analogous to schema theory, which is a theory that prescribes how information is stored and processed in the human memory. A discussion is carried out about how the characteristics of these schemata are realised in ETTHOS and it's subsequent implementation. ETTHOS has also been designed to inform the implementation of services that work in symbiosis with other TEL environments. Essentially ETTHOS is responsible for modelling, tracing, and subsequently supporting the development of learners' cognitive strategy repertoire, whereas a separate TEL service delivers the domain knowledge. The final aim of this chapter is to illustrate the system requirements and the design of Goby[64]. Goby has been developed as a test-bed for the ETTHOS model and is a support system that works in conjunction with the APeLS learning service.

4.1 Influences from the Literature

This research is driven by the research question - *how and to what extent can the cognitive aspects of a learner be modelled to support learning with TEL?* A number of requirements are outlined in this section, each of which is influenced by the research question, cognitive and learning theories, and the successes and shortcomings identified in current TEL approaches. The motivation behind metacognitive modelling is the delivery of adaptive support that can supplement and improve a learner's educational outcomes. This section refers back to the underlying learning theory and TEL concepts outlined in Chapter 2 and 3 and makes specific reference to the observations made about the features of cognitive and metacognitive supports in these systems in order to derive research requirements.

64 In nature the Goby fish lives in symbiosis with the burrowing shrimp. It serves as a watchman in return for a place to live. The shrimp builds a burrow in the sand where the two live. In return, the Goby fish alerts the shrimp if danger approaches. For this reason, they are often called watchmen. ETTHOS is manifest within a cognitive support service – Goby, which works in symbiosis with a TEL system to deliver assistance to learners.

Table 4.1 below outlines how this chapter makes use of keys to annotate connections to features and requirements.

Key	*Requirement*	*Description*
R	Requirement	These are the key research requirements (R) identified in this research.
PR	Practical Requirement	These are the practical requirements (PR) that are considered necessary for a functioning system but secondary to the research requirements.
SR	System Requirement	The system requirements (SR) describe the functional and non-functional requirements for developing a service with ETTHOS.
F	Feature	Observations on features (F) of TEL environments, modelling approaches, and underlying theories relevant to the research or underlying.

Table 4.1 - Description of Keys

TEL environments enable learners to engage in learning tasks, scaffold behaviours, and provide supports in order to enable learners to become autonomous and self-regulated [F2]. Metacognition is an important component of SRL, which enables learners to become autonomous, pro-active and adaptive. For a TEL environment to support metacognition and SRL, the learner should be required to make instructional decision about how and when to use cognitive strategies that can help them to achieve their learning goals. This means supporting regulatory cognition – including planning, organising, attending to and modifying their approach, and self-evaluation. Metacognition in TEL is desirable and can be supported in three ways [F1] – simple non-adaptive supports of metacognition, modelling of learner cognition in order to prompt reflection and metacognition, and direct modelling and support metacognition. Common to these supports is that they should provide an environment whereby the learner can practice metacognitive and self-regulatory processes. However, cognitive load needs to be considered, because requiring too much attention from learners on top of the domain learning can result in negative effects to the learning experience [F14]. Thus, a model of metacognition, in particular a model of regulatory strategies is desirable. These strategies can be used at different stages of the learning experience. This means capturing a temporal model of the learner, and making inferences on the state of the learner at discrete stages of the learning process. The goal in designing a new cognitive model is to model and subsequently support metacognition. It is important that any supports that are

provided in the learning environment do not overshadow the learning task at hand – the domain learning should be given the highest priority. Thus, the purpose of defining a model of learner metacognition is to enable the support system to *model, track, and foster a learner's individual metacognitive capabilities* [R1.1]. The aim is to improve educational gains an AEH environment, which means that priority should be given to domain learning while scaffolding metacognitive strategies.

TEL environments can model, prompt, and support the learner's metacognitive and self-regulatory processes [F5]. While metacognitive traits often include FOK, these are simple metrics that do not represent the range of metacognitive regulatory strategies (e.g. planning, comprehension, self-evaluation of cognitive strategies while learning). The quantification of cognitive and metacognitive competencies is possible through the use of inventories [F6]. Although environments have used these as pre-test models to set up static models, the structure of these models has not been used in TEL to trace the learner over time. These inventories have the potential to provide a useful structure with which to trace the leaner over time and to compare the user model to empirical evaluations in post-test evaluations. The MAI is a ratified mechanism with which to measure a set of regulatory strategies. This means that regulatory strategies can be initially modelled (baseline model), traced (adaptation will be carried out according to individual metrics), and subsequently used as the basis for evaluations. The items on the MAI have also been used as a basis with which to prompt metacognition in non-adaptive TEL environments, which points to the usefulness of these items in prompting reflection on cognitive regulation. Thus, the model should be structured in a way that *provides measurements on each of the items on the inventory*, and can be used to examine individual *regulatory* factors (e.g. planning), in order to provide an overview of learner *metacognition* (trait) [R1.2]. In developing this model however, it should be trait-neutral – in order to allow for the future use of other inventories that represent other constructs that are complimentary to learning.

User models in TEL environments enable intelligent adaptation for the needs of the learner as an individual [F12]. The changing nature of learners' abilities and cognition is modelled and measured with dynamic models of the learner through explicit and inferred assessment of their interactions [F11]. A unique user model is thus required

for each learner in order to represent their individual ability to regulate their cognition. This means that the supports provided can be personalised for that learner and that the model can be updated as a result of the response for the learner. A *temporal, real-time and progressive view* is therefore needed of the learner's metacognitive model [R1.3].

Metacognitive strategies are important, particularly for learners engaged in academic reading and who are given more control over their learning [F4]. Enhanced metacognitive awareness is particularly desirable for leaners in AEH environments who are expected to manage and direct their own reading strategies. In particular, this is necessary in the case of adaptive hypermedia environments that deliver academic materials (text, illustrations) in a series of Learning Objects (LOs). The timing of these scaffolds is also important [F9]. Cognitive strategies have been implemented in TEL environments in order to suit alternative phases of learning (e.g. reading strategies before, during and after or SRL strategies for planning, metacognitive monitoring, and implementing strategies). While learner metacognition may be modelled with an inventory, the timing with which they are prompted is of importance. Since the metacognitive supports are provided as a separate service to the AEH environment, a bridge is needed to map the learning tasks with the metacognitive strategies. Identification of the sequence of cognitive tasks that the learner engages in allows for stepping through the phases of learning (e.g. planning at the introduction, self-assessment at the conclusion/summary). Thus a general *task/activity model is required to describe the phases to be stepped through by a learner when engaged in reading the AEH environment* [R2]. In order to contextualise the support (e.g. evaluation strategies should be prompted during the concluding stages), there also needs to be a mapping carried out between the trait and task models [R4.2].

The use of triggers, or schema signals is useful, as this can activate prior information and capabilities that we have available to us but were not necessarily successfully activating [F15]. However, schema theory itself provides a useful mechanism with which to describe how our cognition is stored and processed in our mind. Mental models represent information that is related to other information, has a changing nature, and is used to attend to and respond to our immediate environment. From

this perspective the model will represent learner cognition in a manner *analogous to schema theory*, in order to define the items, factors and traits, as well as the activities and tasks as objects or components that are related to each other and can be activated in order to reason over or to change over time in response to learner responses [R3].

TEL environments emulate the role of the tutor in providing supports, scaffolds, and promoting autonomy through fading, dynamic assessment of capabilities, and the support of a range of knowledge (declarative, procedural and metacognitive) for a range of learners (individual differences) [F7]. Learning about self-regulation and metacognition should be situated within a particular context or suitable learning environment [F10]. This means that the learner should be supported to make decisions regarding the resources or strategies that can lead to more successful learning outcomes. However, the goal of metacognitive supports is not always to change the metacognitive behaviour within the learning task, but can also be designed to support future metacognition. Supports can be in the form of general, domain specific, and task specific strategies. When separating the modelling and support from the learning environment, this means supporting more general or domain related aspects of learning. Regulation of cognition comprises of general abilities that are reusable across multiple learning tasks. However, in order to contextualise supports, harnessing of metadata standards in describing LOs (the current web page) can be used to create simple dynamic prompts. This means *employing a service-oriented architectural patterns* and harnessing the idea of a centralised user modelling approach to deliver a metacognitive service alongside an AEH service in a single *mashup application* [R4.1]. This means that the scaffolds that are delivered should be presented on the same web page, and that there needs to be *cohesion between the support and current learning context* [R4.3] by using the LO metadata to contextualise the supports but also by harnessing the *mapping* approach to ensure that supports are provided as a series of stages [R4.2].

TEL environments support two types of learning experiences – tasks that comprise of a number of steps and activities or conceptual knowledge and facts. Metacognitive abilities similarly comprise of knowledge and strategies [F16]. TEL environments have taken a number of approaches to take the role of the traditional educator in

supporting the development of self-regulation and metacognition [F3]. In designing a model of learner metacognition that will work with a TEL environment (over hypermedia on the web) – there are two paths that can be taken – some environments enable learners to practice (e.g. by viewing a demo of SRL and then implementing the strategy), or provide the learner with knowledge of their strategies (e.g. through prompts or questions). In particular, approaches include reflection through dialog, visual OLMs, reflection at different phases (before, during and after), interactive metacognition through collaboration, and supporting help-seeking behaviours. Scaffolds are determined from user model and adaptation characteristics – in essence they vary in their level of support, timing, implementation phase, assessment procedure, and state of the user model [F9]. There is a range of strategies available to support metacognition – e.g. planning, information management, and self-evaluation. In using items from the MAI as the basis of the user model, there needs to be a mechanism with which to update this model – although the values can be used to trigger self-reflection (e.g. through the use of an OLM) we need to get feedback from the learner. This means either questioning them/prompting them or creating algorithms/rules to assess what strategies they are using in the learning environment. In developing supports for metacognition, it should be capable of selecting from a bank of supports – the first step being to trigger the learner in a way that does not overburden them. Since the model will work with an AEH environment, the use of direct questions and prompts can be used to both trigger the learner and receive feedback. Thus, interactions with the learner will be provided in a non-invasive *pseudo-dialog approach in order to prompt and question the learner and subsequently update their metacognitive model* [R5]. These dialog interactions should satisfice their needs by addressing identified weaknesses and by being delivered in a series of stages (e.g. if the learner has particularly low goal setting ability, this should be questioned at the beginning of the learning experience).

Learners begin their learning experiences with prior knowledge and abilities – both cognitive and metacognitive [F13]. The quantification of prior metacognitive competencies is possible through the use of inventories [F6] and TEL environments have already implemented these types of inventories as pre-test models to set up an initial learner model. This means that regulatory strategies can be initially modelled by assessing the normal values for the typical learner population (baseline model) or

by requiring each learner to respond individually to the MAI. Thus, the learner's *cognitive model shall be initialised with a baseline model that is generated from the population* [R6]. As learners progress through the environment, the model can be updated over time and subsequent scaffolds can be changed in response to the changes in the confidence in the model. Initial, rich supports (e.g. questions) can be used to gather specific feedback from the learner, whereas over time these can be reduced to simple prompts.

There are a number of practical requirements for engaging with and implementing a model of learner metacognition. In particular, the user modelling and adaptation techniques used in TEL environments can provide these types of scaffolds and enable intelligent adaptation reasoning to be carried out about how and when to deliver supports to the learner [F8]. The goal of developing self-regulatory, metacognitive, and self-evaluation abilities is to enable learners to become autonomous. When modelling the learner with a baseline model and subsequent dynamic model to trace their progress, a *decision-making engine is required to interpret and direct interaction* with the learner [PR1]. This can be used to decide when to question the learner in order to update the baseline model and fine-tune it to suit the learner as an individual, or to decide on which metacognitive prompt to deliver to the learner. An algorithmic rule-based prioritising algorithm will be used to define which supports are useful. Also, despite the logical separation of the cognitive support service and learning environment on the back-end, the *user experience should be holistic* [PR2], and apply *good web application* and *user-centric design* [PR3] to ensure that the user-experience does not negatively affect the learning experience.

4.2 Cognitive Model Requirements

This section provides a synopsis of the requirements that have been derived in order to design a cognitive model that can be used to track and foster a learner's metacognitive ability. A number of research requirements [R1 – R6] are defined to describe the components necessary to design this model as well as an approach to implement it. A number of practical requirements [PR1 – PR3] are also described that are necessary considerations when developing an adaptive support system. These requirements are briefly described here. Later in the chapter a more in depth discussion is carried out about their impact on the design of ETTHOS and Goby.

4.2.1 Requirements from the Research – Design

[R1] An approach with which to model and foster learner ***traits*** that are complementary to learning, in particular metacognition –

- [R1.1] The purpose of this model is to enable the system to model, track and foster a learner's metacognition – the aim is to improve the educational gains for the learner by delivering personalised support. Thus, the model shall enable the scaffolding of metacognitive strategies.
- [R1.2] Model cognition in a structured, measurable way that is trait-neutral by using psychometric inventories to inform the technical architecture.
- [R1.3] Capture a temporal, real-time progressive view of the learners' metacognitive model.

[R2] Shall model learner conduct, via a ***task***/activity model, in particular learning tasks undertaken when engaged in academic literature.

[R3] The model shall represent learner cognition in a manner analogous to ***schema*** theory.

4.2.2 Requirements From the Research – Approach

[R4] Work in ***symbiosis*** with a TEL system.

- [R4.1] Employ a service oriented architectural pattern so that the system can be provided/consumed over the web and have the ability to communicate with other systems.
- [R4.2] There shall be a mapping carried out between the trait and task models.
- [R4.3] The metacognitive scaffolds should be delivered within a specific learning context. There should be cohesion between the support and the current learning context.

[R5] Interactions with the learner will be provided in a non-invasive ***pseudo-dialogic approach***. The aim of this dialog is to provide help the learner assess their learning practices, or prompt them to consider their learning strategies. These interactions with the learner should be the best possible with the information available in order to satisfice the learners needs.

[R6] The learner's cognitive model shall be initialised with a ***baseline*** model that is generated from the population.

4.2.3 Practical Requirements – Personalised Learning Systems on the Web

[PR1] A decision-making engine is required to interpret and direct interaction with the learner.

[PR2] Despite the logical separation of the cognitive support service and learning service in the back-end, the user shall experience a holistic application on the front-end that will be accessed using a web browser.

[PR3] Shall apply good web application and user-centric design.

4.3 ETTHOS - Emulating Traits and Tasks in Higher-Order Schemata

This section describes the ETTHOS (Emulating Traits and Tasks in Higher-Order Schemata) model and the model requirements [R1 – R3]. ETTHOS has been designed to represent learner cognition in a measurable and actionable way. It has also been designed to work with a TEL service in order to improve the educational outcomes for learners. ETTHOS models learner traits and the cognitive tasks that are carried out when engaged in academic reading. These traits and tasks have been structured analogously to the way that schema theory prescribes how concepts are stored in human memory. As such, ETTHOS leverages three approaches to describing and analysing cognitive structures: psychometric tests, protocol analysis, and schema theory. It separates the modelling of learner traits, reading tasks, the connection between these traits and tasks. It has also been developed in a manner that allows for the distribution and logical separation of models and services similar to distributed TEL approaches.

Consider the course developer of a learning environment who wants to support some aspect of learner cognition and track this support over time. For example, imagine an introductory programming course, which is delivered alongside support for information management skills. The ETTHOS model supports someone who wants to deliver these two components as a single application, but in the background wants to keep the two aspects as separate services. They may want to assess and track the learner's information management strategies over time – in order to track the learner's growth, provide feedback and cognitive scaffolds or trigger self-reflection.

4.3.1 The ETTHOS Model

The ETTHOS model and its main components are depicted in Figure 4.1. This makes a distinction between the ETTHOS trait, task, and progress models; the learning system LO model; and identifies whether models are static or dynamic.

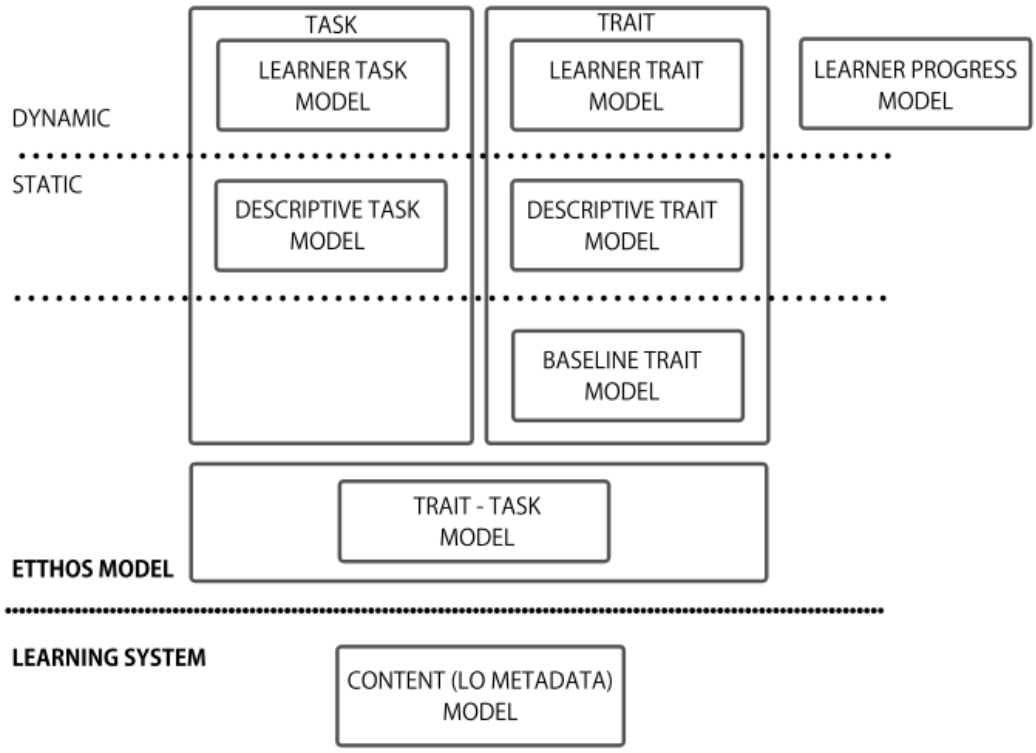


Figure 4.1 - Model Components of ETTHOS

The trait component comprises of a descriptive and baseline trait model, both of which are initialised at the time of implementation. The descriptive trait model is used to represent a psychometric inventory that assesses a trait. The baseline model holds the typical population mean for each item in that inventory. This is used to initialise the dynamic model - the learner trait model. The learner model tracks the learner over time and is used by a decision engine to reason about support delivery. The descriptive task model is similarly static and thus initialised at the time of implementation whereas the learner task model is updated over time. The following describes each of these components in the ETTHOS model:

The **trait** component manages the behaviour and data that represent a learner's cognitive trait; responds to requests for the status of the individual learners state; and responds to instructions to change the learner's trait. There are two main types of trait models utilised in ETTHOS:

1. The ***descriptive trait*** model
2. The ***learner trait*** model

A third has also been introduced in order to reduce the dependency on profiling surveys at registration time.

3. The ***baseline trait*** model

The **task** component manages the behaviour and data that represent the inferred actions of the learner; responds to requests about the learner's current actions; and responds to instructions to change the state of a learner's actions. Similar to the trait model, there are two types of task models utilised in ETTHOS:

4. The ***descriptive task*** model
5. The ***learner task*** model

To bride the gap between these, a mapping is carried out between items in the descriptive trait model and each of the actions described in the descriptive task model. This has resulted in:

6. The ***trait-task*** model

An overview of the learners' path through the service, their selections, inferred tasks, and dialog sent and received is tracked over time. This overview is represented in:

7. The ***learner progress*** model

A dialog generator contextualises the support delivered to the learner. This requires access to the metadata repository in the TEL service, described as:

8. The ***content (metadata)*** model

4.3.2 Traits [R1.1, R1.2]

This section describes how factor analysis can be aligned with the user modelling techniques employed in the TEL domain. The trait model will - enable metacognitive scaffolding [R1.1]; model metacognition in a structured measurable manner [R1.2];

and capture a temporal and progressive view of the learner's metacognition [R1.3]. There are a number of diverse approaches to integrating cognitive support in learning systems, an overview of which was carried out in Chapter 3. The model and subsequent decision-making is carried out with a variety of approaches including dynamic and static modelling, explicit and implicit model creation/updating, a range of support characteristics (e.g. timing, target of support) and utilise a number of intelligent reasoning approaches (e.g. production rules, example-tracing, constraint-based modelling, statistical, and rules based approaches). Despite the work on user modelling, there is no agreed format to describe the structure of a metacognitive model and component metrics used to represent the learner.

Some TEL systems have used inventories to assess learning styles or metacognitive strategies (Canella et al., 10; Russo et al.), however they generate a static model on registration that specifically describes the learner at the point when they register with the system. In ETTHOS, rather than model a specific survey, the structure of psychometric inventories is represented. To achieve this, the factor analysis process that is often used to create and refine psychometric inventories was analysed.

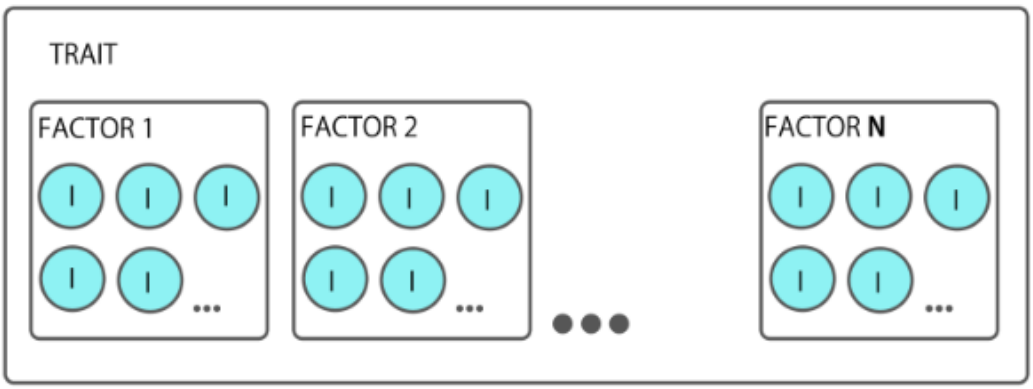


Figure 4.2 - Trait, Factor, Item relationship

The Figure 4.2 above illustrates the trait, factor, item relationship that is commonly used in psychometric inventories. Each test assesses one aspect of a learner that can be described with a number of related factors. For example, regulation of cognition is measured with the MAI. Factors are latent characteristics that are not directly observable. Instead, they are assessed with a number of observable items. Planning is one of the regulatory MAI factors that comprises of items such as the ability to set goals and read instructions carefully. The derivation of psychometric inventories was motivated by the progression in psychology towards the scientific method and the

need to describe cognition in a measurable and observable way (Kline, 08). The representation of the structure of these inventories in ETTHOS is similarly driven for the progression of user modelling towards better measurement of learner cognition.

This involves describing cognitive constructs as psychometric inventories, either current, or newly developed for the problem-domain. There are a number of benefits to taking such an approach. The main characteristics of good psychometric tests are: test-retest reliability; internal consistency; a low standard error of measurement; good evidence of validity; and a high discriminatory power. When applied to TEL, it is hypothesised that they can support useful cognitive skills that are complementary to learning. It should be noted that these inventories result in a limited representation of the learner. They are not necessarily true or all encompassing because there is no true zero on a cognitive scale. Nonetheless, they have useful predictive or comparative power (Kline, 08) and can be used to track the learner's progress over time or compare the effects of educational and metacognitive interventions.

In ETTHOS, traits are represented along a scale (in particular between 1-5, however this could be 1-100, 1-7, etc. depending on the requirements of the model) in order to describe the trends of positive or negative tendencies that a learner reports on the psychometric. These inventories are representational tools that can be used to compare individuals to other individuals or groups and see how this changes over time. The motivation behind the ***trait*** component in ETTHOS is to harness these comparative and modelling abilities, and provide a standard approach to describing the metrics in cognitive models. This is achieved by describing each item in a psychometric inventory as a set of related metrics. In turn, the generalised model should support complementary inventories. Since the purpose of ETTHOS is to model and inform subsequent support, this means that these item values will and should change over time. However, this has implications for the reliability of the measures. However, through repeated interactions with the learner, this value should become more accurate and confidence in the value increase. In turn, the accuracy of the model post-interaction with the learner is one of the experiments outlined in the Chapter 6. In this thesis, the Metacognitive Awareness Inventory (MAI) (Schraw & Dennison, 94) has been identified as a suitable candidate to model because it assesses cognitive aspects that are complementary to learning online.

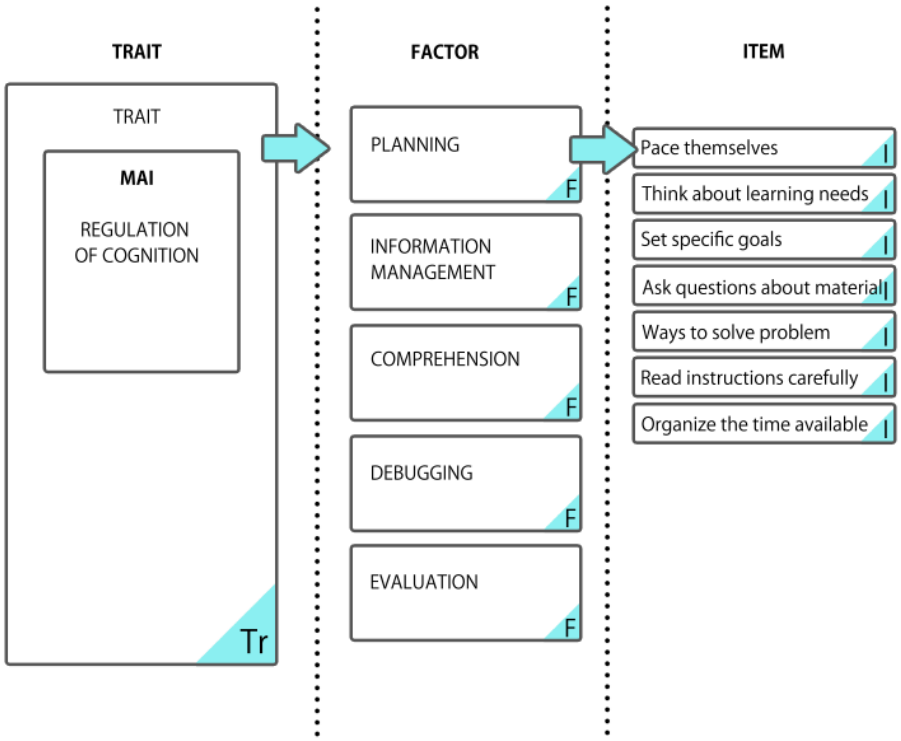


Figure 4.3 - Traits in ETTHOS

Figure 4.3 illustrates how a **trait** is represented in ETTHOS, and shows how the MAI has been applied to this architecture. Here, the trait sub-system (Tr) comprises of a number of component factors (F), each of which has a number of component items (I). The above illustrates how "*regulation of cognition*" is comprised of five factors; "*planning*," "*information management strategies*," "*comprehension*," "*debugging*," and "*evaluation*." Each of these factors is also represented by a number of component items. Here, we can see that "*planning*" is represented by "*pace themselves*," "*think about learning needs*," "*set specific goals*," "*ask questions about the material*," "*think of other ways to solve a problem*," "*read instructions carefully*," and "*organise the time available*."

A breakdown of the each of the items that are used in the MAI to assess regulation of cognition is included in Appendix B. Planning itself is not an observable paradigm, however it may be exemplified by a number of observable items. On the MAI, this includes items such as '*I pace myself in order to have enough time*' and '*I set specific goals before I begin a task*'. The structure of the ETTHOS model represents this breakdown of psychometric inventories rather than implementing an MAI specific solution. In future work, it could be desirable to model other inventories that are

complementary to the learning environment. This could include traits such as social cognition, critical thinking, and affect. For example, if the TEL course is related to learning languages, social cognition or good communication skills may be an appropriate skill to support. In the ***learner trait*** model, each item is categorised along a scale of 1-5. A confidence value, and timestamp is also assigned to each of the items. The timestamp is used to track the progression of the cognitive model over time and assay the most recent status of the learner. An assessment of the learner's abilities with a decision-engine informs the system on which item to support.

4.3.3 Progressive Modelling [R1.3]

The ETTHOS model captures the ***learner trait, learner task,*** and ***learner progress*** over time. This progressive modelling of the learner is a characteristic of TEL systems that supports the adaptive and supportive functionality. In ETTHOS, this temporal view of the learner is used by a cognitive modelling service to decide the next appropriate step in interacting with them. Imagine a scenario where three items would be appropriate for a LO. For example, the learner is reconstructing their understanding of the module. A number of information management strategy items could be useful to apply at this stage, such as asking themselves if they have considered all the options or deliberating on several alternatives. If there was recently an intervention that supported one of these, then the least recent item will be given a higher weighting in the decision-making process. This temporal view of the learner also has interesting possibilities in terms of visual reification of their progress and motivating the learner, however these are outside the scope of the thesis.

4.3.4 Tasks [R2]

In TEL systems, a learner model often describes the path through which a learner should navigate a system or the constraints within which they should operate. This procedural knowledge can be represented using production rules, via example tracing, constraint modelling, or statistical models. However, these approaches to modelling the learner's actions are typically directly related to their actions in the learning system. ETTHOS has been derived as a separate model that is logically separated from the learning systems – this has resulted in [R2] – model learner conduct, via a task model, which describes the learning tasks undertaken when engaged in academic literature. This approach is influenced by the ITS learner

models, however it is distinctly different because it is a general model of the cognitive reading tasks rather than specific learning activity tasks that simply describes the phases of the cognitive strategies.

The descriptive task model has been designed based on the extensive work of Pressly and Afflerbach (1995), which identifies and describes the sequence of strategies and responses that readers carry out consciously as they read. This can include text, examples, diagrams and sample solutions. This work has been used to describe, in general, the activities that a successful reader undertakes when they read academic text. It lists the possible route that a reader can take, and is broken down into discrete activities. This is similar to the learners' cognitive progression in an AEH environment that requires the learner to attend to new reading material and interact with tables, figures and examples.

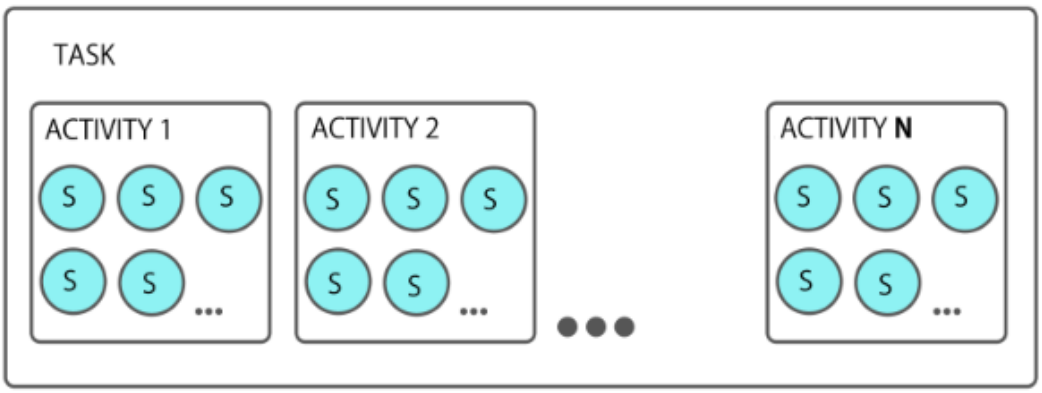


Figure 4.4 - Task, Activity, Sub-Activity relationship

Figure 4.4 illustrates how the cognitive reading tasks are broken down. The reading task comprises of a number of descriptive activities, each of which is represented by a list of actionable sub-activities. This structure been adopted in ETTHOS to outline the descriptive trait model. The motivation behind modelling cognitive tasks is to move away from the implementation of cognitive support that is tightly tied into one specific learning environment. It is acknowledged that the thought processes behind reading a piece of text are not always linear. Not all readers will complete each activity covered depending on their goal. Often readers will engage in recursive and interactive activities. Also, some activities preclude others, such as skipping a section versus front to back reading. Despite these limitations, it is possible to describe the tasks in a quasi-sequential format and provides a mechanism with which to step through a series of learning activities.

Before	
A. Before Task – Planning	
1.	Constructing a goal
2.	Overview the learning object
3.	Decide to only do particular sections
4.	Decide to quit because content not relevant to goal
5.	Activate prior knowledge
6.	Summarise what was gained from preview
7.	Based on overview, generate initial hypothesis
During	
B. Salient Behaviours During Initial Reading	
8.	General front to back interaction with a module
9.	Reading only some sections, ones believed to contain critical information based on prior knowledge about the structures used
10.	Skimming
11.	If easy, tackle using automatic processes
12.	Repeating/Restating module just read to hold in working memory
13.	Pausing to reflect on module
14.	Explicitly looking for related concepts or ideas and using them to construct a main idea, gist, or summary
15.	Resetting learning goals at a different level of understanding because module suggests there might be a more appropriate goal

Table 4.2 – Extract from the Cognitive Task Model

This is illustrated in Table 4.2 above, which shows an extract from the cognitive task model. The entire descriptive task model is included in Appendix C. Each task comprises of a number of component activities and sub-activities. The core activities that could represent the actions are made up of 7 main categorical activities, with 50 individual sub-activities. Each of these is represented using ETTHOS as in the descriptive or learner task model.

Figure 4.5 below illustrates how a **task** is represented in ETTHOS, and shows how reading protocols have been applied to this architecture. Here, the task sub-system (Ta) comprises of a number of component activities (A), each of which has a number of component sub-activities (S).

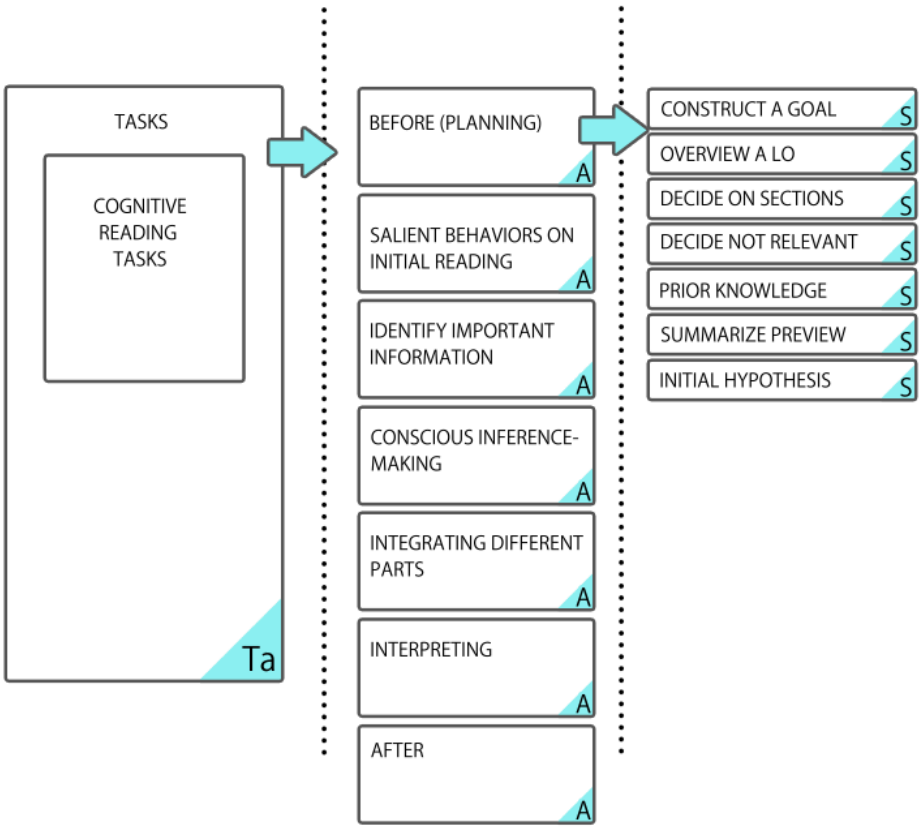


Figure 4.5 - Tasks in ETTHOS

As shown in Figure 4.5, the "*cognitive reading tasks*" are first modelled as a set of activities which include; "*before (planning),*" "*salient behaviours on initial reading,*" "*identify important information,*" "*conscious inference making,*" "*integrating different parts,*" "*interpreting,*" and "*after*". Each of the "*before*" sub-activities are exemplified here including, "*construct a goal,*" "*overview a LO,*" "*decide on sections,*" "*decide not relevant,*" "*activate prior knowledge,*" "*summarise preview,*" and "*generate an initial hypothesis.*" In the ***learner task*** model a timestamp is assigned to each of the sub-activities.

4.3.5 Mapping Traits to Tasks [R4.2]

The complex use of the comprehension processes requires a huge amount of knowledge of when and where various cognitive strategies apply (Pressly & Afflerbach, 95). This means that certain strategies or traits need to be applied during different types of activities. In effect, there is a link between the cognitive processes of reading and the activation of suitable cognitive strategies to monitor and control the process.

In ETTHOS, the ***trait-task model*** represents this link. This mapping is necessary in order to inform the decision-making process that controls the activation of support for particular metacognitive items. By connecting traits to tasks, it means that learning support can be delivered at the right time and in the right context – if effect cognitive support is delivered in symbiosis with learning tasks [R4.2].

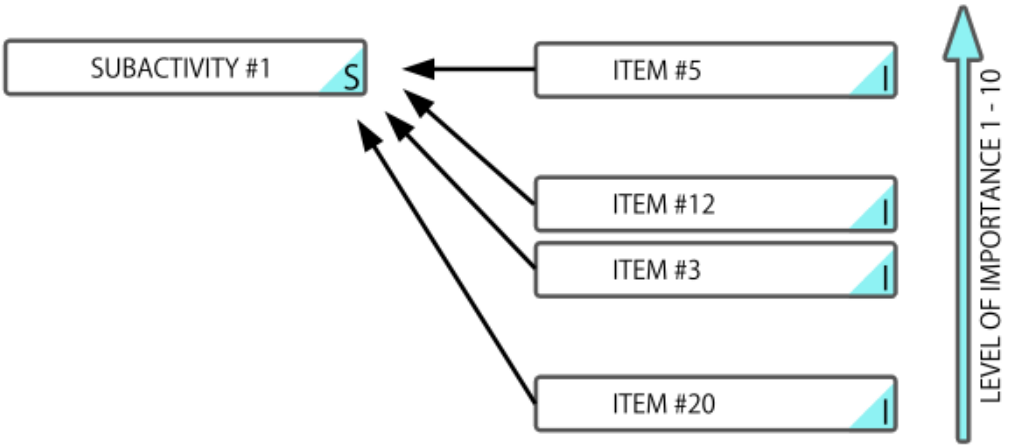


Figure 4.6 – The Trait - Task Relationship Model

Figure 4.6 above illustrates the **trait-task** model in ETTHOS. The purpose of this is to represent a mapping between each of the sub-activity elements with one or more items in the trait model. In the ***trait-task*** model each sub-activity is linked to one or more items, and this relationship is given a measure of relative importance.

4.3.6 Schema Structure [R3]

The structure of the cognitive user model proposed aligns schema theory with the technical architecture [R3]. ETTHOS represents learner cognition in a manner analogous to the way human cognition interprets and represents the world. A schema is "*a data structure for representing the generic concepts in memory…representing our knowledge about all concepts; those underlying objects, situations, events, sequences of events, actions, and sequence of actions*" (Rumelhart, 80). In this sense, a schema may be understood as a set of mental models, which are used to organise information and create predictions, inferences and expectations. Schemata are structured chunks or packages of knowledge that are organised into an overall framework of knowledge (Piaget 29; Anderson, 77; Anderson, 84; Bartlett, 32; Rumelhart 80; Ibrahim et al., 03; Derry, 96). This framework of knowledge is often referred to as mental model because they influence how people comprehend tasks or solve problems. This schema paradigm has helped to derive the processes that are necessary to implement a

technological model of learner cognition. Schemata help the learner to construct meaning from new experiences and elaborate and expand their knowledge – it is similarly the goal of ETTHOS to support an expanding model of learner cognition that can be used to inform the activation of suitable scaffolds in a TEL system. Consequently, the characteristics reported of mental models or schemata have been considered in the ETTHOS model.

Ten observations from the literature are discussed in order describe how schema theory is used as an analogy for representing cognition with ETTHOS:

1. Schemata are *activated* in order to comprehend new events or solve problems. In ETTHOS, this means that the most recent understanding of the learner influences interactions with the learner. From a technical position, this has direct influences on the implementation approach. The recent metrics that are relevant to the current context are represented using an object-oriented approach. The decision making process relies on a rules engine to represent the objects in working memory. Consequently, the rules are run, in order to return the appropriate course of action.
2. Experts structure their mental models differently than novices. Experts tend to use specific, domain based reasoning strategies, whereas novices tend to invoke more general problem-solving strategies. It is traditionally the role of the instructor to activate learners existing schemata and support the development and refinement of more appropriate mental models. The key **trait** component in ETTHOS is the ***learner trait*** model. This allows the interactions with the learner to be directed at the weaker areas. In order to target the support contextually, the ***trait-task*** model is used to give weight to the current position of the learner.
3. The consequence of the point above is that cognitive load is reduced for learners who have access to appropriate schemata. Within ETTHOS, once the weaker traits have been targeted, it is possible to move on to support other problem areas.
4. They are acquired/changed with experience. There are three processes suggested to describe this: accretion, tuning, restructuring. Within ETTHOS, a temporal view of learner progress is persisted in a user model.

5. Schema signals often provide an introduction to text or add contextual information to a learning scenario. These signals help the learner to activate prior knowledge; often highlight the upcoming important parts; and activate suitable encoding strategies. In ETTHOS, once a suitable item has been identified, the interaction with the learner should be contextualised using the metadata that describes the current LO.
6. Schemata are often incomplete. While some individuals may have expert knowledge, their understanding of domains outside their expertise is often partial. Within ETTHOS, both traits and tasks are a limited representation of the cognitive processes and activities that a learner may possess.
7. A person's ability to control their model is limited. In particular novice learners often do not know what skills they have that could be used to support their learning. In ETTHOS, the MAI has been implemented. For example, one of the items on the MAI asks whether a learner would draw diagrams to try to help their understanding of a particular concept. Although people have the ability to do this, they often do not realise that they could. The use of ETTHOS to deliver targeted hints can help a learner increase their awareness of learning strategies or help develop new ones.
8. Mental models are parsimonious. This frugality is similarly seen in the specific set of reading tasks and cognitive inventories in ETTHOS.
9. They do not have firm boundaries. Here, there is a distinct difference, in that ETTHOS represents a specific set of concepts in order to represent a limited view of the learner.
10. Mental models are unscientific. Whereas it is often difficult to gauge or evaluate mental models, it is the goal of ETTHOS to model learner cognition in a quantifiable and measurable way. Consequently, extensive evaluations have been carried out on an implementation of ETTHOS in the Goby service.

4.4 Realising ETTHOS

4.4.1 Symbiosis with TEL Services [R4]

Cognitive support needs to be integrated with learning tasks as a cohesive learning experience. The application that delivers the course content and cognitive support should promote the formal learning objectives of the system in tandem with the

cognitive learning objectives – this means that the cognitive support system works in symbiosis with a TEL system [R4]. This symbiosis comes from understanding and alignment with both abstract cognitive skills, and the goals of the learning system. From an architectural point of view, the service is provided/consumed with a SOA pattern [R4.1]. This means that the logical separation in the delivery and implementation of the services should not be visible to the end-user [R4.3]. A cohesive experience is essential, both in terms of the look and feel of the application, and more importantly in terms of the targeting of cognitive support by mapping the learner trait to reading tasks [R4.2] and contextualisation of that support within the learning domain.

4.4.2 Distributing TEL Services [R4.1]

ETTHOS has been architected to support the integration of a cognitive modelling and support service with a TEL service. These two distinct components have discrete and separate functionality and are owned and managed independently. This type of architecture is supported by the SOA architectural pattern, which is an underlying pattern for many web-based applications. The distribution of services across servers enables reuse of services, the reduction of load on the system by distributing components across multiple servers, and limits the propagation of change. While this logical decoupling allows for reuse, the system as a whole must work together cohesively. This has implications for the modelling functionality provided by ETTHOS. Since the learning service is managed independently, it will fulfil invocation requests without allowing the client see the logic behind the service interface.

In traditional cognitive support services, the link between the LO and cognitive support is carried out by tightly coupling the two. In ETTHOS, as outlined previously, the **task** model has been introduced in order to bridge this gap and allow for suitable abstraction. However, because the services fall under various domains, there is a requirement that the cognitive support is contextualised. This means that there needs to be agreement from learning service to allow access to the LO metadata. This metadata needs to be reachable and visible to a consumer, preferably through a service interface. Once this agreement is in place, it means that the specific inventory being modelled is reusable between different courses. In the current system, Goby

models the MAI as part of a SQL and Database course, however this same model could be used with other courses.

4.4.3 Dialog [R5]

The processes of modelling and supporting learner cognition require interactions with the learner. In the Goby implementation of ETTHOS a pseudo-dialog approach has been taken [R5]. The aim of this dialog is to assist the learner when assessing their learning practices and consider their learning strategies. Currently, two categories of dialog have been supported in Goby: ***prompts*** and ***questions***. This communication is executed within the confines of the web application. Azevedo and Witherspoon (2010) outline a number of guidelines to support learners monitoring during learning with hypermedia (Azevedo and Witherspoon, 10). These proposed guidelines are directed at learning that is web-based and controlled by the learner, however they have implications for any TEL system that is oriented towards supporting learner self-regulation. As such, these guidelines have been taken into account in the delivery of the dialog:

1. Learners should be prompted periodically to plan and activate their prior knowledge. In response, the system shall regularly prompt or question the learner on their approach to regulating their learning.
2. Scaffolds should be designed to encourage the learner to engage in metacognitive processes. In Goby these scaffolds have been derived from the items in the MAI.
3. Static scaffolds could be embedded in the system to prompt the learner to monitor their progress towards completing a task or reaching a goal. This might include having the learner actively access their achievements about each of the sub-goals. This guideline is similarly addressed by communicating with the learner regarding their status on the MAI items.
4. Providing embedded prompts and feedback to scaffold learners' development of effective learning strategies.

A dialog repository stores the key parts of both prompts and questions. These chunks are derived from the psychometric inventory and contextualised at run-time. In particular, the items in the MAI that describe the learner's regulatory process have been used to create chunks of dialog. A non-adapted approach to using the MAI to

deliver prompts has been taken by SlideTutor (Saadawi et al., 11), however these prompts were modelled explicitly and were not delivered dynamically in response the learners needs. Each of prompts or questions therefore relate to individual items in the **trait** model. When a support system is manifest in a learning environment, there can be dissonance between the course and the support. This means that interventions can be distracting for the learner, which is why it is important that the encounters are contextually appropriate. In order to achieve this chunks of the items in the inventory are combined with contextual cues that is collected from the metadata used to describe the current LO. This allows the metacognitive scaffolds to be delivered within the learning context [R4.3]. Whereas a prompt is delivered as a hint or reminder, the learner needs to consider the answer to a question. This results in deeper processing, which means that the learner will have to focus their attention on the question. Prompts are less invasive; so they do not require such a break in momentum or engagement with the course material. The objectives behind this are twofold: to help the learner develop their awareness of their skills or strategies and also to inform the user model.

When deciding on an item to trigger, there may be a number of suitable options. Although the item chosen might not be the most optimal choice, as long as the choice serves the learner well then the interaction can be considered a success. These interactions with the learner might not be the best possible, however they should use the limited information available in order to benefit the learner and satisfice (Simon, 57) their needs. This is a process whereby an option is chosen within a bounded rationality. For example, when people deliberate options they generally consider each option one at a time and pick the first option that is acceptable. Even if it is not optimal, as long as it is suitable then their choice can be considered a success. When ETTHOS is used in a service, a decision-engine is required. This captures the state of the learner from ETTHOS and sends requests for updates to the user model. This decision making engine is rational within limits. The aim of this approach is to make an acceptable selection, even if it is not optimal. Reasoning is guided by the goals of the service – to learn about the learner, model this inference, and to support the learner.

4.4.4 Baseline Model [R6]

There is a tendency in adaptive learning systems to categorise learners by making them carry out a survey when they register with the learning system. In this thesis, it is proposed that this step can be bypassed by using the community or mean responses from the population to initialise the user model. The motivation behind this is to address the malaise that sets in when people are asked to answer surveys. Over-surveying individuals can cause survey fatigue. With an increase in personalised and adaptive systems it is not desirable to ask users to respond too many surveys. If they were, it could have adverse consequences on response rates. One alternative is to have a shorter survey, since the participant's commitment is a lot smaller. However, in the case of a psychometric inventory, each item that measures a factor needs to be assessed. If there are many factors, this means that there will be many multiples of items that must be asked. An alternative approach has been incorporated in this research. The user model is first initialised with baseline metrics that reflect the mean values of the population. As the learner interacts with the system, the user model is refined to better reflect his or her own individual preferences or tendencies. Over time, the model is modified to fit the relevant responses from the learner. This initial baseline model is generated from the population and fine-tuned over time through interactions with the learner [R6]. This approach has been motivated by the need to separate the cognitive support service from the TEL system while limiting the load on the cognitive resources of the learner. In this experimental setting, the baseline metacognitive awareness was calculated from an initial pilot study, which is discussed in Chapter 6.

4.5 The Goby Service

4.5.1 Goby Overview

The Goby service was developed to reflect the architecture of ETTHOS and implemented using the approach specified above. This means that it works as a symbiotic service that interfaces with a TEL service. Consequently, it relies on the learning system to function, and it is not delivered as a stand-alone system. Instead, it supports and adds benefit to the learning environment. Goby is a test-bed system for the ETTHOS model that has been outlined above, and applies the recommendations laid out for using this model. This includes support for a dialogic approach to

communication with the learner. Figure 4.7 below shows the Goby service in context. Goby currently communicates with the APeLS TEL service to deliver contextualised metacognitive support. The two are delivered as a single web application – as a mashup Internet application that is accessed via a browser [PR2]. As illustrated in Figure 4.7 APeLS is a subordinate system that is used by Goby to provide metadata and performs the course delivery processing. The Goby web application provides a holistic experience for the learner, combining the cognitive support with the Database and SQL course content.

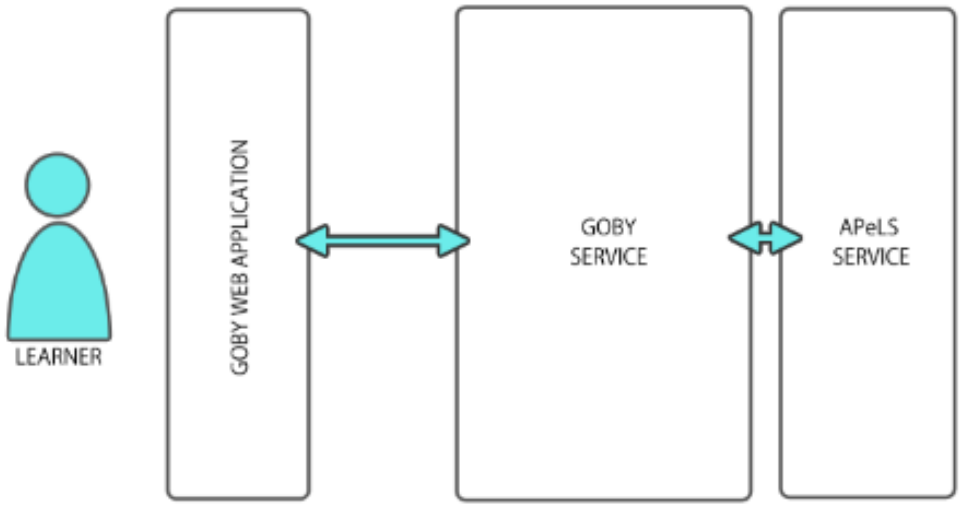


Figure 4.7 - Goby Service in Context

4.5.1.1 Scope

The scope of the service is to model and support learner cognition along side a TEL service that delivers domain knowledge. Each of these sits as separate applications on their own server. These two components are delivered as a mashup application that is accessed using a web browser. A component in Goby controls the communication between the TEL service in order to deliver both course content and metacognitive dialog to the user. Implementation of this system is trait-neutral, describing the learner's traits as factors and component items in order to represent the MAI.

4.5.1.2 Software Context and Constraints

The system is dependent on working alongside a TEL service. For the purpose of evaluation in this research, Goby interfaces with the APeLS learning service, which delivers an introductory database course. APeLS was identified as a suitable system

to work with since it employs a standards-based metadata schema to describe each LO. This metadata is required by the support service to contextualise interactions with the learner – metadata is used in order to create the prompts and questions. The user profile comprises of students who would be suitable for admission on the APeLS database course. In this instance, the MAI is modelled in order to support the regulatory aspects of learners' cognition.

4.5.1.3 User Profiles

There are three main roles of interaction with the system - the learner who has their metacognition modelled and supported; educators who plot the metacognitive mapping; and technical administrators who control the system and connect it to a TEL service. There is also a fourth role in this system – the researchers who are interested in gathering experimental data. The target user group are individuals who would be accepted onto a third-level introductory computing course in Ireland, aged 18+ and satisfied the criteria to be admitted to an Introductory Database and SQL module. Thus, course entry requirements are that they are already engaged in the early stages of a cognate discipline (Computer Science, Engineering), or that they have sufficient prior experience, or a Level 8 degree or its equivalent.

4.5.2 High-Level Goby Architecture

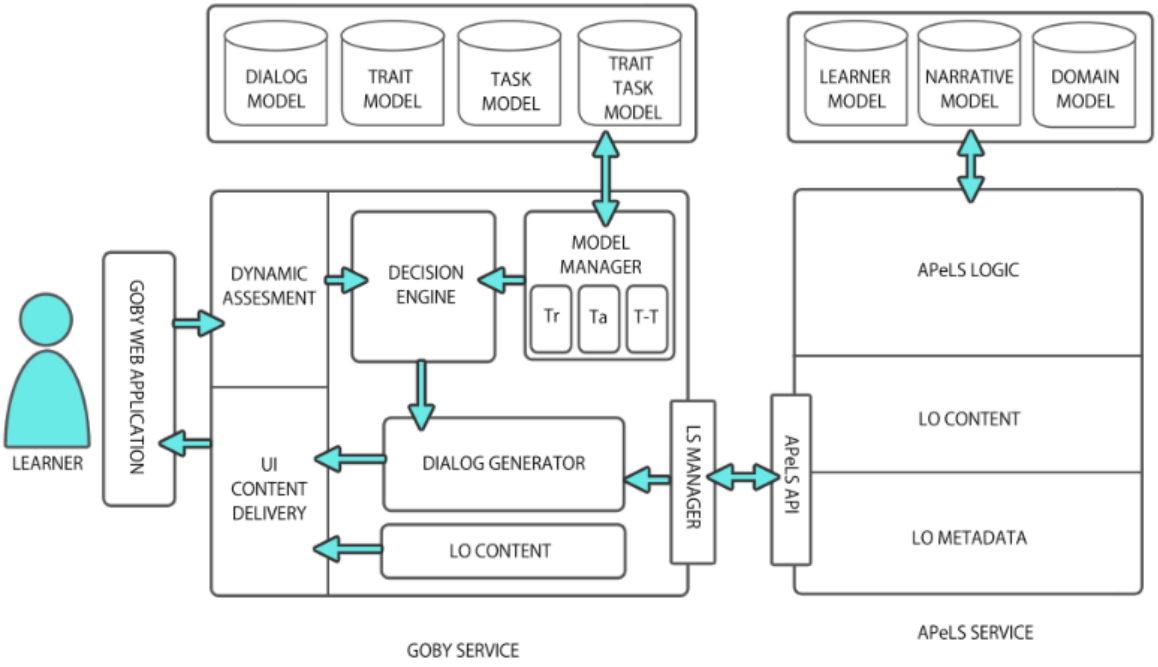


Figure 4.8 - Goby Architecture

Figure 4.8 shows the high-level design architecture of the Goby. This shows the design architecture of ETTHOS in the context of a modelling and support framework. This shows the complementary components that make ETTHOS an actionable service. These include the baseline user model, decision engine, and dialog generator. It is designed to support interoperable interaction over the web. This results in contextualised dialog, which is delivered to the learner in the form of a prompt or a question. The framework manages the interactions with the metacognitive modelling system and the learning system. Interactions with the learning environment or metacognitive dialog are fed back in order to update the user model. The core component is the ETTHOS model, which represents learner cognition, and links the cognitive traits to learning tasks. Requests from the interface are assessed dynamically. The MAD (Multi-Attribute Decision making) rule-engine is essential to the service because it manages the communication with the learner. The state of the learner is dynamically assessed in order to identify their position in the ***task*** model. An activity identifier is output, and a request is sent to the MAD engine to calculate which complementary item in the ***trait*** model should be supported. The MAD engine responds with a suitable candidate and sends instructions to track the dialog sent. The following describes the decision making process that has been implemented for use with ETTHOS.

4.5.3 Decision Engine [PR1]

TEL systems comprise not only of user models but also incorporate some form of decision engine in order to assess the implications of the learner's actions and subsequently present suitable feedback or support to the learner. In accordance with [PR1] a decision-making engine is required to interpret and direct interaction with the learner. There are a number of approaches to delivering this kind of logic in TEL[65] – knowledge-tracing belief models (Mitrovic, Koedinger, Martin, 03), constraint-based modelling (Mitrovic, Koedinger, Martin, 03; Mitrovic, Martin, Suraweera, 07), case-based reasoning (Ohlsson & Mitrovic, 07), example-tracing (Koedinger, Aleven & Heffernan, 03; Aleven et al., 09), task analysis (Lesgold et al., 92), Bayesian belief modelling (Rainer, 89; Beal, Mitra & Cohen, 07), and the use of rule-based languages (Conlan et al., 02, Conlan & Wade, 04) that can carry out reasoning with multi-attribute normative decision-making rules (Kabassi & Virvou, 06). This decision-

[65] For an overview of these approaches please see further Appendix A

making process has been identified as an appropriate approach because of the nature of the method - Multi-Attribute Utility Theory (MAUT) (Wright, 84) is a normative approach to decision-making that calculates the utility of alternative choices. Utility is a measure of how well an outcome suits some goal. Each option is broken down into a number of independent dimensions. These dimensions describe some aspects of the options. For example, if you were buying a car, the dimensions that might influence your decision would be the price, engine size and fuel efficiency. Each of these dimensions is given a numerical weighting relative to each other. Figure 4.9 below illustrates this calculation. Here, the sum across the utility of each dimension results in the total utility of an option. Then each option can be compared, and one selected. This model describes how the ideal decision should be chosen with a limited amount of data available.

$$v_i(x) = \sum_{a \in A_i}^{n} w_{ai} v_{ai}(i(a)) \quad v(x) = \sum_{i=1}^{n} w_i v_i(x)$$

Figure 4.9 - Multi-Attribute Decision Making Equation

In Goby, a MAD engine applies this model of decision-making is used to infer which item should be highlighted next. A task identifier is input into the MAD engine and a list of related items is identified using the trait-task mapping model. Each item is assessed on a number of dimensions including the current value for that item, confidence in that value, the recency of that item in the learner trait model, and the strength of the relationship between the activity and the item.

4.6 Goby Functions

The process narratives of a number of system requirements for the Goby service are described in this section. These requirements have arisen out of the practical requirements necessary for developing a personalised learning system [PR1 – PR3] and most importantly from the research requirements [R1 – R6]. A set of process diagrams, which illustrates each of these system requirements [SR1 – SR10], is included to illustrate the core functions of the Goby system.

4.6.1 [SR1] Model Learner Metacognitive Awareness

The purpose of this activity is to retrieve notifications that the learner has responded to some metacognitive dialog, update the ***learner trait*** model and persist the results.

This activity measures the metacognitive awareness of the learner. Each of the items on the MAI that describe cognitive regulation is represented in the learner cognition repository. When the learner responds to an item, the response should be recorded and the current values that represent it updated. This modelling will subsequently enable the scaffolding of metacognition [R1.1] through understanding their strengths and weaknesses. The model represents traits, component factors, and subsequent observable items. This approach is trait-neutral and parsimonious – representing a limited view of the learner – in this case a set of related metacognitive factors that describe the learner's regulatory abilities [R1.2]. This model is refined over time through interactions with the learner in order to capture a temporal, and progressive view of their metacognitive abilities [R1.3].

Process Actions

Each time the learner responds to a piece of dialog, this has an effect on the cognitive user model. Questions require deeper processing than the prompts. Since one of the main hypotheses under evaluation is that this dialog can support the learner, the questions trigger a greater change in the ***learner trait*** model. The most recent metric for the item being updated is found, this value is updated and the new value persisted. The progress and responses are also stored. Figure 4.10 showing the flow of information through the function and the transformation it undergoes:

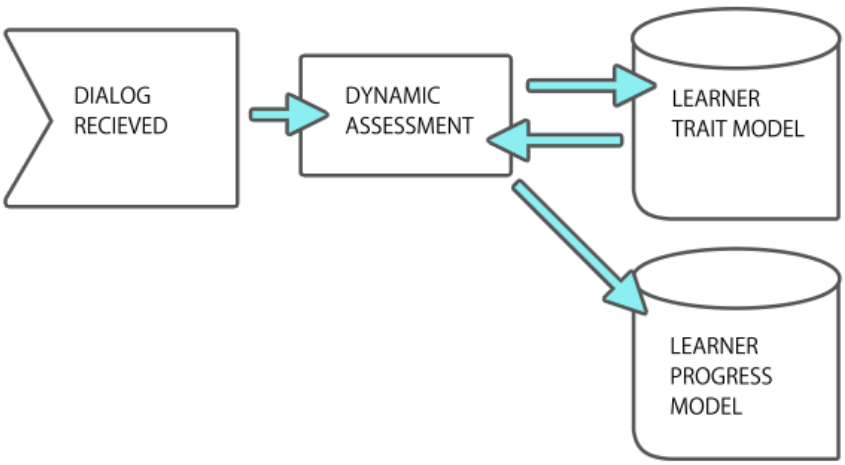


Figure 4.10 - Modelling the learner

Interface Description

The user ID, item identifier, type of response, and timestamp are input. The previous value and confidence for that item in the learner's history are retrieved. These

metrics are updated, and a new entry in the repository is written to track this progress.

Data

The learner identification, trait ID, type of dialog (prompt or question), and response are input. This is persisted in the ***progress model*** and the ***learner trait*** model is updated.

4.6.2 [SR2] Model Reading Tasks

The system will infer the current activity using the current position in the learning environment. This means relating the current position in the learning environment to a place in the task model. This task model represents the learners cognitive strategies that are undertaken when engaged in academic literature [R2]. This model is aligned with learning in an AEH environment where students are delivered personalised academic multimedia content – such as text, diagrams, tables, and figures.

Process Actions

The ***descriptive task*** model, illustrated in Figure 4.11 below, provides a generic way of representing activities that a learner undertakes as they progress through a learning object. These tasks are overlaid over the overall course, and are also overlaid over each section. This means that there could be a couple of activities that would be suitable at a particular point in time. Each of the potential activities is listed. The one that is selected is not necessarily the most accurate, but should satisfice the needs of the learner. The least recent activity in the ***learner task*** model is identified and output.

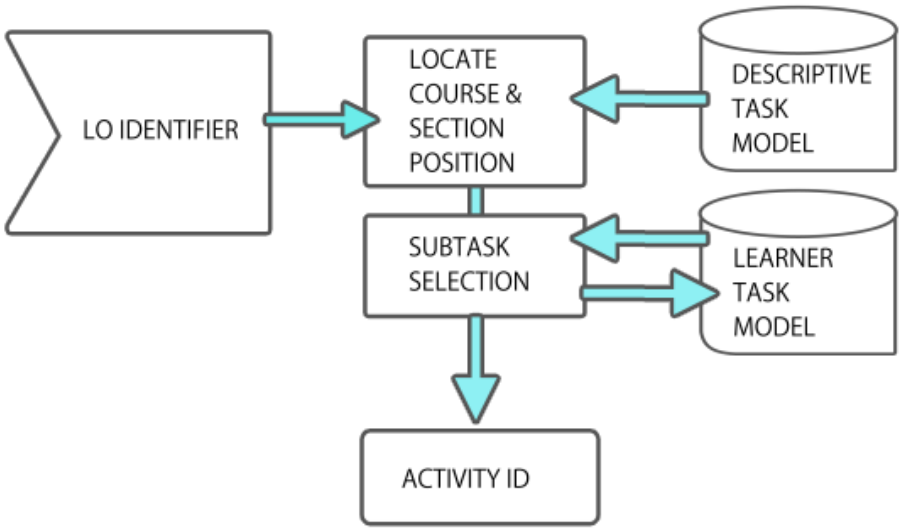


Figure 4.11 - Tracking the learners tasks

Function Interface Description

The LO identifier is input. The current position in the task model is identified in the depending on the LO input. An identifier for this is output, and stored. This identifier is also used to inform the decision engine.

Data

The learner identification, LO identification, and task ID are persisted in the ***progress model*** and the ***learner task*** model is updated, to indicate which task was chosen. This activity identifier is output for processing in the decision making engine.

4.6.3 [SR3] Map Tasks to Traits

The ***trait-task*** model stores the links between activities and items. There shall be a mechanism in place to link the cognitive traits to the reading tasks [R4.2]. This mapping should indicate the relative importance of individual tasks to one or a number of items. During the decision process, one of these items is selected.

Process Actions

This process requires an activity ID and returns a list of items that are linked to that activity. The mapping process is illustrated in Figure 4.12 below. Each of these items has a corresponding measure of relative importance. This is output for use in the decision-making engine.

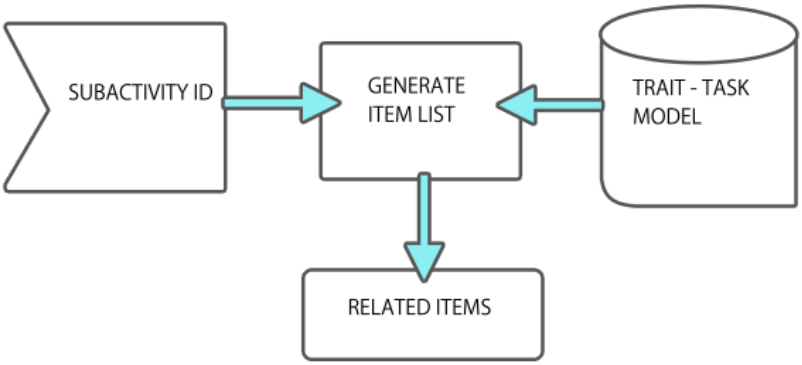


Figure 4.12 - Mapping tasks with traits

Function Interface Description

A task identifier is input in order to output a list of potential items, and their relative importance.

Data

An activity ID is input, and a list of items and their relative importance returned for further processing.

4.6.4 [SR4] Deliver Metacognitive Support and a TEL Service as Single Web Application

The front-end web application requests learning content and metacognitive dialog/responses via the Goby interface. The user interface delivers the course content and metacognitive support as a single application. When the user requests new content, the content is queried and metacognitive state assessed in order to deliver the new page with suitable dialog. The TEL and cognitive support are delivered over a SOA so that they can be provided and consumed as a complete web application [R4.1] and enables the scaffolding of metacognition within a particular learning context [R1.1].

Process Actions

There are number of different types of requests that are dealt with via an interface with the Goby system. This includes indexing the learning content, displaying a page of content, metacognitive dialog delivery and response, and administrative activities such as login and registration, and experimental responses. As illustrated in Figure 4.13 below, requests from the learner and subsequent responses are stored in the learner progress model. Once the correct LO is identified the system can then model the inferred reading task [SR2].

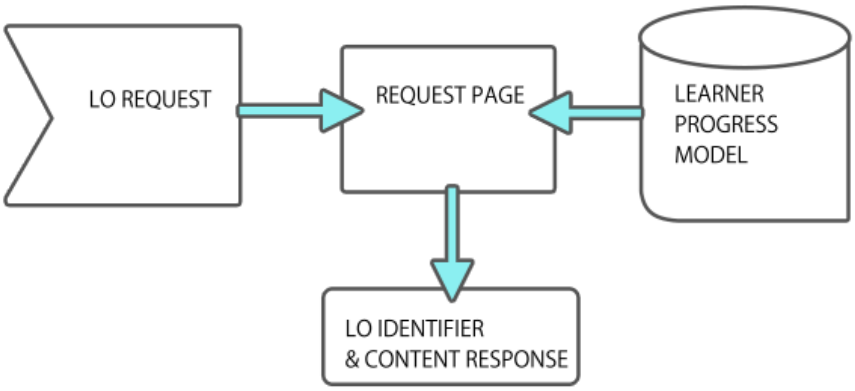


Figure 4.13 – Learning and metacognition mashup

Function Interface Description

Each user request should include the unique user ID and a sufficient identifier for the LO being requested. This request is persisted in the learner progress model. The learning content and prompt/question are output on the UI. The LO identifier is used to inform [SR2] – model the learners task.

Data

Any request for data that is consumed is processed through the Goby interface.

4.6.5 [SR5] Initialise the Cognitive Model

On registration, the ***learner trait*** model is initialised with either the baseline MAI metrics or with the results from a survey. On registering with the system, the learner profile should be initialised. The initial metrics for each item in the metacognitive model need to be written to the repository. This means that the learner's cognitive user model is initialised with a baseline model that is updated over time [R6].

Process Actions

The user model must be initialised once the learner registers with the service. As shown in Figure 4.14, each item that is modelled should be given an initial value, and confidence metric.

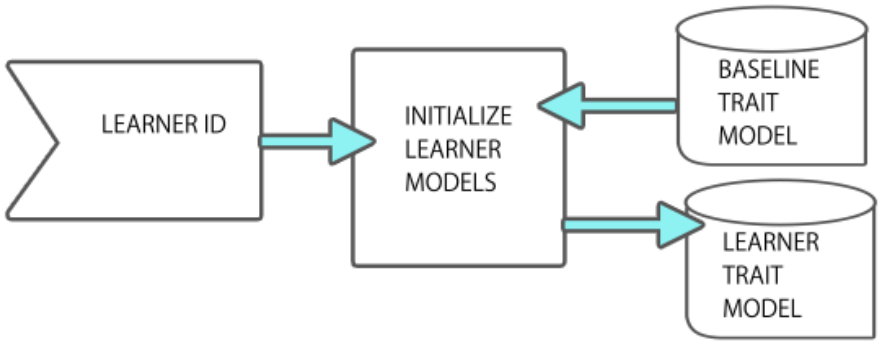


Figure 4.14 - Initialise the Cognitive Model

Function Interface Description

The user should have been assigned a unique ID before their user profiles are initialised. This identifier is input, and will be stored in their cognitive trait model. The current metrics for each metacognitive item are output to this model. In the experimental setting, this will either be from the MAI survey they submitted, or else from the stereotypical baseline model.

Data

Data are input from the client or from the baseline model and stored in the learner model. The value, confidence, item ID and timestamp are stored for each item in the MAI.

4.6.6 [SR6] Decide on a Trait Item to Trigger

A task and learner ID are required to find a suitable item to trigger. As the learner engages with the course content, the possible state of the learner, or current task is identified. Using this task, and based on the learners history, one of the metacognitive items is chosen, as shown in [SR3]. Here, the item with the highest relative utility is chosen in order to enable the system to select an appropriate metacognitive item to support [R1.1]. This decision process is analogous to the activation, accretion, tuning and restructuring of learners schemata [R3] that can enable the system to activate suitable schema signals in the form of prompts and questions. This model is limited to the items in the MAI – however a temporal log is persisted to track the learner's change and progress.

Process Actions

The multi-attribute decision making process is carried out to pick an option. The relative utility is calculated for each item that is listed as suitable. Dimensions that are weighed up are: recency, rating, confidence in the rating, and the strength of the relationship between the activity and item. This process is illustrated in Figure 4.15 below.

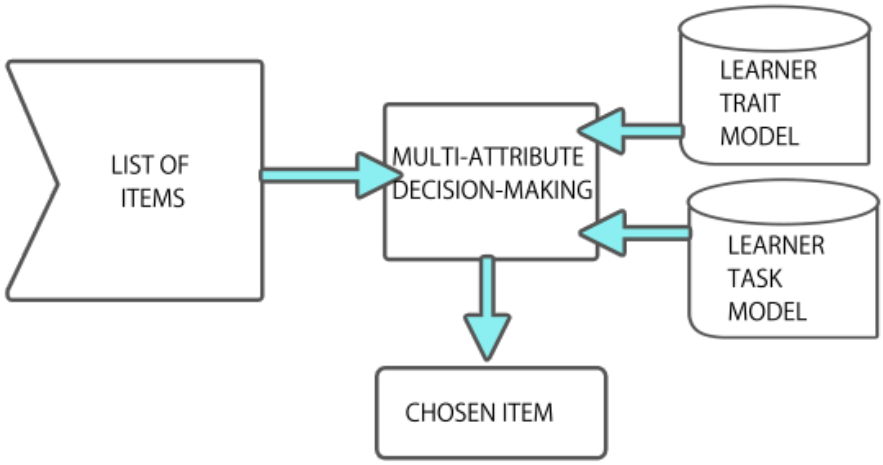


Figure 4.15 –Select an item

Function Interface Description

A unique activity ID is input. There will be one or a number of mappings between this activity and the metacognitive items. The item is chosen based on the mapping strength, and the recent status of each of those items – their value, the confidence in that value, and which was most/least recent.

Data

The activity and learner ID are input and a in a single item ID is output. This item sent to the dialog generator for further processing.

4.6.7 [SR7] Deliver Metacognitive Prompts and Questions

The system shall prompt metacognitive reflection and update the user model to reflect responses to these prompts. An item is chosen with the decision engine, and suitable contextualised prompt/question returned. The system shall prompt metacognitive reflection and update the user model to reflect responses to these prompts. The resulting pseudo-dialog [R5] aims to enable the scaffolding of metacognition [R1.1] by delivering the hints/support within a specific learning context [R4.3].

Process Actions

The item ID and confidence value of the most recent state of that item are input in order to decide whether to generate a prompt or question.

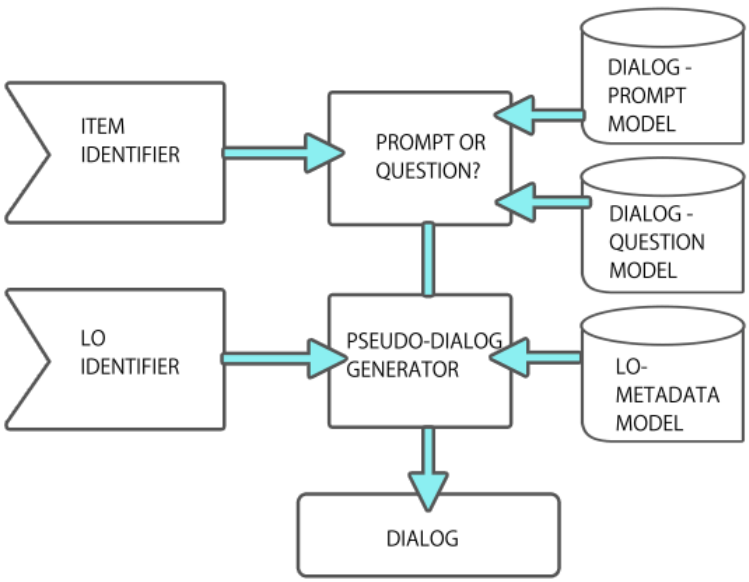


Figure 4.16 - Contextualised prompts and questions

This dialog is pulled from the dialog repository. The LO identifier is also input, which is used to query the metadata description of the current page. As shown in Figure 4.16 above, the two components are combined in order to contextualise the prompt/question.

Function Interface Description

An item identifier needs to be input, the current LO identifier, as well as the confidence in the most recent instance of that item. Depending on the confidence level, a question or a prompt will be chosen. Metadata that describes the current LO will be used to contextualise the prompt/question. This sentence is output to the UI.

Data

Item ID and the current confidence of that item as well as the LO identifier are required. Dialog is output and this process tracked in the ***learner progress*** model.

4.6.8 [SR8] Provide a Visual Open Learner Model

On completion of the course, the users shall have the chance to view an OLM visualising their metacognitive awareness. This approach has been taken to motivate the learner to complete the course by providing them with a visual overview of their progress. The Goby OLM displays a bar chart overview of each of the MAI factors: planning, information management strategies, comprehension, debugging and evaluation.

Process Actions

On completion of the course, learners have the option to see a visual representation of the ***learner trait*** model. In Figure 4.17, they are provided with a visual overview of each of the metacognitive regulatory factors.

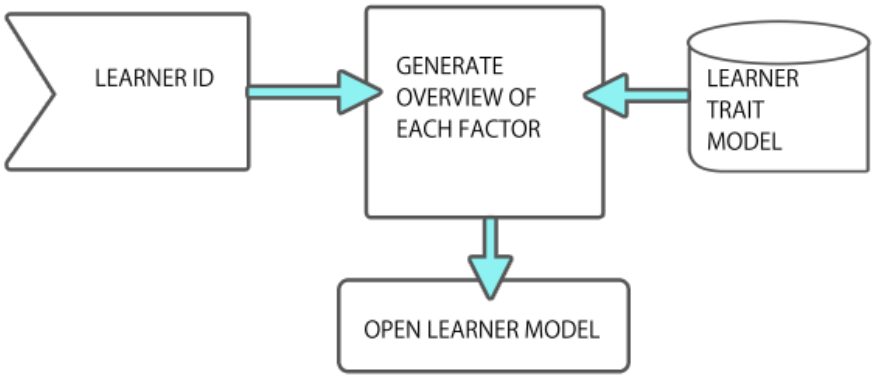


Figure 4.17 - Open Learner Model

Function Interface Description

In the experimental setting, participants do not get access to this view until they complete the post-test survey. The user ID is input, and if they have completed the post-test, then the most recent values describing their cognitive profile are used to create a chart for each of the factors. A percentage for each of the factors is output.

Data

Learner ID is input in order to calculate what the most recent metrics are for each item in the ***learner trait*** model (and the post-experiment MAI survey scores).

4.7 Operational Requirements

4.7.1 [SR9] Mashup with APeLS

The APeLS service will be interfaced with in order to provide the course content and LO metadata that is required by the metacognitive support service. APeLS is comprised of thee components – the learner modeller, the rule engine, and the candidate selector. APeLS was developed using the multi-model approach (Conlan & Wade, 04; O'Keefe et al., 06). This means that course content, and the logic for putting the content sequencing are separated so that a course can be adaptively put together for individual learner needs.

In the APeLS SQL course, learners fill out the VARK (Visual, Auditory, Read, Kinesthetic) learning styles (Fleming & Mills, 92) questionnaire prior to commencement. Using the results from this survey, a narrative model can be generated in order to sequence their course. Different content was designed to emphasise the different elements of VARK. For the purpose of evaluation, personalisation within the APeLS SQL course was not carried out for each individual. Instead, in Goby only one narrative, or course structure was defined and used for all participants. In order for the APeLS system to be delivered as a service, an Application Programming Interface (API) was developed in order to allow requests for LO content and metadata to be taken.

4.8 Goby Look, Feel, and Application Design [PR3]

4.8.1 [SR10] User-Centric Design

While the Goby user interface is not a contribution in this research, it is nonetheless important to get right. The User Interface (UI) must be of a suitable standard for use and learnability to ensure that participants can engage fully with the evaluations. A user-centric design approach was taken, whereby the UI and interaction design patterns and principles were followed, and subsequently tested during the implementation phase. A number of design considerations are listed in this section, which address the practical requirement [PR3] - the system shall apply good web application design and be developed using a user-centric design approach.

4.8.2 [SR10.1] Site Navigation and Organisation

The UI organisation needs to apply good interface design principles and design patterns. This includes providing the course content the main real estate on the page and follows the stay on the page principle. Metacognitive dialog will be provided in a non-invasive manner. The navigation strategy is as follows:

- The course content will be indexed automatically as a collapsible menu.
- User registration, login/logout, completion of the experiment, and summative feedback will be accessed via a slide-in control panel.

4.8.3 [SR10.2] Ease of Use

The ease of use and learnability (of the navigation controls) will be evaluated in the early stages of the implementation process through a number of unstructured interviews. These studies will assess the suitability of the UI style, and ensure that novice users will be able to use the system with ease. A summary of the results from these is included in Chapter 5. The first step in creating a successful user experience is to adhere to good design principles. The following section outlines the principles that will be considered when designing the front-end of the system.

4.8.4 [SR10.3] Rich User Experience

A number of interface design principles (Scott & Neil, 09) for rich Internet application design will be followed in order to deliver a rich user experience:

- [SR10.3.1] *Stay on the Page*

  Reduce the cognitive load by updating components of the page rather than changing to another page. A dialog overlay or lightbox should be used for extra content that is important, but not directly related to the goals of the system, e.g. registration.

- [SR10.3.2] *Lightweight*

  For each of the features in the application, the number of steps required should be minimal. The key tools of the system should always be visible, whereas other tools can be hidden/revealed.

- [SR10.3.3] *Make It Direct*

  Objects in the page are directionally actionable where possible. For example, mouse overs should indicate that functionality is available. The length of interactions should be shortened where possible.

- [SR10.3.4] *Provide Invitations*

  The key functions of the application should have sufficient discoverability. Panels that are hidden when they are not in use should include mouseover invitations to click on control buttons. This means prompting the user on how to interact. Next and previous buttons for the course content will lead them through the process.

- [SR10.3.5] *Use Transitions*

  Animation should be used to indicate that a process is underway/completed. This includes sliding in and out of control panels or dialog areas, and fading parts of the page if a dialog is important.

- [SR10.3.6] *React Immediately*

  There should be immediate reactions to the users actions. This includes responding to requests for new content or replying to dialog on the page. They should be given feedback to indicate that they have responded successfully, for example, this could mean sliding a dialog closed after they hit the response button.

The visual and interaction design of Goby is important for user experience. This section briefly discusses the design. The design is not a contribution of the research; nonetheless, it is an important component for the participants of the experimentations. The six interface design principles [SR10.3.1 – 10.3.6] listed in the requirements were considered: stay on the page, keep it lightweight, make it direct,

provide invitations, use transitions, and react immediately. Interactions only result in part of the page reloading asynchronously, sustaining a continuous visual experience.



Figure 4.18 - Master – Detail UI Pattern (from Neil, 10)

The screen layout was designed to reduce the cognitive load by eliminating unnecessary navigation. The course content is displayed using the master/detail layout pattern (Figure 4.18 above) so that the user stays on the same screen while the user navigates between items. A horizontal view allows for more identifiers to navigate between the course topics. The course content is the main delivery for the learning system, thus it is given the largest amount of real estate. The metacognitive dialog is incorporated using a sliding panel at the bottom of the page. If the user wishes they can close this panel. There are a number of related processes that are secondary to the application, such as registration, and related information. These are vital but infrequently used, so they are displayed in a modal lightbox. An overview of the main user interactions that take place in the Goby web application is included in Appendix D.

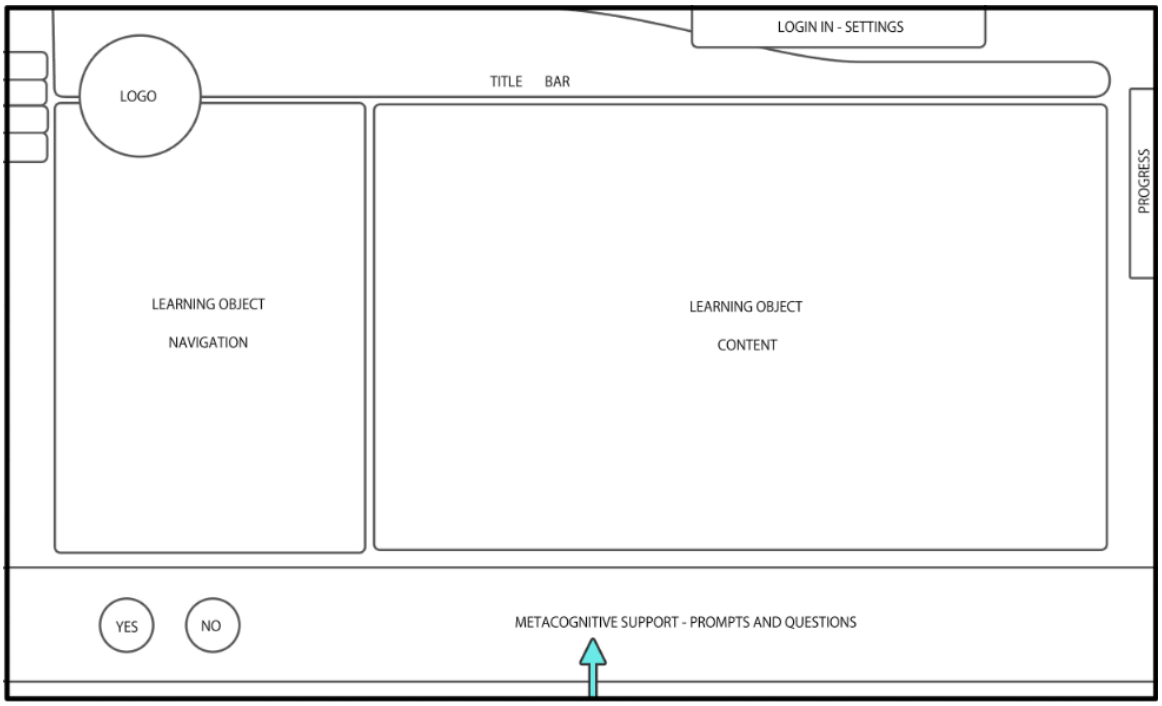


Figure 4.19 - Goby UI Layout

Figure 4.19 above illustrates the Goby UI layout. Users can register or login from the control panel that slides down from the top of the page. This control panel also controls access to their profile and lets them view a visual OLM. The main area is used for the Database and SQL course - both the navigation and content are given the largest space. Navigation is carried out in the right panel – the LO navigation box. This comprises of a number of sections in the database course; "Database Concepts," "Creating a Database," "Populating a Database," and "Database Retrieval." The content in each section is accessible via a drop down menu. The main LO content is delivered in the largest panel on the page and includes descriptions, examples, and screenshots. A quick-link navigation bar on the left allows the learner to return to the first page of the course, logout, or access information and settings. Below the LO content area, the metacognitive support is delivered in a panel that slides up when there is a new prompts/question. The learner can close this panel and it will also slide closed automatically when they respond to some dialog. On the left, a progress bar visualises the overall frequency of responses from the learner to this dialog.

4.9 Constraints and Assumptions

This section outlines constraints and assumptions that affect the design and implementation of the system.

4.9.1 Solution and External Constraints

- The environment is delivered over the web, and will be accessed with web browsers. The server does not initiate any requests, the client must request changes in the application.
- The system requires a user to be identified with a consistent ID. This will be automatically assigned to users when they register with the system. This means that learners should login/logout of the learning environment to access the database course and metacognitive support.
- The TEL system that is mashed up with Goby needs to be delivered as a service. Communication between the cognitive support service and learning service requires an agreed communication method.

4.9.2 Legal Requirements

For the purpose of this research, the TCD School of Computer Science and Statistics ethics review board has approved evaluations on Goby. Participants were given an informed consent form before participating. All the data collected are private, and no one other than the investigator (and research assistants/research lecturers) can have access to responses. All information collected is recorded anonymously and processed only for research purposes and, notwithstanding the fifth data protection principle, may be kept indefinitely. The resulting data may be made available to other researchers in the future for research purposes not detailed in the original consent form. In these cases, the data will contain no identifying information that could associate any participant with it, or any study. The records of this research will be stored securely and kept confidential. Participation is voluntary; participants had the option to withdraw at any time for any reason and omit questions without penalty. Other legal requirements might apply when Goby is available outside of a research setting, however these are outside the scope of this thesis.

4.10 Requirements Traceability Table

Table 4.3 illustrates the requirements derived from the research question and the state of the art analysis, compared to specific requirements of the system. The 'key' refers to the requirement key, main related features (F) connect the requirements to the observations made on the literature that have informed the requirement, a description is provided for each feature and short description provided on how these are addressed. Finally, a brief overview is given on how the research requirements are evaluated. This table will be revised in the evaluation chapter where it will include a summary of the results.

Key	*Main Related Feature*	*(R) Description*	*Addressed By*	*Evaluated With*
R1		Model learner ***traits*** - metacognition		R1.1, R1.2, and R1.3
R1.1	- Scaffold metacognition to support domain learning (F2) -Explicit metacognitive modelling (F1) - Prioritise domain learning when offering metacognitive supports (F14)	- Improve the educational gains for the learner by delivering personalised support.	Learner trait model and subsequent learner support.	Evaluation of knowledge gain, metacognitive gain, and qualitative response to metacognitive hints.

R1.2	- Quantification of cognitive and metacognitive competencies is possible through the use of inventories (F6) - Model, prompt, and support the learner's metacognitive and self-regulatory processes (F5)	- Model cognition in a structured, measurable way that is trait-neutral by using psychometrics.	Psychometric – MAI regulation of cognition – factors and items.	Implementation Modelling Accuracy
R1.3	- Learners' metacognition modelled and measured with dynamic models (F11) - Enable intelligent adaptation and to suit the needs of the learner as an individual (F12)	- Capture a temporal, view of the learner.	Persisted in learner models over time.	Implementation
R2	- Address timing of these scaffolds is also important (F9) - Metacognitive strategies are important when engaged in academic reading (F4)	- Shall model learner conduct, via a ***task***/activity model.	Descriptive and learner task model to describe learner's activities.	Qualitative response regarding suitability of metacognitive hints.
R3	- Schema signals can activate prior information available. - Schema theory itself provides a useful mechanism with which to describe how our cognition is stored and processed (F15)	- Model analogous to ***schema*** theory.	Activation and update of the learner model.	Implementation
R4		- Work in ***symbiosis*** with a TEL system.		R4.1, R4.2, R4.3
R4.1	- Metacognition supports be situated within a particular context or suitable learning environment (F10)	- Employ the SOA pattern for integration and consumption of functionality.	Integration of cognitive support system with TEL system.	Implementation
R4.2	- Metacognition supports be situated within a particular context or suitable learning environment (F10) - Emulate the role of the tutor in providing supports (F7) - Address timing of these scaffolds is also important (F9)	- Mapping between trait and task model.	Trait-task model used to inform decision-making.	Qualitative responses
R4.3	- Metacognition supports be situated within a particular context or suitable learning environment (F10)	- The metacognitive scaffolds should be contextualised.	Dialog chunks from MAI and LO metadata used to generate prompt/questions.	Educational outcomes Qualitative responses
R5	- Dialog approaches have been used in TEL emulate role of tutor (F3) - Scaffolds are determined from user model and adaptation characteristics (F9) – feedback from dialog can be used to update the learner model.	- Interactions with the learner will be provided in a non-invasive pseudo-***dialogic approach***.		Educational outcomes Qualitative responses
R6	- Learners begin their learning experiences with prior knowledge and abilities – both cognitive and metacognitive (F13) - Quantification of prior metacognitive competencies is possible through the use of inventories (F6)	- Initialise user model with a ***baseline*** model.		Compare baseline model to Goby model

Table 4.3 - Features Traceability Table

4.11 Conclusion

This chapter has presented the ETTHOS model and recommendations for implementing this model. The aim behind ETTHOS is to provide a general model of metacognitive skills that are useful to learners. The purpose of the model is to inform the development of a cognitive modelling system that can be used to model and subsequently help learners develop these useful cognitive strategies. This work directly implements current best practice and successful technologies where possible. For example, the APeLS service is used as a test-case learning service with which to connect the proposed cognitive modelling solution. This research also draws from current approaches that have proven beneficial, such as the integration of a decision engine to reason about how to learner support and the separation of services so that they are logically discrete, and are owned and managed independently. This work also addresses the new challenges that have arisen from developing a cognitive learner model. For example, the replication of current practices such as adopting a distributed architecture has implications for assessing the status of the learner and subsequent delivery of support. There is also a strong influence from psychological and pedagogical theories. Whereas current systems that trace learner cognition do so through techniques such as production rules or example-tracing algorithms, the solution proposed in this work draws from modelling capabilities of psychometrics. A number of design requirements that describe ETTHOS were outlined [R1 – R3]. It also described an approach to guide future implementations of this model [R4 – R6] as well as the practical system requirements that arise from the application of ETTHOS in a service [PR1 – PR3]. The Goby service design is subsequently illustrated as a proof of concept for ETTHOS. The second part of this chapter illustrated the design of the Goby service, addressing system requirements [SR1 – SR10] that were necessary to develop a test-bed system. The design of the Goby service that uses this model was illustrated and each of the system processes discussed.

Chapter 5 Implementation

This chapter describes the implementation of the Goby system, a manifestation of the ETTHOS model. Goby is targeted at the modelling and support of metacognitive skills that are antecedent of positive lifelong learning. Goby has been implemented as a web-based service and development was carried out to allow interoperation with the APeLS learning environment. The ETTHOS model and approach have previously been discussed in terms of the Goby system requirements. This chapter now describes the implementation of the core ETTHOS elements in Goby including the trait, task, and mapping components. A discussion is also included surrounding the functionality, architecture, and technologies underlying the implementation of Goby.

5.1 The Goby service

5.1.1 Traits

There are three trait models in ETTHOS, as illustrated in Figure 5.1 below: the descriptive trait model, the learner trait model and the baseline trait model.

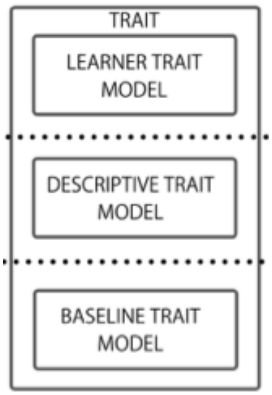


Figure 5.1 – ETTHOS Trait Component

The ***learner trait model*** is used to represent a view of the learner's metacognitive ability over time. This model is updated dynamically in response to learners' replies to prompts and questions. In Goby, the ***descriptive trait model*** is used to describe the learner's regulatory metacognition using the MAI. This is a static model that was initialised at development time. The ***baseline model*** is used to describe the typical values found in the population for each item on the MAI. Similar to the descriptive model, the baseline is a static model that is input in to the Goby system at

development time. The generation of this baseline model is further discussed in Chapter 6.

In Goby the trait component depicts regulatory metacognitive factors from the MAI – planning, information management strategies, comprehension, debugging, and evaluation. Each factor comprises of a number of subordinate items.

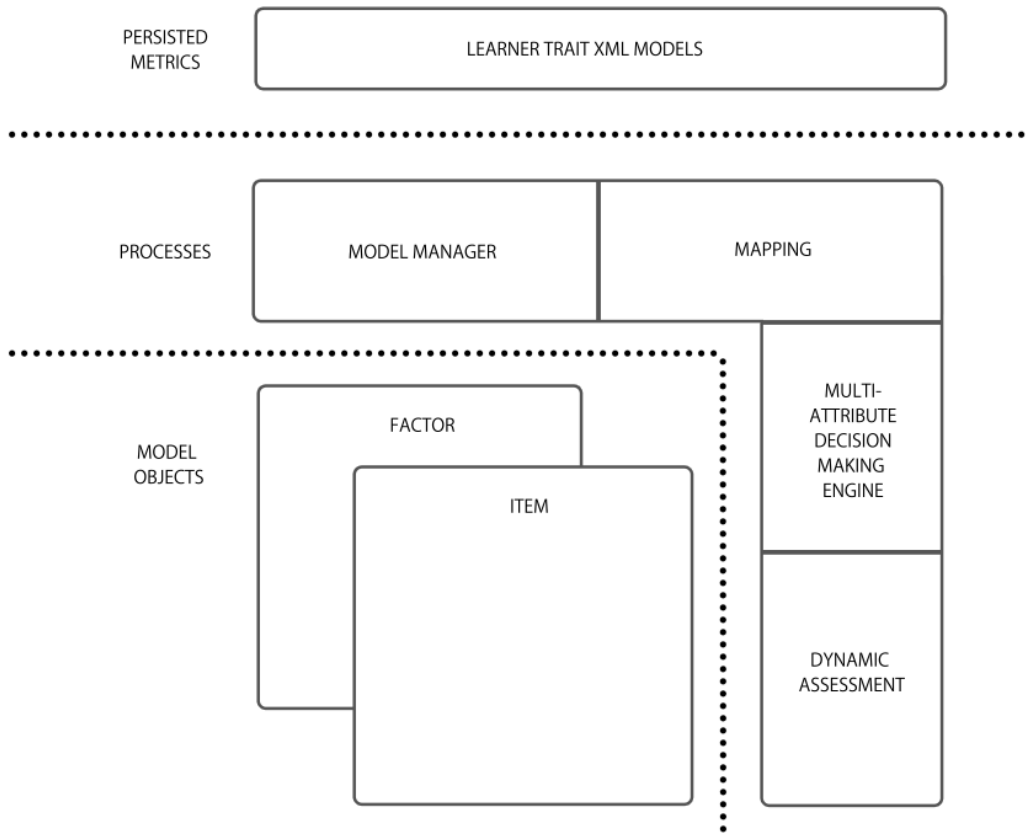


Figure 5.2 - Goby Trait Component in Context

A number of processes use these items, as shown in Figure 5.2 above. Model objects are represented as objects in Java in order to assess the state of the learner and are persisted to XML. The model manager deals with requests for model data and updates the learner models. The mapping manager is used to select a list of relevant items depending on the state of the learner When the learner responds to prompts or questions in the Goby web application, this response is processed with the dynamic assessment tool, and the result is input to the model manager to update the learner trait model. The decision engine has been implemented in JBoss rules (www.jboss.org) – potential items are input to the working memory of the decision engine in order to select the item with the highest utility.

```
<factor id="trait_inf" name="Information Management Strategies">
    <item confidence="5" desc="I try to break studying down into smaller steps"
        name="info_step" rating="3.5" timestamp="2010-12-19 13:39:40"/>
</factor>
<factor id="trait_cmp" name="Comprehension Monitoring">
    <item confidence="3" desc="I ask myself periodically if I am meeting my goals"
        name="comp_goal" rating="2.25" timestamp="2010-12-19 13:39:47"/>
</factor>
```

Figure 5.3 – XML Learner Trait Model

The learner trait model is a dynamic model that tracks the learner over time. Figure 5.3 illustrates an example of the learner trait model. Here we can see that each item is within a root factor element. The factor has an identifier (id), and name. Each item is represented with an identifier (name), description, rating measure (1 - 5), a confidence measure (confidence in the rating 1 – 10), and timestamp.

```
<factor id="trait_evl" name="Evaluation">
    <item name="eval_well"
        desc="I know how well I did once I finish a test" />
    <item name="eval_easy"
        desc="I ask myself if there was an easier way to do things after I finish a task" />
    <item name="eval_sumr"
        desc="I summarise what I've learned after I finish" />
    <item name="eval_goal"
        desc="I ask myself how well I accomplish my goals once I'm finished" />
    <item name="eval_optn"
        desc="I ask myself if I have considered all options after I solve a problem" />
    <item name="eval_lern"
        desc="I ask myself if I learned as much as I could have once I finish a task" />
    <comment>
      Analysis of performance and strategy effectiveness after a learning episode.
    </comment>
</factor>
```

Figure 5.4 - Extract from the XML Descriptive Trait Model

The descriptive trait model and baseline trait model are used to initialise the learner trait model. These are static models that were written during the implementation time. Figure 5.4 illustrates an extract from the descriptive trait model, exemplifying how evaluation is identified by "trait_evl". It also shows how a number of child items are associated with evaluation. Each of these is described using an identifier and a description.

```
<factor id="trait_evl" name="Evaluation">
    <item name="eval_well"
        desc="I know how well I did once I finish a test"
        rating="3.485148515" />
    <item name="eval_easy"
        desc="I ask myself if there was an easier way to do things after I finish a task"
        rating="3.811881188" />
    <item name="eval_sumr"
        desc="I summarise what I've learned after I finish"
        rating="3.198019802" />
    <item name="eval_goal"
        desc="I ask myself how well I accomplish my goals once I'm finished"
        rating="3.178217822" />
    <item name="eval_optn"
        desc="I ask myself if I have considered all options after I solve a problem"
        rating="3.277227723" />
    <item name="eval_lern"
        desc="I ask myself if I learned as much as I could have once I finish a task"
        rating="2.782178218" />
    <comment>
      Analysis of performance and strategy effectiveness after a learning episode.
    </comment>
</factor>
```

Figure 5.5 – Extract from the XML Baseline Trait Model

Figure 5.5 shows each of the component items that are used to measure evaluation strategies. In the descriptive model there is no rating, however in baseline model a rating is included. This rating was generated from a study to assess the mean values reported by the target population who would use Goby. The complete baseline model is included in Appendix E and the creation of baseline metrics is further discussed in Chapter 6.

5.1.2 Tasks

Two task models are represented in ETTHOS, as illustrated in Figure 5.6 below: the descriptive task model and the learner task model. In Goby, the ***descriptive task model*** is a static model used to describe the sequence of cognitive activities that the learner engages in as they navigate through the learning environment. This model describes the sequence of cognitive reading steps a learner can take when reading through domain knowledge. This declarative knowledge is presented in APeLS in a number of sections – each section comprising of an introduction, a breakdown of concepts, and related figures and examples. The ***learner task model*** is used to represent a view of the learner's cognitive activities over time. This model is updated dynamically in response to learners' navigation through the learning environment.

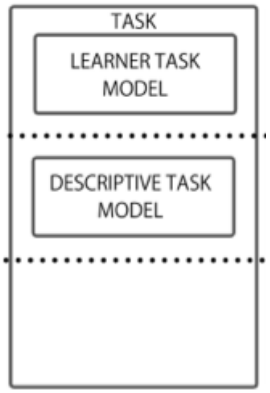


Figure 5.6 – ETTHOS Task Component

The learning task model comprise of a number activities – each of which comprises of a number of subordinate sub-activities. An extract from the implemented descriptive task model is illustrated in Figure 5.7. The complete model on which this is based can be accessed in Appendix C. The learner's progress through the learning environment is aligned with this model in order to make an estimate of their current status – this means identifying a suitable sub-activity.

```
<stage name="start">
    <activity name="Before the Task" id="start_1">
        <subActivity name="act_1_1" desc="Constructing a goal"/>
        <subActivity name="act_1_2" desc="Overviewing the learning object"/>
        <subActivity name="act_1_3" desc="Decide only to do particular sections, and what sections"/>
        <subActivity name="act_1_4" desc="Decide to quit because the content is not relevent to the goal"/>
        <subActivity name="act_1_5" desc="Activate prior knowledge and related knowledge"/>
        <subActivity name="act_1_6" desc="Summarize what was gained from previewing"/>
        <subActivity name="act_1_7" desc="Based on overview, generate initial hypothesis"/>
        <comment>
    Relates to the planning trait
    Planning, goal setting and allocating resources prior to learning

</comment>
    </activity>
</stage>
```

Figure 5.7 – XML Descriptive Task Model

In Goby, when the learner requests a new LO (a new page of course content) in the SQL course, the position of the LO within the course and current section is assessed and compared against the descriptive task model. This approach provides a mechanism with which to estimate the stage the learner should be at and a method with which to step through each of the cognitive sub-activities that a learner should carry out as they address academic material. For example, at the beginning of the course or a section, the learner is likely to be engaged in the sub-activities such as 'constructing a goal' or 'activating prior knowledge and related knowledge' as illustrated in Figure 5.7 above.

```
<activity actId="during_4" name="Identifying different parts">
    <subActivity
        desc="Combining structure and contextual cues to determine meaning"
        subActId="act_5_3"
        timestamp="2010-12-22 21:25:27"/>
</activity>
<activity actId="during_4" name="Identifying different parts">
    <subActivity
        desc="Looking elsewhere in the learning object for information related to a point currently encountered"
        subActId="act_5_4"
        timestamp="2010-12-22 21:38:50"/>
</activity>
<activity actId="during_5" name="Interpreting">
    <subActivity
        desc="Visualising concepts and relations"
        subActId="act_6_1"
        timestamp="2010-12-22 22:01:44"/>
</activity>
```

Figure 5.8 – XML Learner Task Model

When engaged in a LO that is mid way through a section, they should be engaged in sub-activities such as 'combining structure and contextual cues to determine meaning' and 'visualising concepts and relations' as illustrated in Figure 5.8.

5.1.3 Mapping Traits to Tasks

Within Goby, it was the role of an educator to generate the mappings in the trait-task model. This mapping model is accessed once an appropriate sub-activity has been identified given the state of the learner in the learning environment in order to assess which items are important or relevant. Subsequently, this item is addressed by the system – the learner might be prompted or asked a question about that item.

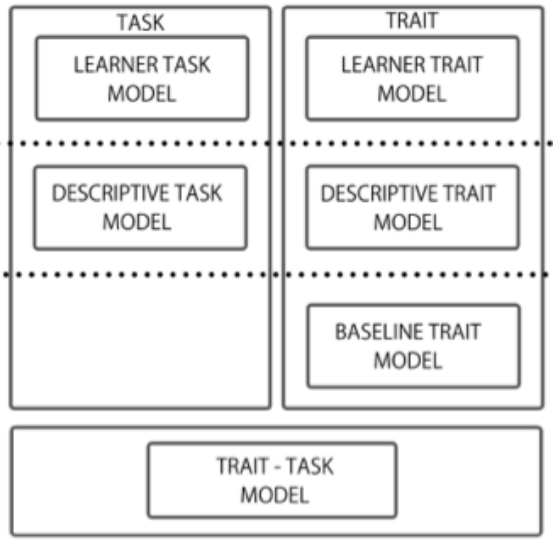


Figure 5.9 – ETTHOS Trait-Task Mapping

As shown in Figure 5.9, the trait-task model links the trait and task models. In particular, in Goby this means mapping reading activities to metacognitive awareness. The mapping of traits to tasks by lecturers has been carried out on the premise that educators are metacognitive professionals. It has been reported in

qualitative studies (Graesser, D'Mello & Person, 09) that teachers possess adaptive metacognition. This means that they possess the ability to regulate their cognitive activities in response to the individual differences of learners to promote learning.

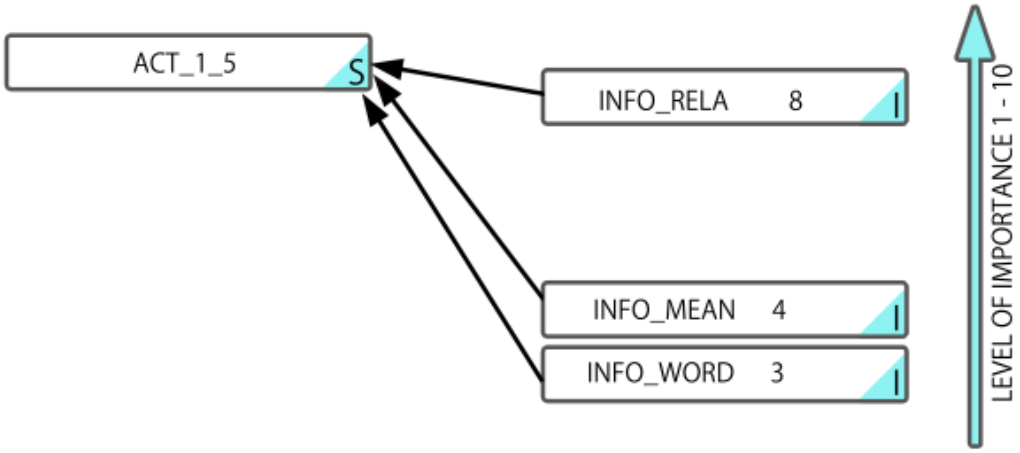


Figure 5.10 - Example of the Trait - Task Mapping

For each activity undertaken, there are one or a number of corresponding observable items that are related conceptually. Take for example Figure 5.10 - the component activity '*activate prior knowledge'*, would require that the learner was someone who '*focuses on the meaning and significance of new information*, '*asks if what they are reading is related to what they already know*' and '*translates new information into their own words'*.

A consultation process was undertaken to initialise the trait-task model. The motivation behind this consultation was to generate a mapping between reading tasks and the metacognitive traits. An analysis of the amount of time needed to generate mappings and subsequent trends of agreement and disagreement of 10 Computer Science lecturers was carried out. The aim of the process was to see if a mapping could be generated by academics within a reasonable timeframe to what level they would agree. The mapping task was typically completed within one hour (40min to 1hour 10minutes; mean 50 min). Although there were trends of agreement in the results (which compared the metacognitive factors to reading activities), there was still a significant difference between lecturers' responses (planning ($F(9,84)=2.53$, $p=0.013$), information management strategies ($F(9,274)=8.43$, $p=0.00$), evaluation ($F(9,60)=5.55$, $p=0.000$), debugging ($F(9,56)=2.24$, $p=0.032$), comprehension ($F(9,120)=6.91$, $p=0.00$)). Some metacognitive factors were more important for particular phases, for example comprehension (factor) was important

when identifying important information (activity). Post-hoc analysis revealed that for each factor some lecturers agreed, however they differed on others. The responses from an individual lecturer were chosen after removing sets of responses that varied greatly and were not as complete as others. The resulting mapping was encoded in XML in order to model this link in Goby. The complete trait-task XML mapping is included in Appendix F.

```
<subActivity subActId="act_1_5" desc="Activate prior knowledge and related knowledge">
    <rel item="info_mean" importance="4"/>
    <rel item="info_rela" importance="8"/>
    <rel item="info_word" importance="3"/>
</subActivity>
```

Figure 5.11 - Extract from XML Trait - Task Mapping model

An example of the resulting mapping is outlined in Figure 5.11 above. Here the cognitive activity 'activate prior knowledge' has been linked to three items: 'Focusing on the meaning and significance of new information', 'relating what they are reading to what they already know', and 'trying to translate new information into their own words.' This mapping is used by the decision engine – for example, if the sub-activity identified is 'act_1_5', then the mapping as shown in Figure 5.11 links this to items 'info_mean', 'info_rela', and 'info_word.' For that learner, the most recent metrics of each of these items are assessed in order to choose one of the three. The selected item will be used to deliver a prompt/question to the learner. A sample of the learner models generated is included in Appendix G. Responses to the dialog are dynamically assessed in order to update the learner trait model. Learner interactions, including the prompts, questions, responses, navigation, and response from the system are tracked in the dynamic learner models.

5.1.4 Conclusion

This section has described the implementation of the ETTHOS model in Goby. The trait components include the learner trait model, descriptive trait model, and baseline trait model. The task components comprise the learner task model and descriptive task model. A trait-task model represents the mapping between traits and tasks. There are two others that are tangential, but important to the use of ETTHOS – a learner model traces the learners actions and interactions with the learning environment, and a LO metadata model is consulted in order to inform the interactions with the learner. The learner models (trait, task, and progress) are dynamic, meaning that they are generated and updated at run-time through dynamic

assessment of requests and responses from the learner. The baseline, descriptive, and mapping models have been initialised during the implementation phase. The trait-task mapping was initialised with a consultation of computing educators. Traits comprise of the regulatory metacognitive factors in the MAI – planning, information management strategies, comprehension, debugging, and evaluation. Each of these factors is represented using a number of observable or actionable items. The baseline model that is used to initialise the learner trait model was created using the mean values from the target population. This study is further discussed in Chapter 6 because it was used to inform the design of experiments with learners.

5.2 Goby Development

The Goby and APeLS services have been delivered as web services over an SOA. The learner can access the Goby web application using their browser, and it is the Goby service that manages requests for both domain content via APeLS and the related cognitive support. This means that they both offer a specific service via a programmatic interface and are owned and managed independently. However, they are delivered in a way that the learner has no knowledge of this decoupling – instead the web application provides a holistic user experience. The user-centric design approach undertaken to ensure this user experience is discussed later in this chapter. The Goby web application handles requests from users and communicates with and controls the cognitive support logic, processes the communication, and deals with requests for content from APeLS.

This type of SOA can be described as Software as a Service (SaaS), which is an architectural pattern whereby an application is hosted for clients via the Internet. Since the application is hosted, the client does not have to maintain or support it – instead all the processes are carried out by the service provider. This is typical for enterprise business applications, however learning environments can also be delivered in this manner. The main benefits of this approach are that the underlying models and functionality can travel (platform independent), grow (web based distribution), be upgraded, the service can be accessed remotely, and the learner or client is not expected to download and install any software.

5.2.1 Goby Technologies

The Goby web application was developed as a rich Internet application that implements a RESTful (Fielding, 00) SOA over AJAX. The core requests are carried out with AJAX on the client side, which conveys XML messages over HTTP (W3C HTTP Protocol, 11). This means that requests can be focused on the necessary content updates rather than updating the entire page. Handlers control access to functionality to process the data, and can query and return specific content or dialog. The main handlers include learner initialisation, content requests, and dialogic interactions. Responses are updated to the page asynchronously, ensuring that the learner gets to stay on the page, resulting in a holistic user experience.

The main components and the technology used to implement them are illustrated in Figure 5.12 on the next page. The Goby web application comprises of a client-side application that controls communication with the Goby service. It is the role of the Goby service to deliver cognitive support, manage data processing, as well as control the delivery of domain knowledge and LO metadata via APeLS. The client-side application comprises of XHTML (displays the content), CSS (styles the content), AJAX (requests content) and other JavaScript (primarily jQuery (www.jQuery.com), and Prototype (www.prototypejs.org) which are used to update the content on the page, and create animations to invite the learner to interact with the application or to provide immediate feedback to let them know that they have completed an action). With AJAX, once the learner or client has requested the page, subsequent requests for new content stay on the page. The Document Object Model (DOM) is accessed in order to dynamically change the content, alter the presentation, and provide feedback to the learner.

Requests from the learner to initialise their model (on registration), for new LO content, and responses to dialog (prompts or questions) are dynamically assessed by the system. A request for initialisation sets up the learner model by accessing the baseline model (or in the experimental setting, some participants have their model initialised by asking them to complete the MAI survey).

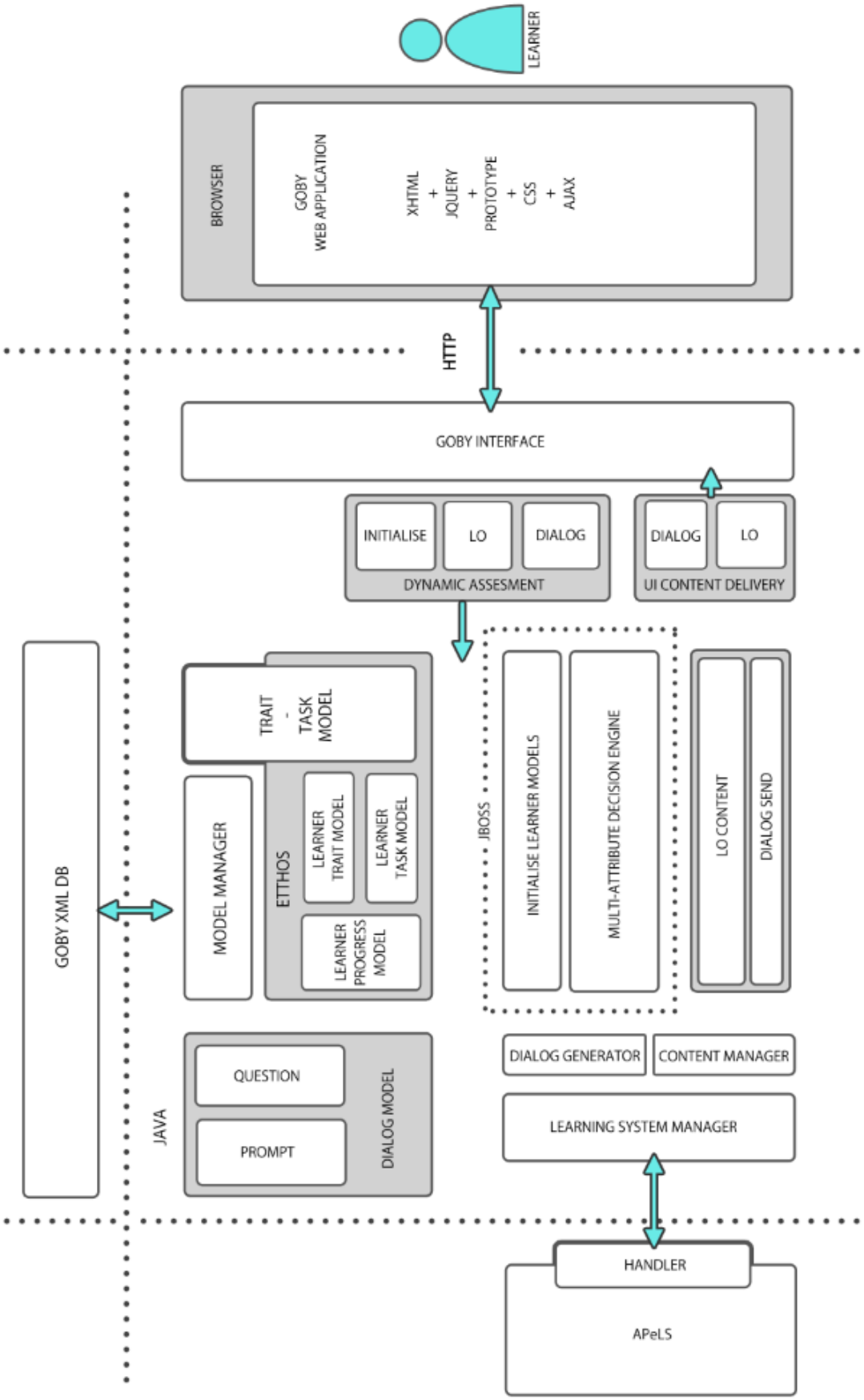


Figure 5.12 - Goby Technological Architecture

The Goby service has been implemented using Java in order to take an object-oriented programing (OOP) approach. This approach is aligned with schema theory since concepts or chunks of knowledge are organised within an overall framework of concepts. The relationship between these models is often hierarchical – for example items are subordinate to a root factor element. The OOP approach to representing learner cognition means that objects can be instantiated or activated in order to make sense of the state of the learner and inform cognitive support decisions. A JBoss rules-engine is used in conjunction with Java in order to carry out any of the complex event processing. In particular, this includes the initialisation of the learner models and the normative decision making processes. With JBoss, Java objects are input into the working memory of the rule engine in order to organise information, create inferences and make decisions.

A model manager communicates with the Goby XML DBMS over HTTP in order to access the baseline and descriptive models, as well as consult the dynamic learner models and update them over time. Requests for LO content are dynamically assessed in order to identify a sub-activity from the descriptive task model. The LO content itself is requested via the content manager, which formats the request so that it can be sent to APeLS. A learning system manager controls these requests to the APeLS handlers. An interface was written for the APeLS service in order to allow Goby to make requests for LO content (database material) and LO metadata (used to create the dialog). This mashup process will be discussed in the following section. The resulting LO content is delivered to the UI along with suitable metacognitive dialog.

The Goby service delivers metacognitive hints using pseudo-dialog – chunks of prompts and questions are also stored in the XML database, and are accessed by a dialog generator. A JBoss decision engine selects an item to prompt/question when a sub-activity identifier is input. This generator creates contextualised pseudo-dialog from the dialog model (each item has a related prompt and question) and metadata that describes the current LO.

5.2.2 Goby Mashup with APeLS

The APeLS learning environment was delivered as a service for use with Goby. Figure 5.13 demonstrates how the server-side components are distributed.

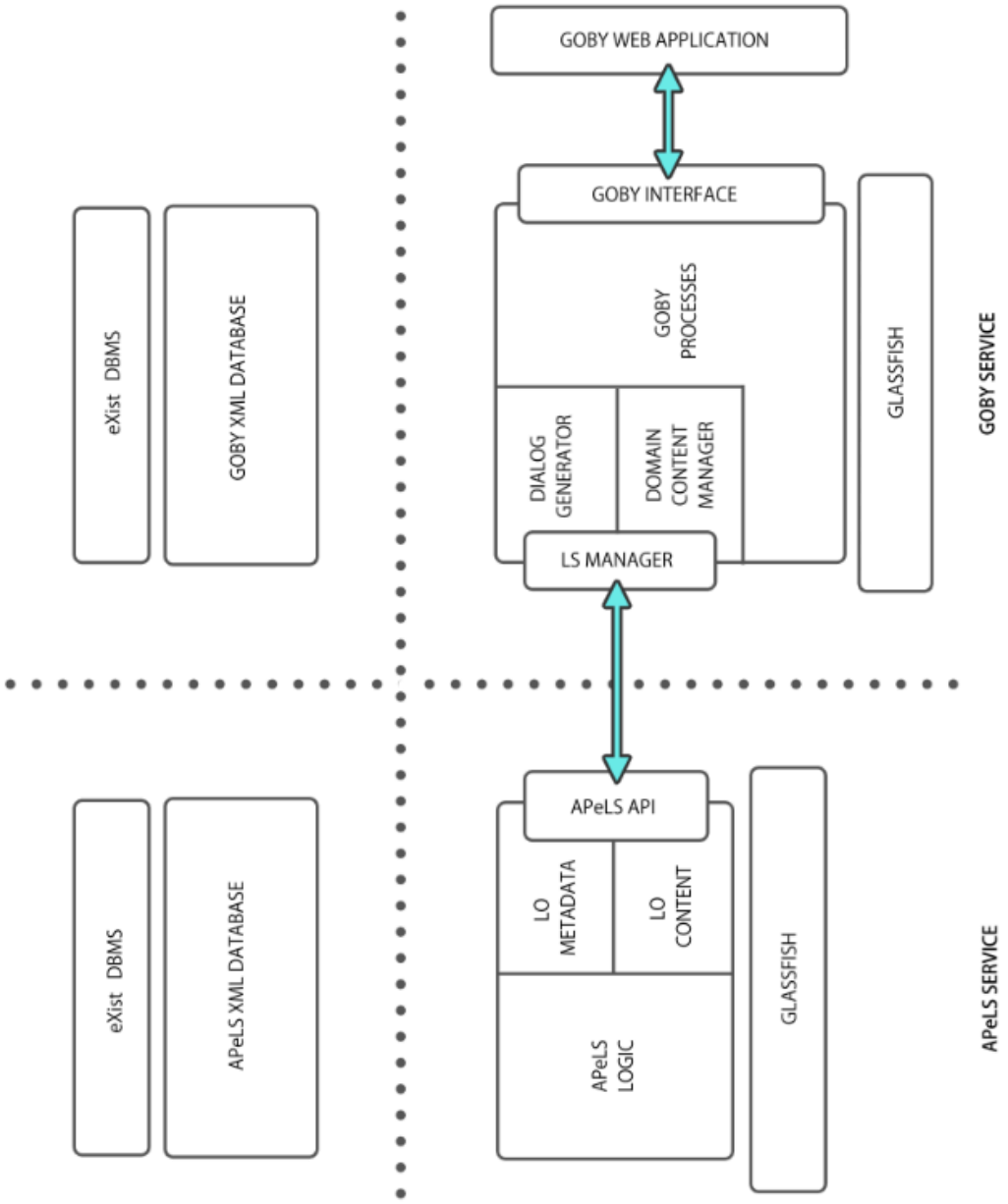


Figure 5.13 - Distribution of APeLS and Goby Web Services

As in Figure 5.13,the server-side components are delivered over four servers: the Goby service on Glassfish v3 and the ETTHOS XML models on open-source native XML DBMS (eXist) to store the static and dynamic modelling data. APeLS has similarly been delivered as a service on a Glassfish server with the APeLS XML models available on an eXist DBMS that is managed by APeLS.

APeLS comprises of thee main components – a learner modeller, rule engine, and candidate selector. An adaptive course is created by determining what content is an appropriate candidate for each learner. The output is an XML list that references each page of content in a course tailored for that learner. In this implementation of Goby, only one learner narrative has been generated and this is delivered to all participants. There are two files used to represent each LO: the web file which displays the LO content and the content metadata XML file (which is compatible with metadata standards such as IEEE LOM). It describes each page, highlights keywords and categorises the type of content, as well as describing the type of adaptivity supported.

Figure 5.14 illustrates the exposed API that was written to deal with requests from the Goby service. A handler object has been implemented for each type of request, including LO content requests and LO metadata requests.

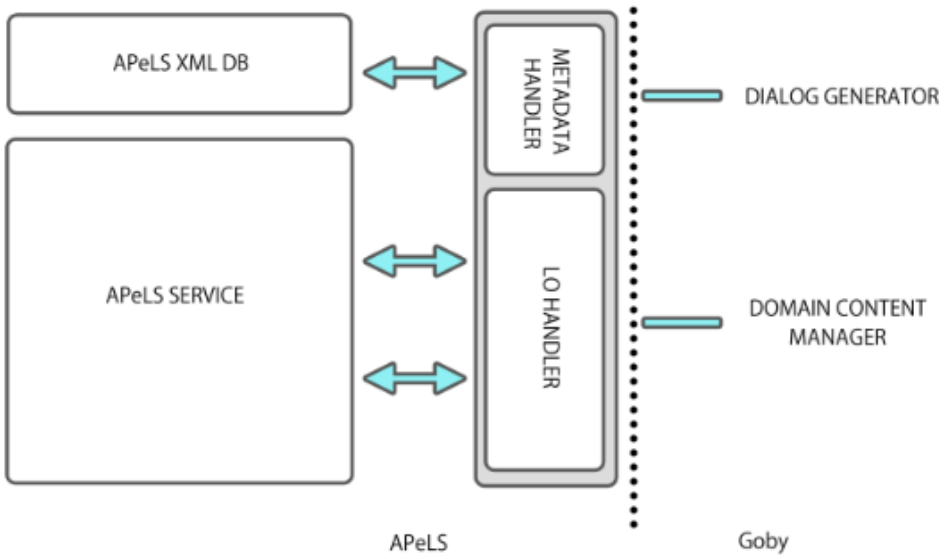


Figure 5.14 – APeLS - Goby Interface

The LO handler in Figure 5.14 handles requests for page content, and for the table of contents for the database course. APeLS originally delivered dynamic content using JavaServer Pages (JSP). The script that dealt with requests from the JSP pages asked for learner, course, section, and page details. A pluggable API was added in order to resolve AJAX requests for the same data. None of the underlying adaptive course was modified in order to access the domain material, however the API was necessary to ensure that there was an agreed communication channel between APeLS and Goby. The APeLS course originally did not use the metadata on the front end. In Figure 5.14, the metadata handler takes requests from the dialog generator. It was necessary to

implement support in APeLS to serve up the metadata associated with the LOs. The dialog generator was then able to access descriptive metadata for the current LO. This generator uses the metadata to create pseudo-dialog prompts and questions. The following section describes how the Goby service delivers prompts and questions.

5.2.3 Dialog Models

As the learner navigates through the domain material, metacognitive support is delivered through the form of prompts and questions. These can be described as pseudo-dialog hints because they are generated from chunks of strings. The dialog generator combines LO metadata descriptions, with an item from the prompts or question repository, and a bridging string to combine the two. Each of the items modelled have an associated rating and a confidence measure in that rating. Questions are presented to the learner when the systems confidence in a metric is low, whereas prompts are delivered when the system has high confidence in the rating. If the "comp_ans" item is selected as an appropriate item to present to the learner and there is low confidence in the current learner trait model about that item, then the dialog generator will select the question chunk from the dialog model. The sample string is illustrated in Figure 5.15.

```
<item name="comp_ansr"
    qu="Imagine that the material in this section will be covered in an assesment.
    Would you consider alternatives to the problem before you answered?"/>
```

Figure 5.15 – Goby XML Question Chunk

A sample of the dialog models is included in Appendix H. The dialog string is combined with descriptive metadata from the APeLS learning system that describes and contextualises the page content. Typically this metadata highlights the important parts of the LO content. Figure 5.16 shows an extract from the LO metadata. This shows how the description element describes the aims of the LO.

```
<lom>
    <general>
        <identifier>learningobject32</identifier>
        <title>The Relational Model</title>
        <keyword>relational</keyword>
        <keyword>model</keyword>
        <keyword>relation</keyword>
        <keyword>attribute</keyword>
        <keyword>domain</keyword>
        <keyword>tuple</keyword>
        <keyword>database</keyword>
        <keyword>set</keyword>
        <keyword>data</keyword>
        <keyword>mathematical</keyword>
        <keyword>value</keyword>
        <keyword>row</keyword>
        <keyword>column</keyword>
        <description>
            Describes some basic terminology associated with the relational model
            e.g. relation, attribute, domain and tuple.
            Also provides background information about the association between the
            relational data model and set theory.
        </description>
        <language>en</language>
    </general>
```

Figure 5.16 - Extract from LO XML metadata in APeLS

These two strings are combined with a bridging string. From example, if the question from Figure 5.15 and the description from Figure 5.16 were combined the output to the learner would similar to:

> "This section describes some basic terminology associated with the relational model e.g. relation, attribute, domain, and tuple. Also provides background information about the association between the relational data model and set theory. Imagine that the material in this section will be covered in an assessment. Would you consider alternatives to the problem before you answered?"

The learner can ignore the question, close the popup, or respond with yes or no.

5.2.4 Goby Functionality

The core models, components, functionality, and technologies implemented in Goby have been described. Chapter 4 previously described a number of system requirements that stemmed from the research and practical requirements. This section returns to these requirements in order to overview how they were implemented. The Goby web application delivers metacognitive support that is processed in the Goby service and domain knowledge that is requested from the APeLS learning service. Although the two services are discrete and logically separated

on the server-side, the learner has no knowledge of the underlying processes or this separation – instead the web application provides a holistic user experience [SR4]. To achieve this, a learning system manager in Goby controls requests for APeLS resources.

The aim behind Goby is to improve the educational and metacognitive outcomes for the learner by [SR1] modelling learner metacognitive awareness. The learner trait model is used to model and trace the changing status of the learner over time. When a response from the learner to dialog is received it is dynamically assessed, in order to identify the item, the response, and assess what the most recent metrics for that item were. A new item is then created with updated rating and confidence metrics. The reading tasks are similarly modelled [SR2]. Each item or sub-activity is processed in memory as a Java object and persisted to the learner trait model, task model and learner progress model in the XML database. The learner trait model is initialised [SR5] using JBoss rules when the learner registers with the system. This includes setup of the learner profile and initialisation of each item in the learner trait model using the baseline model.

A request from the learner for new learning resources triggers the metacognitive support – the Goby service delivers metacognitive prompts and questions [SR7]. The state of the learner within the course or section is compared to the descriptive task model in order to list a number of relevant sub-activities. One of these is chosen and output to the learner task model and is output. The first step in the decision-making process is to use the trait-task mapping [SR3] in order to assess which items are related to the sub-activity. Given that there are a number of items from which to choose, one of these must be chosen [SR6]. The rule engine that carries out the multi-attribute decision making processes is implemented with the JBoss rules language.

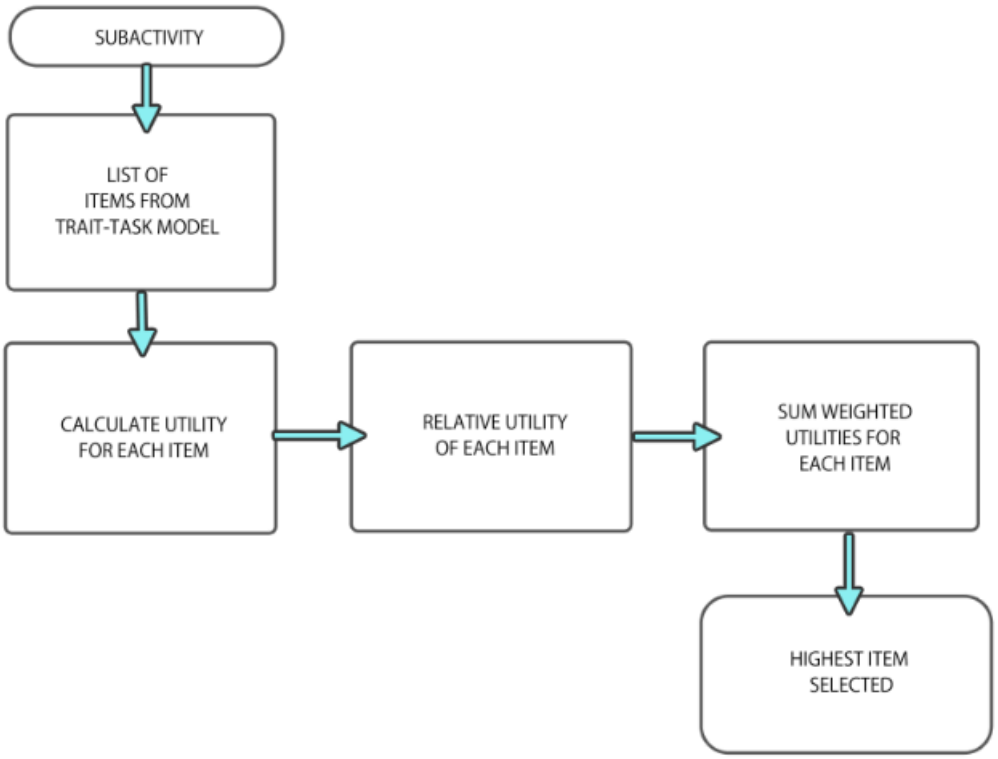


Figure 5.17 - Multi-Attribute Decision Engine Process

An overview of the normative decision process is illustrated in Figure 5.17 above and a flow chart in Appendix I illustrates this process in detail. The list of items that maps to the sub-activity is used to query the learner trait model. The most recent entries for each of these items is assessed in order to compare the utility of each and choose one. The utility for each is first calculated in terms of the recency, mapping, item rating, and the confidence in the rating on a common scale. Each of these is then given a weighted score - Recency was given the highest weighting. The second most important metric was the mapping between the task and metacognitive item. Finally, the rating of the metacognitive item and confidence in the rating were given similar importance. These weightings were implemented on the advice of the participants in the user-centric design study, in order to avoid repetition of the same item if there was another suitable option. These weighted scores are summed for each item. The item with the highest relative utility is selected and appropriate dialog output to the learner. Finally, once the learner completes the database course, they can request to view their learner model – an OLM [SR8] provides a visual overview of their metacognitive profile. A screen shot of this OLM is available in Appendix J. Each of the factors are visualised on a bar chart along with supporting material to describe each.

5.2.5 User Interface

The Goby web application delivers both cognitive support and domain content in a holistic manner. The master-detail UI pattern was used to ensure emphasis on the core message of the application – the SQL and database domain learning. This also reduces the memory load by hiding unnecessary navigation or functionality until it is needed. The SQL content is given the prime real estate to ensure that the learner gives it the most attention. The metacognitive dialog is incorporated using a sliding panel at the bottom of the page. If the user wishes they can close this panel. Figure 5.18 illustrates the final Goby UI, showing how the popup appears at the bottom of the screen, the reduction of light on the content when they hover over the popup, and finally the return to normal luminance when they have responded. A complete overview of the functionality available to learners is also included as a sequence of screen shots in Appendix J. The user-centric design approach taken to developing the web application is discussed later in this chapter.

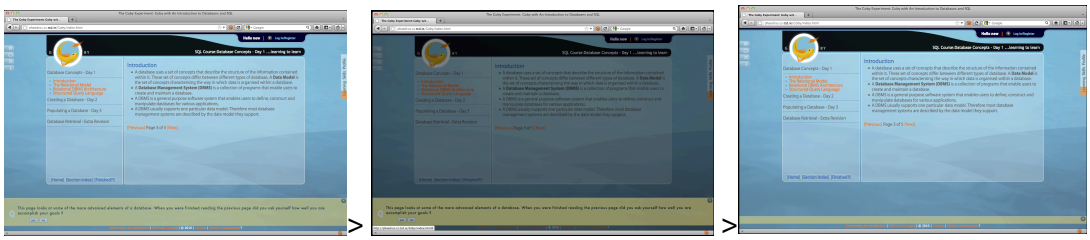


Figure 5.18 - User Interface Walkthrough

The six interface design principles listed in the requirements were considered: stay on the page, keep it lightweight, make it direct, provide invitations, use transitions, and react immediately. The main content – SQL course content and metacognitive dialog are ever-present. Requests for updates to the content, dialog, or responses to the dialog are dealt with AJAX over HTTP, and the use of JavaScript means that the DOM can be utilised to dynamically update the page on the fly. The application is kept as lightweight as possible by keeping the focus on the learning and cognitive support. There are a number of related processes that are secondary to the application, such as registration, and related information. These are vital but infrequently used, so they are displayed in a modal lightbox. Interactions with the learner are direct – objects in the page are directly actionable and jQuery transitions are used to invite the learner to interact with the navigation. Prototype is used to grey out the domain content when the learner is responding to the metacognitive dialog – after they respond the content returns to normal luminosity. The web application reacts immediately to interactions from the learner. For example, once the learner replies to a question, the

sliding panel minimises itself and the SQL content returns to normal luminosity to indicate that they should return to their domain learning.

5.3 User-Centric Design Approach to Developing Goby

A user-centric design approach was taken prior to rolling out the system to the users. A number of early evaluations were necessary to ensure that the system was both usable and performed in an acceptable way. These informed the development of the UI and the user experience that would be provided to the learners. Five participants, who were identified as suitable because they possessed a range of related experience, carried out initial user studies on Goby. The consultation process took between one-two hours. One participant had experience as a designer; another was a lecturer who gave database tutorials; a third had experience in developing user-modelling systems; and the other two had experience in developing databases and web applications. Participants were asked to think-aloud as they navigated through the Goby web application. Each participant completed the registration process, and completed the experiment surveys.

5.3.1 Usability and Learnability

As participants worked their way through the learning system, they identified any issues, and potential solutions, which were later written up as action points. These actions were tackled before the system was released. The overall layout and design of the system was considered suitable fit for purpose. For example, it had a, "*nice layout, easy to navigate*." (UR[66]1) and it was, "*well written and clear examples*" (UR2), and a "*very interesting system, I think it would be beneficial to undergraduate computer science students*" (UR4). They were also asked to comment on the metacognitive dialog components. These responses were positive overall, "*added to the workload but good to stop and think from time to time*."(UR2). However, there were times where the sentences did not flow because the structure of the metadata changed from LO to LO. This although it could be a "*very good way of collecting information and getting users engaged…but it was difficult sometimes to understand the metadata question*" (UR4). The following is a brief discussion of the main changes made to the system subsequent to this consultation process.

[66] UR = User-Centric Response. These (UR*n*) identifiers are used to codify the responses from the pilot study participants.

The initial version of Goby used the LO metadata from APeLS without any editing of the <descriptions>. This meant that sometimes the sentences did not follow good grammatical rules. It was necessary to go back and edit each of the metadata entries for all the LOs to ensure that the sentences would flow.

A number of participants responded that they would like to see a "*reward"* (UR2) to chart their progress through the metacognitive dialog. In response to this a bar chart, tracking the number of replies that a user made was included on the side of the page. An OLM was also incorporated into the Goby web application to provide a visual overview of the learners' regulatory strategies.

The popup dialog that displays the prompts and questions was initially one colour. It was suggested that this should change depending on whether it was a prompt or question. In response, the colour changed depending on the type of dialog, and a large transparent P or Q icon accompanied the text. The database quiz used to assess the learner knowledge was reduced from 40 to 20 questions, to help reduce the amount of time needed to take the test. Rather than letting the user submit long questions, the input box was shortened to a few sentences.

5.3.2 Time to Complete

Two participants with database knowledge were asked to complete some of the course without pausing to give feedback. They could think-aloud through the process, but were timed on how long it took to complete each of the three main sections: Database Concepts, Creating a Database, and Populating a Database. Each section took between 19 and 46 minutes. Since a novice user might pause and spend more time on this content, it was decided that the participants in the experiment should spend at a minimum 20 minutes in a section, but ideally they would spend at least 40 minutes per section.

5.3.3 Frequency of Prompts/Questions

Initially, the weightings used to define the utility of each of the items meant that recency and mapping were more highly weighted than the value and confidence metrics. This was updated on the advice of the participants so that recency was the most important, in order to overcome repetition of the same item when there was

another suitable option. The second most important metric was identified as the mapping between the current task and metacognitive item. Finally, the rating of the metacognitive item and confidence in the rating were given similar importance. In the experiment, on average participants would see an item three times. This figure is based on the number of course pages in relation to the number of items being modelled on the MAI. Since the system delivers both prompts and questions, they should see either two questions and one prompt for that item, or alternatively one question and two prompts.

5.3.4 Goby Open Learner Model

This section briefly outlines the usability survey done on the formative metacognitive feedback that was given to participants. As an added incentive for participants to sign up to the Goby experiment, they were offered the chance to see a visual OLM. This meant visualising each of the regulatory cognitive factors on the MAI: planning, information management strategies, comprehension, debugging strategies and evaluation. Access to this overview is only available after users have completed the set of post-test surveys. A System Usability Scale (SUS) (Brooke, 96) assessment was carried out with three participants at random before it was rolled out for all participants. These three participants were in different experimental groups. They completed the SUS survey, which provides an indicative measure of usability. This resulted in a SUS score of 82 - which can be considered good as it is in the higher end of the scale (Bangor, Kortum & Miller, 09).

5.3.5 Conclusion From Analysis

A number of actions were taken to upgrade the system in order to improve the learnability and usability in Goby. Good interaction design and layout is not considered as a contribution of this thesis. Nonetheless, it was necessary to ensure that Goby delivered a successful user experience. This is because, in an experimental setting, a bad user experience could have led to a poor learning outcome or participant drop out which would have been to the detriment of experimental power. It is for this reason that a user-centric design approach to developing Goby was taken. The resulting system can be considered suitable in terms of performance, dialog frequency, and user experience.

5.4 Conclusion

This chapter has described the implementation of Goby and the manifestation of the ETTHOS model within it. The metrics in the static trait, task and mapping models in ETTHOS were setup at the time of implementation. A consultation process was undertaken in order to setup the mappings. The descriptive task model was derived from the literature on the cognitive reading tasks undertaken by successful readers engaged in academic material. The descriptive trait model was created using the MAI, a psychometric inventory that addresses regulatory metacognitive processes. The metrics in the baseline trait model were derived from an initial study on the population – this study is discussed in the subsequent evaluation chapter. The dynamic models were also discussed – the learner trait, task, and progress model are used to model and trace the learner over time. The dynamic assessment and normative decision making processes used to control interactions with the learner and update the dynamic models were also discussed. Finally, this chapter concluded with a discussion of the user-centric design approach taken to implementing Goby.

Chapter 6 Evaluation

This chapter describes the analyses and experiments carried out to evaluate the ETTHOS model. This includes quantitative and qualitative evaluations as well as critical discussion to ratify the work. Having introduced the steps undertaken in the research and analysis conducted, an overview is provided of each of the analyses undertaken, the data gathered, and findings that resulted. The chapter discusses the extent to which the research supported the learner by examining educational, metacognitive and behavioural outcomes. Analysis of the approach taken to implement ETTHOS is carried out by assessing the baseline modelling approach and through comparison of how ETTHOS implements the features and requirements previously defined. Subsequent sections look at the design of ETTHOS, describing and evaluating architectural decisions taken to implement ETTHOS and the modelling accuracy afforded by the Goby service. Finally, the limitations that arose are similarly considered and the results from the evaluations analysed.

6.1 Introduction

TEL research reports a range of approaches for capturing and classifying learner cognition, which vary in their complexity, level of granularity, pedagogical or psychological perspective. The ETTHOS model has been designed to trace, model, and foster cognitive competencies alongside a TEL service. The Goby service was developed in order to test this model and is specifically designed to capture and foster metacognitive regulatory components. This chapter describes the evaluation and analysis of the extent to which the ETTHOS model can be said to model and support metacognitive aspects of the learner. Previously, the thesis question was posed: *how and to what extent can the cognitive aspects of a learner be modelled to support learning with TEL?* In answering the research question, three goals were identified. These goals are represented here, in order to contextualise the evaluations carried out.

The three goals that will be revisited are:

(i) To what extent does this approach result in *educational benefits* for knowledge gain and cognitive awareness?

(ii) What *approach* can be taken to integrate ETTHOS with a TEL system?

(iii) What is an *appropriate design* for a cognitive model?

In assessing the extent to which these aims have been met a number of evaluations and analyses have been carried out. These include quantitative statistical analysis on the learning and metacognitive gain, analysis of the log data to examine learner behaviour (e.g. time taken, pages visited, supports responded to, and the influence of learners' prior ability), examination of use of the baseline model, qualitative feedback from learners on the perceived benefits and suitability of Goby interactions, and a critical analysis of ETTHOS compared to the technological requirements. Where possible, the relevant parametric statistical analysis is carried out on the data. A probability plot with an Anderson-Darling (AD) test for normality was carried out to ensure the data were normal, and any outliers removed. However, in the case that this is not possible or that there would be many entries to remove, the non-parametric test equivalent was carried out. The probability chosen to define an exceptional outcome was significance level $\alpha=0.05$. In this chapter it is the *t*-test, ANOVA, or general linear model that are reported since these parametric tests are considered quite robust and there were no cases where the non-parametric result indicated a different outcome.

The overarching goal of developing a service to trace and model cognitive competencies alongside a learning environment is to foster a learner's knowledge gain and improve their metacognitive strategies. An initial pilot study was carried out to understand the target population using the MAI. This evaluation was completed in order to appreciate the standard deviation of the target population and inform future assessments – in particular pointing to a suitable sample size. These data were also gathered in order to generate the stereotypical metacognitive user model. A subsequent set of evaluations was carried out on the Goby service to assess the ETTHOS model and the educational outcomes in situ. Participants were assigned to three experimental groups: the cold start group – completed an initial survey to generate their user model; the stereotype group – their user model was generated using the baseline population metrics; and a control group – took part in the SQL

course with no metacognitive support from the system. Learner behaviour (through analysis of the Goby log data) and the influence of their prior-ability (domain and metacognitive) were also analysed in order to examine the trends within the data. These groups are described in greater depth later in this chapter.

The first set of analyses addresses the overarching aim for developing ETTHOS:

(i) To what extent does this approach result in *educational benefits* for knowledge gain and cognitive awareness?

In response to this, the ETTHOS model was used to inform the architecture of the Goby service. It was hypothesised that prompts and questions would trigger metacognitive reflection and result in educational benefits. To assess the educational benefits a number of evaluations were carried out using the Goby service, including:

- A comparison of the knowledge gain between the three groups to see if there was any significant increase for each group.
- A comparison of the participants who engaged with the learning environment to see if they had any increase in metacognitive awareness after using the system.
- A comparison of the metacognitive awareness of participants after they had completed the course in order to see if there was a difference between groups.
- A qualitative analysis of the perceived benefits of using a system that integrates metacognitive prompts and questions.
- Examination of the Goby log data to assess how learner percentile (prior-domain or metacognitive ability) or the intervention as a whole (metacognitive supports vs. none) influenced learner behaviour (e.g. time, pages visited).

The second set of analyses was carried out in order to assess the extent to which the approach taken to implement ETTHOS in Goby was successful. This addresses the second aim of this research:

(ii) What *approach* can be taken to integrate this model with a TEL system?

The ETTHOS model incorporates not only a component to model and foster a learner's cognitive traits; it also incorporates a cognitive task model and baseline model to initialise the individual learner's profile. The cognitive task model allows for a loose coupling between the learning environment and the Goby service over a distributed architecture. The goal of the baseline model was to work towards overcoming the need to ask learners to complete a survey when they sign up to a

personalised learning environment. A number of assessments were carried out to assess these strategies:

- An analysis of the Goby service compared to the approach requirements and features of state of the art distributed learning services.
- A comparison of the baseline 101 MAI scores collected to initialise the stereotypical user model with 154 participants who signed up to Goby. This is to assess whether the initial pilot study generated a suitable stereotype model.

The final component that must be considered is the model in situ – in particular, how has Goby implemented the ETTHOS design and how accurate is the current Goby implementation at modelling metacognition. The final set of analyses outlined address the third aim of the research:

(iii) Can ETTHOS be considered as an *appropriate design* for a cognitive model?

A number of requirements derived from the research questions and the state of the art informed the design of ETTHOS and the Goby service. Two analyses were necessary to assess the effectiveness of ETTHOS -

- An analysis of the accuracy of the Goby service at measuring metacognitive awareness.
- A comparison of ETTHOS to the state of the art features from which the design requirements were derived.

6.2 Experimental Setup

This section outlines the design of the Goby experiment. First, it describes an initial pilot-survey of the population that was used to decide on an appropriate sample size and to generate a baseline model of metacognition that has been used to initialise the cognitive user model. Having described the Goby experimental platform, it then describes the experimental groups. Finally, it provides summary statistics, which describe the learner population who undertook the Goby experiment.

6.2.1 Assessing the Metacognitive Awareness of the Population

This section outlines an evaluation of the baseline metacognitive awareness of the target population. This evaluation was necessary to prime an in situ test case of ETTHOS. This population is a reflection of the types of students who would be accepted onto an Introductory Databases course. The motivation behind this analysis

was to understand the target population in order to inform future experiments. This evaluation provided two key sets of results. First, the mean results from the population have been used as the baseline user model within Goby. Second, by understanding the patterns of difference within the population, or standard deviation, it was possible to design further evaluations with sufficient power. Here, the objective is in understanding the normal state of typical learners and understanding the type of variation between learners, based on a sample population in order to define the necessary sample size. The data are regarded as a random sample from all the potential Database and SQL students in Ireland.

6.2.1.1 Overview

Metacognitive awareness was sampled from 101 participants (male 67, female 34, age 18 to 50) using the Metacognitive Awareness Inventory and assayed for variance. In order to take part in the experiment, participants were gathered from Ireland, aged 18+ and satisfied the criteria to be admitted to an Introductory Database and SQL course. The course entry requirements were that they were already engaged or would be admitted to the early stages of a cognate discipline (Computer Science, Engineering) or that they have completed a Level 8 degree or its equivalent. The inventory was available online via SurveyMonkey.com for two days and participants were gathered through two third-level mailing lists, Facebook and Twitter.

6.2.1.2 Test Setup

The MAI inventory describes knowledge and regulation of cognition. The following study focused on the regulation of cognition, which includes five factors as follows: *planning, information management strategies, debugging, comprehension* and *evaluation*. The survey asked the participants to assess items on the MAI inventory on a 5-point Likert scale.

6.2.1.3 Test Results and Summary Statistics

n=101	Planning	Info Mgmt	Comprehension	Debugging	Evaluation
SD	0.6738	0.4515	0.6835	0.5623	0.6823
Mean	3.1641	3.767	3.3918	3.9861	3.2888
SE Mean	0.0670	0.0454	0.0680	0.0560	0.0679

Table 6.1 - Regulation of Cognition - Descriptive Statistics

Table 6.1 above shows the summary data from the baseline MAI study. The mean response of each item in this survey has been used to initialise the user model for learners who engage in the Goby service. The baseline model and metrics used are included in Appendix E. The success of this approach is evaluated later in this chapter. This analysis was also useful in order to understand the variance in the population that will be encountered when evaluating learners using Goby.

6.2.1.4 Conclusions from Analysis

The results presented here have informed the design of experiments by carrying out a power analysis to indicate the sample size needed to show a difference of 1, as follows: planning (n = 16), information management strategies (n = 8), debugging (n = 16), comprehension (n = 11) and evaluation (n = 16). Thus, in order to carry out an experiment with three groups and satisfactorily identify a difference of 1 using an ANOVA[67], 48 total participants would be required.

6.2.2 The Goby Experimental Platform

Goby was implemented in order to assess the effectiveness of ETTHOS in modelling and subsequently supporting learner metacognition. The Goby web application delivers metacognitive support via the Goby service and delivers database domain knowledge via the APeLS learning service. Although APeLS can deliver adaptive content, at the time of evaluation, adaptation on learning content was not carried out. This would have added an extra degree of complexity to the experiment. In order to ensure that the experimental conditions were as similar as possible for each group, there was no personalised database content. The web application delivers the learning environment alongside metacognitive support. This is illustrated in Figure 6.1 below, where the course content is currently greyed out as the learner interacts with a metacognitive notification.

[67] In order to identify successfully a difference of .5, it would have been necessary to have 177 (59x3) participants.

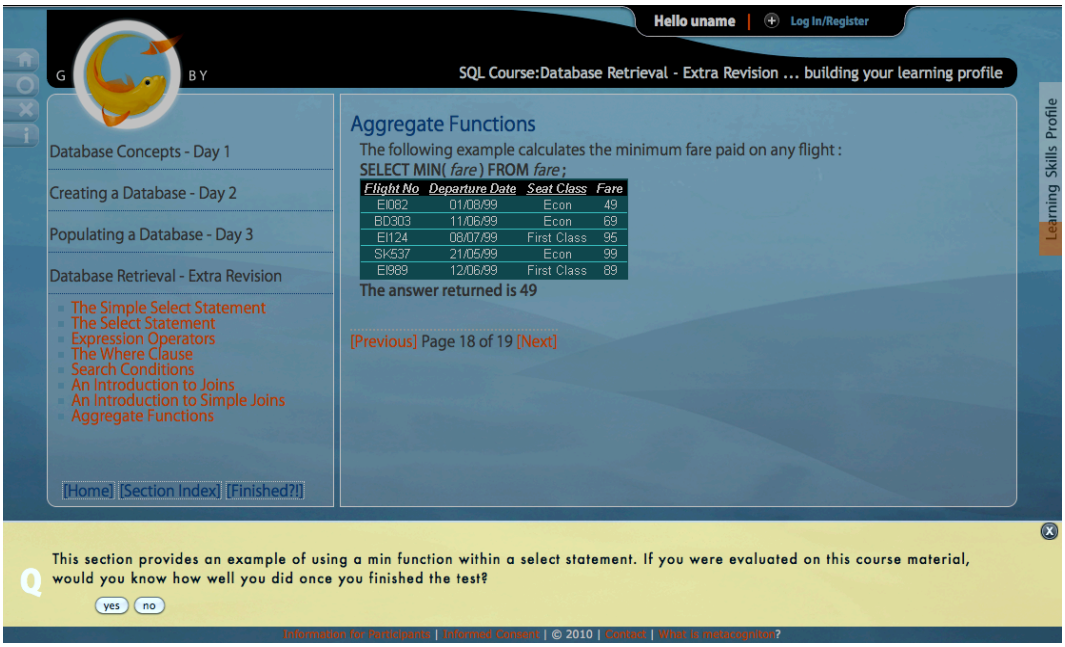


Figure 6.1 - The Goby UI combines metacognitive notifications with a database course

Metacognitive interactions are undertaken using a pseudo-dialogic approach – a dialog model contains suitable chunks of sentences that are dynamically combined with metadata that describes the current LO. The dialog serves two functions: to update the user model as well as prompting reflection in the learner. Goby works in symbiosis with the learning system, and aims to satisfice the needs of the learner.

A number of evaluations have been carried out on using the Goby service in order to assess the effectiveness and suitability of the approach. These include:

a) A *comparison of the metacognitive awareness* of participants after they had completed the course in order to see if there was a difference between groups. In this set of analyses, we are interested in looking at the differences in metacognitive gain between the three groups. This comparison was completed across each of the three groups for each of the five MAI factors. The log data was also used as an additional source of information with which to compare how the intervention and learners' prior-domain ability affected metacognitive gain.

b) A comparison of the participants who engaged with the learning environment to see if they had any *increase in metacognitive awareness*. The main goal of ETTHOS is to provide a modelling framework for learner cognition. However, the overarching motivation behind this is to support the cognitive development of the individual in order to promote positive learning experiences. In Goby, this support was provided via prompts and questions. Here, we are interested in evaluating whether the participants had any metacognitive gain.

c) A comparison of the *knowledge gain* between the three groups was made to see if there was any significant increase for each group. By supporting metacognitive awareness, it is hoped to improve the learning experiences of individuals and increase their effectiveness during learning. This analysis evaluates the knowledge gain of each of the three groups in order to determine if there was a learning benefit. The first group received more metacognitive prompts. The second group received more questions. The final group was a control, so did not have any assistance. The log data is also used as an additional source of information with which to examine the domain-learning gain by comparing how learner's prior domain and metacognitive ability and the intervention as a whole influenced learning gain.

d) *Learner behaviour* in the Goby environment was examined by analysis of the system's log data. Learners' prior-ability, the intervention as a whole (combination of results from Group A and Group B) compared to the control (Group C) and interactions between prior-ability and intervention were examined for their influence on learner behaviour. These evaluation included analysis of *overall learning time*, *number of pages visited*, amount of *time spent per page*, *learning efficiency*, *response rate* to the metacognitive supports, and *time taken* to respond to the metacognitive supports.

e) A *qualitative analysis* of the *perceived benefits* of using the Goby environment to analyse learner perception on; *motivation and learning support;* the *relevancy of the metacognitive prompts/questions to learning;* and the *prompt/question interaction workload.* Here, learners were categorised according to their experimental groups initially. The log data was further used as a source of data with which to categorise learners and examine whether having low or high prior-domain-ability influenced their opinions.

f) Examination of the *accuracy of the baseline model* that was generated from the pilot study in comparison to the actual pre-test MAI results. This was carried out to assess whether the baseline model was sufficiently accurate to represent the learner population that signed up to the Goby experiment.

g) An analysis of the *accuracy of Goby at measuring metacognitive awareness*. This analysis assays the final user model that Goby has calculated through interactions with the learner. The end user model is compared to a post-test MAI survey that each learner completed after finishing the course. Each of the five MAI factors is

compared: planning, information management strategies, comprehension, debugging and evaluation. There are two groups under analysis. In the first group, the user model was initialised with a pre-test MAI survey. In the second group, instead of getting the user to complete a survey, the stereotypical MAI values initialise the user model.

h) A reflection on the implementation of ETTHOS within Goby and analyses of how well Goby represents both the model and fit the research requirements. The features from which these requirements were derived are returned to and discussed, with an overview provided in a requirements traceability table (c.f. Table 6.41) towards the end of this chapter.

6.2.3 The Goby Experiment Design

6.2.3.1 Admission Criteria

Three experimental groups were required in order to evaluate each of the goals of the system. Initially, it was hoped that enough participants could be gathered that were currently enrolled in an introductory databases course. The intention was that Goby would act as a study guide. While initial sign-up was positive, there were not enough learners in each group, so the experiment was opened up to other suitable candidates. Participants were invited from the computer science departments in TCD (Trinity College Dublin) and NCI (National College of Ireland) using the email lists, and by short talks/flyers given in their lectures, and via Facebook and Twitter. In order for individuals to qualify for the experiment, participants had to be based in Ireland, aged 18+ and had to satisfy the criteria to be admitted to an Introductory Database and SQL course - that they are already engaged, or would be admitted to the early stages of a cognate discipline (Computer Science, Engineering, or similar) or that they had completed a Level 8 degree or its equivalent. Gender was not a factor in participant selection. For each group, there was a required number of 16+ participants, or 48+ participants in total for a three way ANOVA. The power data were collected as part of a pilot study to understand the target population and the standard deviation. This analysis has been outlined previously.

6.2.3.2 The Experimental Learning Environment

Each participant was asked to interact with the Goby service over a number of days. They were required to log in for at least three learning sessions. These sessions were

to last between 40min to 1 hour each. This time frame reflects the traditional time spent in a lecture or tutorial as well as results from the pilot study during the implementation of Goby. The course content was broken into four main categories: *Database Management Systems*, *Creating a Database, Populating a Database*, and *Retrieving Data from a Database*. The first three were required reading, and the fourth was added for extra revision. This extra section was delivered as a support for students who were already enrolled in a database course, so that Goby would cover a suitable range of content to complement their study. The two experimental groups received metacognitive dialog (as illustrated in Figure 6.1 previously) in a slide-up menu. It is here that the metacognitive dialog is delivered to the learner. Participants can respond to the dialog, or ignore it and continue through the learning environment. Responses gathered were used to update the metacognitive user model, increasing the value of the metric and the confidence in that value. At first, they were questioned about their items regarding their metacognitive regulation. After the systems confidence in the user model metrics had increased for particular items, learners started receiving prompts rather than questions for that item.

After the experiment was closed, each participant had the opportunity to see an Open Learner Model (OLM) overview of their post-MAI scores, with a description of each of the factors. If they were not in the control group they could also view the MAI model that Goby had built for them. The overall time for completion, including the course interaction and both sets of surveys was around two and a half hours, however some participants took up to six hours if the used the extra material. This time was spread over at least three or four unique sessions.

6.2.3.3 Participant Data Gathered

Every group completed a number of surveys; both prior to and post using the Goby web application, including:

1. Each of the regulatory factors in the MAI was assessed on a 5-point Likert scale including; Planning, Information management strategies, Debugging strategies, Comprehension, and Evaluation.
2. A 20-question short answer exam on basic databases and SQL. These questions assessed the learners on each of four main topics: Database Management Systems, Creating a Database, Populating a Database, and

Retrieving Data from a Database. A marking scheme was created in order to grade the answers after the experiment.

3. Participants were also asked to complete a demographic survey.
4. Subsequent to completing the course they completed a qualitative analysis to assess the perceived benefits and accuracy of Goby. This included their perceptions of the system by providing feedback on a 5-point scale with the option to include free text answers.

The log data from the Goby environment was also used as an additional source of information to allow for more nuanced analyses. Through analysis and examination of the Goby log data further comparisons between learners were possible by comparing learners by *percentile* and *intervention*. Prior-ability was used to categorise these learners into their *percentile*. Learner percentile is described as high (H), medium (M), and low (L). A MiniTab[68] script was used to categorise learners using indicator variables into the low (below 40th percentile), high (60th percentile and above) and mid (those between low and high) groups[69]. Learner behaviour was also measured by converting the raw model data into tabular format. This meant that it was possible to examine *overall learning time*, *number of pages visited*, amount of *time spent per page*, *learning efficiency* (a comparison of the amount of time spent learning vs. the post-test quiz), *response rate* to the metacognitive supports, and *time taken* to respond to the metacognitive supports. In-depth log data reports are provided in Appendix M, which provides effects, interaction and value plots with discussions of the statistical tests and power analyses carried out.

6.2.4 Goby Experiment Groups

On registration with the Goby participants were assigned at random to one of three groups. This process was not completely random however – the system placed the participants into groups at random while ensuring that sample size was similar in each group. The three conditions were as follows:

[68] MiniTab is the statistical package used to carry out all of the analysis. An example of this script to automatically categorize learners is provided in Appendix M.
[69] For example, c.f. Checkoway et al., 12; Wynn-Williams et al., 05, who similarly break down learners according to the 40th and 60th percentiles.

6.2.4.1 Experimental Group A

The *cold start group*. The pre-test MAI scores were used to initialise the user model. This reflects the typical approach to modelling learner cognition for personalisation in AEH. The responses to this survey are represented in the metacognitive user model. These values have been given a high confidence value since the users have self-reported their metacognitive ability. All of the participants in Group A will interact with prompts and questions via the Goby service. Since the confidence is high, participants will typically receive one question on an item. If that item is used again, it will have previously increased in confidence to the level that they will be prompted.

6.2.4.2 Experimental Group B

The *stereotype group*. The stereotypical MAI scores from a previous study will by used as a baseline to initialise the user model. These values will be given a lower confidence since the learner is likely to be close to the population standard but not quite the same. Again, these participants will interact with the Goby service during the online course. Since the confidence in these values is lower, two questions will be generally asked about an item before it is prompted.

6.2.4.3 Experimental Group C

The *control group*. During the SQL course they will not interact with the Goby prompts or questions. They will complete the pre and post-test survey but will not be asked to complete the qualitative section that asks for feedback on the popup dialog.

6.2.4.4 Summary Statistics for the Goby Experiment

51 participants (male 38, female 13, age 19 to 63, mean age 33) completed the Goby experiment. Initially database students were enlisted, however the experiment was opened up to other suitable candidates in order to reach sufficient sample size. An overview of the participants' data is described in Table 6.2 below.

Group	***A***	***B***	***C***
Total	17	16	18
Age Range	19-55 (mean 33)	25-54 (mean 32)	19-63 (mean 35)
Sex	13 m, 4 f	9 m, 7 f	16 m, 2 f
CS Students	13 CS	11 CS	14 CS
DB Students	6 DB	5 DB	6 DB

Table 6.2 - Goby Experiment Participant Data

The majority of participants were computer science (CS) students, and several of these were enrolled in a database (DB) course. There were a larger number of males than females, however this is reflective of the breakdown in the CS courses from which they were recruited.

This section has described the experimental setup taken to assessing ETTHOS. An initial study was carried out on the target population to assay the average state of the learners. This analysis has informed the implementation of the Goby service by providing the metrics for the baseline model. It was also necessary in order to assess what sample size would be suitable for an evaluation of Goby. Summary statistics of the Goby participants were also introduced.

6.3 Supporting the Learner

The first set of analyses addresses the overarching aim of this research -

(i) To what extent does this approach result in *educational benefits* for knowledge gain and cognitive awareness?

Lifelong learning, particularly in the TEL environments requires the learner to self-regulate (Azevedo & Witherspoon, 09) – a good learner will monitor, modify, and adapt their goals and strategies in response to changes in the learning context (Azevedo & Witherspoon, 09). It is the aim of ETTHOS to provide a mechanism to model and subsequently foster metacognitive strategies that are essential to self-regulated and autonomous learning. As illustrated in Figure 6.2 below, there are four hierarchical goals of metacognitive support in TEL environments.

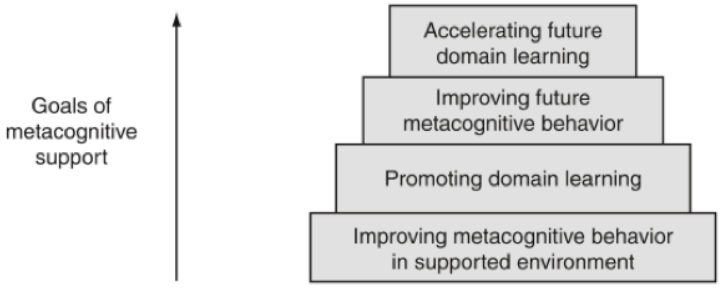


Figure 6.2 - Goals of Metacognitive Tutoring (from Koedinger et al., 09)

ETTHOS is manifest in Goby service in order to address the first three of these goals. The *underlying* goal of metacognitive tutoring is to improve the metacognitive behaviour during learning. Consequently, a qualitative evaluation has been carried out in order to assess the perceptions of the learner on the Goby service. The motivation behind this is to understand the learners' perceptions and inform future versions of the Goby service. The log data was analysed in order to examine whether learner behaviour was influenced by the intervention (by metacognitive supports) or learners' prior-ability. This included examination of *overall learning time*, *number of pages visited*, amount of *time spent per page*, *learning efficiency*, *response rate* to the metacognitive supports, and *time taken* to *respond* to the metacognitive supports.

Promotion of domain learning is the *second* goal of metacognitive tutoring systems and is subsequently addressed in a quantitative evaluation that compares the learning gains of learners who used Goby with and without metacognitive assistance. A comparison is also carried out between the groups to see whether there was a difference for learners who engaged in dialog and whether those who had more prompts or questions performed better. Further analysis of the log data was used to categorise learners according to their prior-ability (domain and metacognitive) and assess how ability and the metacognitive intervention influenced learning gain.

The *third* goal of metacognitive tutoring above is that metacognitive strategies are internalised, so that they can transfer them to learning beyond the learning environment. This is assessed in the Goby experiment by comparing the metacognitive ability of learners prior to and post using Goby. Each of the five regulatory metacognitive factors is examined - planning, information management, comprehension, debugging and evaluation. Here, log data was also examined for influences of prior-domain-ability on metacognitive gain.

6.3.1 Evaluation of Learning Gains [R1]

6.3.1.1 Overview

The overarching aim of ETTHOS is to provide a model that is discrete and separate from the learning environment while delivering complementary support. The ability to self-reflect and apply self-monitoring and regulation is considered antecedent to better lifelong learning. By separating the model from the learning environment it means that this model could travel and grow with the learner over their lifetime. However, it is important that the model first shows that it can support individual learners to improve their educational experience. The support of learning skills, such as metacognition can result in better learning experiences and improved knowledge gain. This study assesses whether the ETTHOS model can be used to deliver this type of support. It describes a comparison of the three experimental groups and also compares whether the intervention groups, prior-ability (domain or metacognitive), or their interaction influenced the learning gain. Here, we are interested in evaluation of whether or not the metacognitive prompts and questions supported the learner. Ultimately, we are interested in whether the learning gain was improved for those learners who interacted with the metacognitive interface.

6.3.1.2 Test Setup

Participants were asked to complete a short database quiz both before and after completing the Goby experiment. 33 participants completed both the pre and post database quiz (male 27, female 6, age 19 to 63), in each of the three groups; Group A (n = 13), Group B (n = 7), and Group C (n = 13). Initially, their database expertise was assayed to see if there were any differences of note in their knowledge. Subsequently, learning gain was measured and compared between groups.

The first hypothesis to be tested here is that each group will have the same score on a database quiz. This is to test whether the groups are of equal ability prior to commencing the database course in Goby. Thus the null hypothesis is that there is no difference between the three groups:

Ho: μ1 (Group A pre-database quiz) = μ2 (Group B pre-database quiz) = μ3(Group C pre-database quiz) = μ

H_1: μ1 ≠ μ2 ≠ μ3 ≠ μ

An ANOVA was carried out to assess whether measures departed from the null hypothesis. The probability chosen to define an exceptional outcome was significance level α=0.05.

The second hypothesis to be tested is that each group will have the same learning gain. This is an important evaluation, because here we are interested in assaying whether any of the groups performed better than their peers. Similarly, an ANOVA was carried out, at significance α=0.05.

Here, the null hypothesis is that there is no difference between the three groups.

Ho: μ1 (Group A learning gain) = μ2 (Group B learning gain) = μ3 (Group C learning gain)= μ

H_1: $\mu 1 \neq \mu 2 \neq \mu 3 \neq \mu$

6.3.1.3 Summary Statistics of Knowledge Prior to Using Goby

	N	Mean	StDev
Group A	13	42.08	28.17
Group B	7	26.57	23.36
Group C	13	44.77	31.35

Table 6.3 - Initial Database and SQL Knowledge Assessment

As illustrated in Table 6.3 above, the mean values for each of the groups prior knowledge varies quite a lot, however so does the standard deviations between the groups. In Figure 6.3 below, you can see the boxplot range of responses with similar coverage for each of the three groups. An AD test for normality showed the data were not normal; this was illustrated in a probability plot with some skewing to the left. An ANOVA is reported here, as it is more interesting to talk about the means, however a Kruskal-Wallis test was also carried out with similar results. This is reported in Appendix K. The one-way ANOVA was used to test for database knowledge differences among the three groups. This did not differ significantly across the three groups $F(2,30)=0.98$, $p=0.386$.

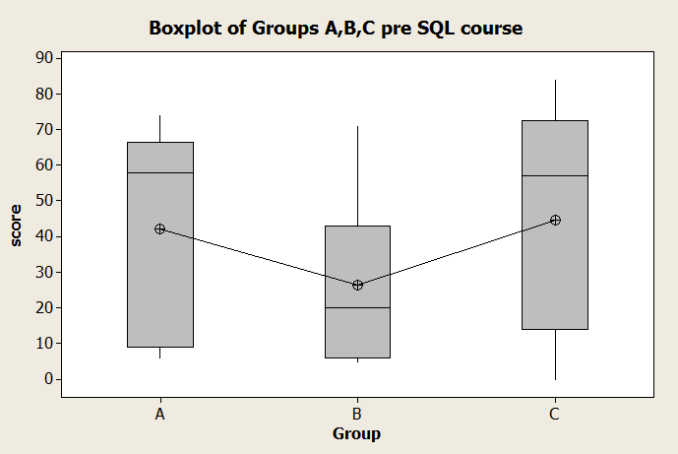


Figure 6.3 - Boxplot of Experimental Groups before the SQL course

6.3.1.4 Test Results and Summary Statistics for Knowledge Gain

	N	Mean	StDev
Group A	13	26.15	21.6
Group B	7	39.14	18.03
Group C	13	12.23	13.71

Table 6.4 - Comparison of Knowledge Gain

As illustrated in Table 6.4 above there is a range of differences in both means and deviation for knowledge gain after using the Goby web application. A one-way ANOVA was used to test for database knowledge differences between the three groups. This did differ significantly across the three groups $F(2,30)=5.29$, $p=0.011$. In Figure 6.4 below, the range of responses is illustrated in a boxplot. The outlier seen in Group A was removed and data were within the AD range of normality. A subsequent ANOVA returned similar statistical *significance*. Consequently, in Figure 6.4 below, the outlier was left in for a better visual representation of the learning outcomes.

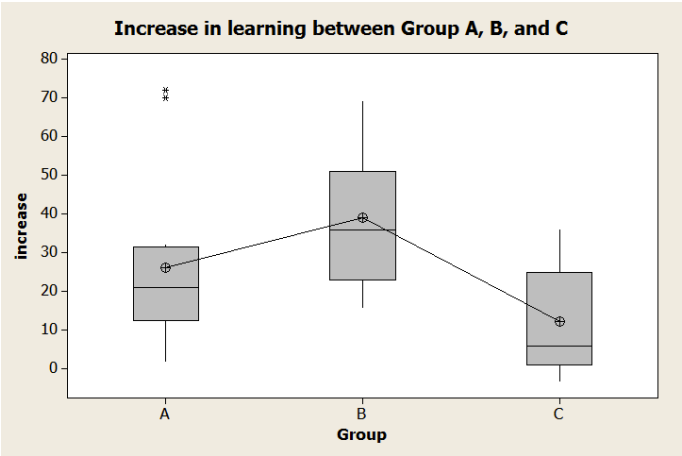


Figure 6.4 – Comparison of Knowledge Gain

Post-hoc analysis revealed no significant improvement for Group A over the control group C; t(20)=1.96, *p*=*p*=.064 M diff = 13.92 (95% CI (-0.88,28.72)). There was a significant improvement identified for Group B over the control group; t(9)=3.45, *p*=0.007 M diff = 26.91 (95% CI (9.26,44.57)).

6.3.1.5 Examining Influences on Learning Gain

Learning gain was examined for influences on the learners' prior (domain) ability, the intervention (metacognitive support vs. control), the interaction between prior ability and intervention, as well as prior ability in each of the five metacognitive factors (planning, information management, comprehension, debugging, evaluation) using a general linear model and subsequent ANOVA and t-tests. This process of analysis is described in depth in Appendix M. In each case, learners were categorised according to their prior-ability percentile[70]. None of the tests revealed a significant effect when comparing prior-metacognitive ability to the learning outcome. This does not indicate the metacognitive ability is not important in learners' educational outcomes however. As described previously in Chapter 2, the MAI is often correlated with broad measures of academic achievement (e.g. overall end of course grades) rather than specific tests (e.g. such as continuous assessment quizzes).

Significant effects were found for learners' prior domain-ability (SQL percentile, $F(2,9) = 43.00$, $p = 0.000$) the intervention (M vs. C, $F(1,9) = 31.31$, $p = 0.000$) and the interaction of the prior-domain-ability and the intervention ($F(2,9) = 6.23$, $p = 0.020$). There were no significant effects for each metacognitive variable. Although this model explained some of the variation in the data (R-Sq adj 89.23%), there are most likely other cofounding variables or influences at play (e.g. motivation, interest). With such a small data set (n = 25) to analyse such a range of conditions, there is most likely not enough power. Also, including explanatory variables that may be independent of the dependent variable can mask other results.

On subsequent analysis of prior-ability, using a two-sample t-test to compare the low to high prior-domain ability learners, there as a significant difference reported (t= -5.31, *p*= 0.000 M diff = -21.17 (95% CI (-29.58, -12.76)). The influence of prior ability is to be expected, as those with lower prior ability would have more to learn and

[70] C.f. Section 6.2.3.3 above for a description on how this breakdown was carried out.

should benefit more from the learning intervention. Conversely, although those in the higher-ability group may be able to improve on their domain knowledge, they can be affected by a ceiling effect because they do not have as much of a range within which to improve. This effect has been similarly shown in a number of studies, whereby lower ability learners benefit the most (in terms of learning gain) compared to those with higher ability who have less to learn (For example, c.f. Koedel & Betts, 08; Sadler & Good, 06).

On analysis of the learning gain for learners in the metacognitive support cohort (M) versus those in the control (C), there was a significant difference reported (t= -3.36, *p*= 0.004 M diff = -14.16(95% CI (-23.84, -5.40)). However, it is difficult to separate this result from the previous analysis of the intervention. Indeed, while it may be that learners who received metacognitive supports reported greater learning gains because of the intervention, this result may simply be because of the interaction between low prior ability and the experimental cohort to which they were assigned. In the Goby experiment, learners were assigned to experimental groups before completing the pre-test meaning that they were not stratified for prior-domain-ability.

On examination of separate value plots for high (H, n=12) and low (L, n=9) prior-domain-ability to compare the control to the metacognitive supports, it appears as though those who received metacognitive support (M) reported larger learning gains, with significant results reported by high ability learners (t= -7.10, *p*= 0.000 M diff = -14.54(95% CI (-19.18, -9.19)). Thus, high ability learners who received metacognitive supports had greater learning gains than high ability learners who did not receive the metacognitive support. This may be because the metacognitive supports helped those with higher prior ability to better overcome the ceiling effect. Indeed, it may be that those with higher ability were able to attend to the metacognitive supports and implement the strategies suggested because they were not as cognitively taxed as there lower ability peers. However, it is difficult to have confidence in these results because of the low number of participants meaning that these tests are not sufficiently powered. Thus, these results may be due to random variability in the data and points to the usefulness of future analysis that explicitly considers learner percentile.

6.3.1.6 Conclusion From Analysis

This set of analyses was interested in whether Goby could significantly improve the educational outcomes for learners through personalised supports, which provided questions/prompts on how they could improve their metacognitive strategies. The learning outcome results are promising. Both of the experimental groups (Group A M = 26.15, Group B M = 39.14) reported greater improvement over those participants in the control group (Group C M = 12.23), with significant differences in the case of group B, however are most likely other influences that affected the learning gain. On analysis using the learner prior-domain-ability, the intervention as a whole and the interaction between prior ability and intervention, it appeared that each of these influences had an effect on the learning gain. Prior-domain ability influenced the subsequent learning gain found in learners, most likely because of celling effects in learners who had higher prior ability and the greater range within which lower ability learners had the opportunity to improve. When comparing the intervention (both Group A and B combined) overall with the control, greater learning gains were also found in the experimental groups. In an attempt to separate this effect from the influences of prior-ability the results were broken down into separate percentile populations to compare high ability learners on their own and lower ability learners on their own. It appeared that high ability learners who received metacognitive supports had greater learning gains than high ability learners who did not receive the metacognitive support. Similarly low ability learners who received the metacognitive supports had slightly better learning gains than low ability learners in the control. Although these comparisons, which look at individual percentile populations, were underpowered, they show that participants in this data set reported greater learning gains when in the intervention group, regardless of prior-ability. Indeed, one of the limitations on analysis of learning gain was response rate. Many of the Goby experiment participants skipped the database quiz component of the pre and post-test questionnaires. Although sufficient numbers of participants were gathered to assess metacognitive modelling and improvement, this part of the experiment would have benefited from a better response rate and stratification of learners into groups according to their prior-ability.

Although learners' prior-metacognitive-ability was not correlated with the learning gain in this experiment, this does not mean that metacognitive ability does not

influence learning gain. As previously discussed in Chapter 2, the MAI has been shown to correlate with broad measures of academic achievement such as overall course scores and GPA rather than specific continuous assessment results. This is because there may be other confounding issues other than one's utilisation of metacognitive regulation and knowledge skills. From this perspective, the MAI is better correlated to broad measures of academic achievement and end of course grades rather than single measures. Nonetheless, the results presented are promising and point to the benefit of future use and in particular examination and evaluation of how metacognitive supports in this form can benefit the learner. Most likely, prompts and questions are not sufficient – while they are useful in gathering information about the learner, supportive tools (e.g. digital sketchpads or goal setting features) could provide richer support.

6.3.2 Assessment of Metacognitive Gain [R1.1]

One of the important goals behind ETTHOS is to support the acquisition and encoding of metacognitive skills for use beyond the learning environment. In the Goby service, ETTHOS is used to support the learner through pseudo-dialogic interactions. The learners were questioned or prompted on a particular metacognitive item. Three sets of evaluation were carried out in order to assess whether this use of ETTHOS resulted in an improvement for any of the metacognitive regulation factors – planning, information management strategies, comprehension, debugging and evaluation. The first evaluation described here is a comparison of the metacognitive awareness of participants after they had completed the course in order to see if there was a difference before and after. This test compares the pre-test MAI scores to the post-MAI scores for each of the groups. The second evaluation described is a comparison of the participants who engaged with the learning environment to see if they had any increase in metacognitive awareness. This test compares the three groups to see if whether a particular experimental setting resulted in better metacognitive gain. Finally, the log data was used to categorise learners according to their prior-domain ability and compare this against the metacognitive interventions and the interaction between intervention and prior-ability.

6.3.2.1 Metacognitive Skill Gain Post Interaction with Goby

6.3.2.1.1 Overview

This analysis is concerned with the influence that the prompts and questions had on the learners in the Goby experiment. The intended application of ETTHOS is the modelling and subsequent support of learner cognition. Here, we are interested in whether interactions with a system that implements ETTHOS and engages with the learner via prompts and questions can stimulate a lasting improvement in their metacognitive abilities.

6.3.2.1.2 Test Setup

This test compares the pre-test MAI scores to the post-MAI scores for each of the groups A, B and C. The premise to be tested here is whether each factor measured will have the same mean values before and after interacting with the Goby service. Essentially, the question that is being asked is whether Goby can improve a learner's metacognitive repertoire? Thus the null hypothesis is that there is no difference between the pre and post reposes. The alternative hypothesis is that both sets of metacognitive factors have different means.

Ho: $\mu 1$ (pre MAI survey) = $\mu 2$ (post MAI survey) = μ

H_1: $\mu 1 \neq \mu 2 \neq \mu$

A paired *t*-test was carried out to compare metacognitive regulation for each factor in pre and post conditions. Exceptional outcome were defined at a significance level of α=0.05.

6.3.2.1.3 Test Results and Summary Statistics for Group A

The following summarises the results for Group A – the cold start group. This group is characterised by the fact that pre-test MAI scores were used to initialise the user model. Subsequently, this means that the learners in this group received on average one question and two prompts for each item. These levels vary depending on the path the learner takes through the learning environment. However once they had received one question they would subsequently be prompted because of the high level of confidence given to the initial user model metrics.

	N	Mean	StDev	SE Mean
Pre	16	3.345	0.492	0.119
Post	16	3.303	0.569	0.138

Table 6.5 - Group A: Planning scores pre and post Goby

There was not a significant difference in the scores for the planning level; t=0.3, *p*=0.765 M diff = 0.042 (95% CI (-0.25,0.334)). Table 6.5 shows very small mean difference that could not be considered significantly different – there was no lasting improvement in the participants' ability to plan.

	N	Mean	StDev	SE Mean
Pre	17	3.629	0.353	0.086
Post	17	3.594	0.530	0.128

Table 6.6 - Group A: Information Management Strategies scores pre and post Goby

There was no significant difference in the scores for the information management strategies, as illustrated in Table 6.6; t=0.23, *p*=0.819 M diff = 0.035 (95% CI (-0.286,0.357)). This means there was no information management strategy improvement.

	N	Mean	StDev	SE Mean
Pre	16	3.250	0.507	0.127
Post	16	3.384	0.432	0.108

Table 6.7 - Group A: Comprehension scores pre and post Goby

There was not a significant difference in the scores for the comprehension (Table 6.7) level; t=-1.19, *p*=0.253 M diff = -0.134 (95% CI (-0.374,0.106)). The participants' level of comprehension ability stayed the same after using Goby.

	N	Mean	StDev	SE Mean
Pre	16	3.962	0.401	0.1
Post	16	3.975	0.593	0.149

Table 6.8 - Group A: Debugging Strategies pre and post Goby

There was no significant difference in the scores for the debugging level; t=-.0.8, *p*=0.934 M diff = -0.013 (95% CI (-0.33,0.305)). As illustrated in Table 6.8 above there is only a small difference between means. Participants did not have a lasting improvement in debugging ability after using Goby.

	N	Mean	StDev	SE Mean
Pre	17	3.343	0.525	0.127
Post	17	3.490	0.406	0.098

Table 6.9 - Group A: Evaluation scores pre and post Goby

There was not a significant difference in the scores for the evaluation – again results show that there was no improvement in evaluation ability after using Goby. As illustrated in Table 6.9, there is only a small difference in the mean scores; t=-1.59, *p*=0.131 M diff = -0.147 (95% CI (-0.3431,0.049)).

6.3.2.1.4 Test Results and Summary Statistics for Group B

The following describes the results for Group B - the stereotype group. Participants in Group B had their metacognitive user model initialised using the stereotypical MAI scores from a previous study of the population. These values will be given a lower confidence level since the learner is likely to vary around the population mean. This means that when they are engaged with Goby they will receive more questions than prompts. Participants in Group B generally received two questions for an item before receiving prompts about that item. The results from Group B were not normal in an AD test for normality, however the probability plot was almost normal with some skewing towards the tail of the scale. The paired-t was carried out and is subsequently reported for each of the factors. However a Mann-Whitney test was also carried out to try to ensure that no unusual or conflicting results were missed. In this case, there were no differences in significance findings between the paired-t and Mann-Whitney. These Mann-Whitney statistics are included in Appendix K.

	N	Mean	StDev	SE Mean
Pre	16	3.304	0.594	0.149
Post	16	3.375	1.009	0.252

Table 6.10 - Group B: Planning scores pre and post Goby

There was no significant difference in the scores for the planning level; t=-0.3, *p*=0.765 M diff = -0.071 (95% CI (-0.576,0.434)). Table 6.10 shows a very small mean difference between pre and post scores. This means that there was no real lasting improvement in planning for Group B after using Goby.

	N	Mean	StDev	SE Mean
Pre	16	3.281	0.615	0.154
Post	16	3.637	0.799	0.2

Table 6.11 - Group B: Information Management scores pre and post Goby

There was no significant difference in the scores illustrated is Table 6.11 above for the information management level; t=-1.80, *p*=0.092 M diff = -0.356 (95% CI (-0.779,0.066)). Again, this means that using Goby did not result in a lasting improvement for information management strategies.

	N	Mean	StDev	SE Mean
Pre	16	3.045	0.735	0.184
Post	16	3.411	0.917	0.229

Table 6.12 - Group B: Comprehension scores pre and post Goby

There was not a significant difference in the scores for the comprehension level; t=-1.59, *p*=0.132 M diff = -0.366 (95% CI (-0.856,0.124)). Table 6.12 shows only a small difference between means that can be considered to be on par.

	N	Mean	StDev	SE Mean
Pre	16	3.575	0.915	0.229
Post	16	3.9	0.803	0.232

Table 6.13 - Group B: Debugging Strategies scores pre and post Goby

There was no significant difference in the scores for the debugging levels illustrated in Table 6.13 above; t=-1.40, *p*=0.181 M diff = -0.325 (95% CI (-0.819,0.169)). This means that there was no improvement or difference for debugging strategies.

	N	Mean	StDev	SE Mean
Pre	16	3.167	0.748	0.187
Post	16	3.583	0.905	0.226

Table 6.14 - Group B: Evaluation scores pre and post Goby

There was not a significant difference in the scores for the evaluation levels illustrated in Table 6.14; t=-1.90, *p*=0.077 M diff = -0.417 (95% CI (-0.884,0.051)). Again, there was no improvement in the participant's evaluation prior to using Goby.

6.3.2.1.5 Test Results and Summary Statistics for Group C

The following describes the results for Group C – the control group. This group completed the pre and post-test survey but did receive any metacognitive support. The results in post-test survey for Group C were almost normal on a probability plot with the AD value being close to 0.05 so the paired-t was carried out. Nevertheless, a post-hoc Mann-Whitney test was also carried out to but there were no differences in significance findings between the paired-t and Mann-Whitney. These Mann-Whitney statistics are included in Appendix K.

	N	Mean	StDev	SE Mean
Pre	18	3.333	0.523	0.123
Post	18	3.389	0.530	0.125

Table 6.15 - Group C: Planning scores pre and post Goby

There was no significant difference in the scores for the planning level shown in Table 6.15; t=-0.54, p=0.593 M diff = -0.056 (95% CI (-0.271,0.160)). The planning responses have not changed for the control group.

	N	Mean	StDev	SE Mean
Pre	18	3.7	0.445	0.105
Post	18	3.589	0.689	0.162

Table 6.16 - Group C: Information management score pre and post Goby

There was not a significant difference in the scores for the information management strategies levels in Table 6.16; t=0.86, p=0.401 M diff = 0.111 (95% CI (-0.161,0.383)). Information management strategy responses have not changed significantly after engaging in the controlled Goby environment.

	N	Mean	StDev	SE Mean
Pre	18	3.302	0.492	0.116
Post	18	3.373	0.695	0.164

Table 6.17 - Group C: Comprehension score pre and post Goby

There was not a significant difference in the scores for the comprehension level; t=-0.41, p=0.684 M diff = -0.071 (95% CI (-0.436,0.293)). Table 6.17 shows a small difference between the mean values that can be said to be on par.

	N	Mean	StDev	SE Mean
Pre	18	3.933	0.578	0.136
Post	18	3.8	0.636	0.158

Table 6.18 - Group C: Debugging scores pre and post Goby

There was no significant difference in the scores for the debugging levels shown in Table 6.18; t=0.85, *p*=0.409 M diff = 0.133 (95% CI (-0.199,0.466)).

	N	Mean	StDev	SE Mean
Pre	18	3.426	0.694	0.163
Post	18	3.537	0.643	0.215

Table 6.19 - Group C: Evaluation scores pre and post Goby

There was no significant difference in the scores for the evaluation level; t=-0.85, *p*=0.612 M diff = -0.111 (95% CI (-0.564,0.342)). The mean results shown in Table 6.19 can be considered as on par.

6.3.2.1.6 Conclusion From Analysis

The results suggest that there is no increase or decrease in metacognitive awareness for each factor across each of the groups after interacting with Goby. In most of the experimental settings the metacognitive mean value was larger after interacting with the Goby service – eight out of the ten assessments reported a small non-significant increase. However, this cannot be attributed to the experimental setting because the statistics reveal that the results can be considered as on par. This means that participants who interacted with the metacognitive dialog did not improve their regulatory metacognitive repertoire. Consequently, there was no lasting improvement in participants planning, information management, comprehension, debugging, or evaluation abilities as assessed by the MAI.

6.3.2.2 Comparison of Metacognitive Awareness Between Groups

6.3.2.2.1 Overview

This evaluation addresses whether there is any difference between the MAI scores reported from participants after engaging with the Goby service. This means comparing each of the three groups: A the cold start group, B the stereotype group and C the control group. The purpose of this evaluation is to assess whether any of the three conditions resulted in a significant difference in the level of metacognitive

regulation factors – planning, information management strategies, comprehension, evaluation, or debugging.

6.3.2.2.2 Test Setup

This test compares the metacognitive ability of learners as measured in self-reports from the participants. The hypothesis to be tested here is that each group will have the same mean value. The purpose of this is to assess whether the experimental groups achieved higher MAI scores than the control or if there was a difference between them. An ANOVA was carried out to assess whether measures departed from the null hypothesis. Thus, the null hypothesis is that there is no difference between the cold start, stereotype and control. The alternative hypothesis is that there is a difference in means:

Ho: μ1 (cold start) = μ2 (stereotype) = μ3 (control)= μ

H_1: μ1 ≠ μ2 ≠ μ3 ≠ μ

6.3.2.2.3 Test Results and Summary Statistics

	N	Mean	StDev
Group C	18	3.3889	0.5296
Group B	16	3.375	1.0086
Group A	17	3.3025	0.6466

Table 6.20 - Comparison of Planning scores for group A, B and C post Goby

The mean values in Table 6.20 for each of the groups are quite similar as illustrated in Figure 6.5 below. A one-way ANOVA was used to test for comprehension ability differences among the three groups. Comprehension strategies did not differ significantly across the three groups ($F(2,48)=0.07$, $p=0.936$). This indicates that the experimental groups did not have any lasting improvements in their planning ability over the control group.

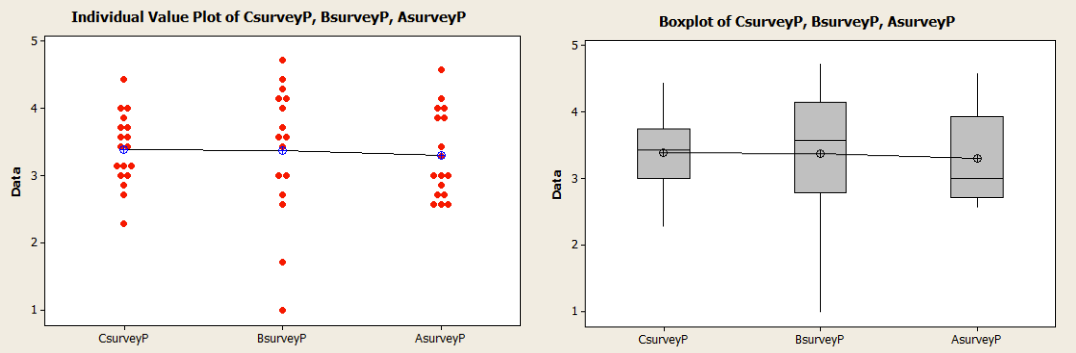


Figure 6.5 – Planning after using Goby

	N	Mean	StDev
Group C	18	3.5889	0.6893
Group B	16	3.6375	0.7991
Group A	16	3.7	0.3098

Table 6.21 - Information Management Strategies for group A, B and C post Goby

As illustrated in Figure 6.6 below, the mean value for Group A was slightly higher that the other two groups, however the line between the means is almost horizontal. A one-way ANOVA was used to test for information management strategies ability differences (outlined in Table 6.21) among the three groups. Information management did not differ significantly across the three groups ($F(2,47)=0.13$, $p=0.879$). Here, the three groups can be said to be on par after interacting with the Goby service. The Goby service did not result in lasting improvements to the information strategies for participants.

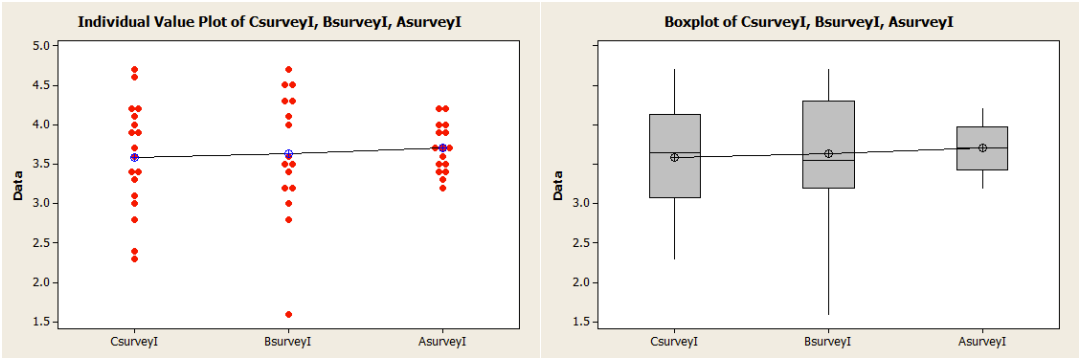


Figure 6.6 - Information Management Strategies after using Goby

	N	Mean	StDev
Group C	18	3.373	0.6949
Group B	15	3.5714	0.766
Group A	16	3.4464	0.4234

Table 6.22 - Comprehension for group A, B and C post Goby

As illustrated in Table 6.22 above, the mean value for Group B was slightly higher that the other two groups. A one-way ANOVA was used to test for comprehension ability differences among the three groups. Comprehension strategies did not differ significantly across the three groups ($F(2,46)=0.43$, $p=0.652$). Although Group B had a higher mean, this was not significantly larger. As can be seen in Figure 6.7 below, Group B has a slightly larger comprehension mean than the other two groups. However, according to the statistics, each of the groups can be considered to be on par.

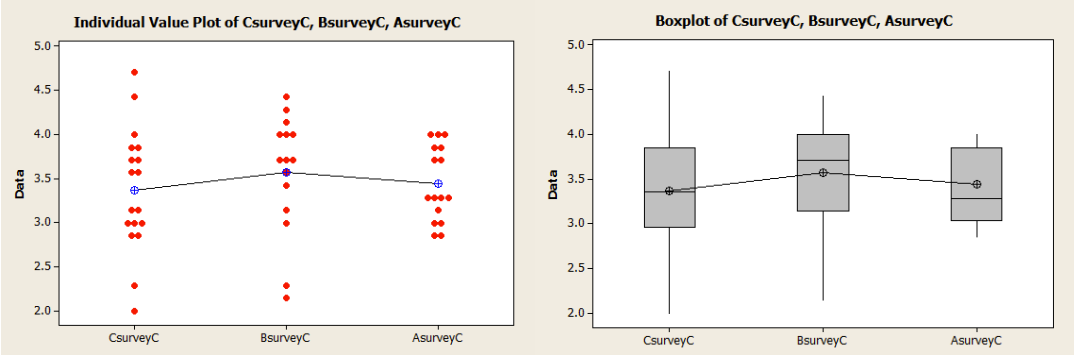


Figure 6.7 - Comprehension Strategies after using Goby

	N	Mean	StDev
Group C	13	3.9692	0.4461
Group B	15	4.04	0.5962
Group A	17	3.8118	0.8845

Table 6.23 - Debugging Strategies for group A, B and C post Goby

Figure 6.8 below indicates that the mean value for Group B is higher than the other two. A one-way ANOVA was used to test for debugging ability differences among the three groups (summary statistics in Table 6.23). Debugging ability did not differ significantly across the three groups ($F(2,42)=0.46$, $p=0.632$). Again, the results for debugging strategies can be considered as on par for each of the three groups.

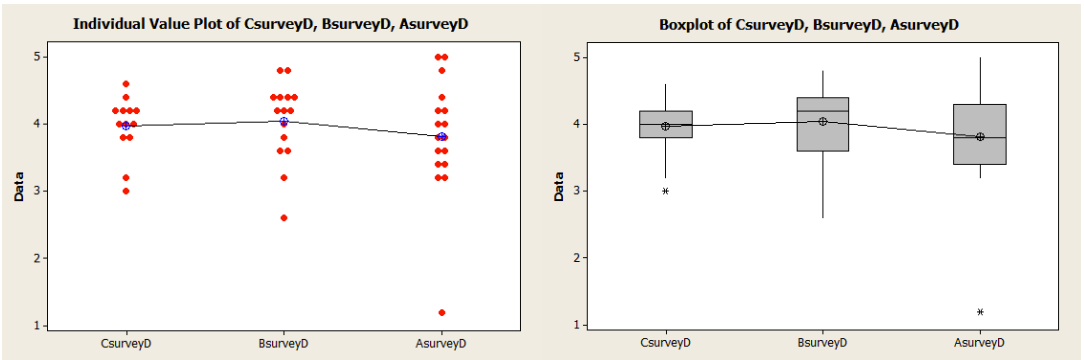


Figure 6.8 - Debugging after using Goby

	N	Mean	StDev
Group C	18	3.537	0.6431
Group B	16	3.5833	0.9047
Group A	17	3.4902	0.4060

Table 6.24 - Evaluation for group A, B and C post Goby

As reported in Table 6.24 the mean value for Group B is slightly higher than the other two. A one-way ANOVA was used to test for evaluation ability differences among the

three groups. Evaluation strategies did not differ significantly across the three groups ($F(2,48)=0.08$, $p=0.925$). This similarity can be seen in Figure 6.9, where each of the three groups responses are clustered around like means.

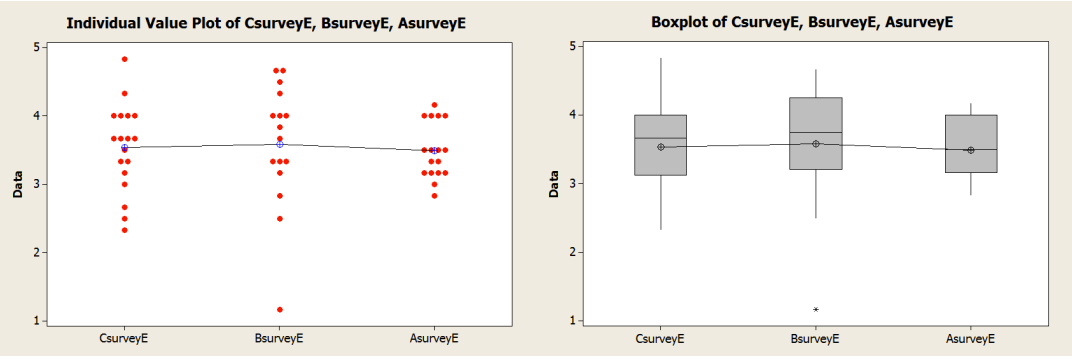


Figure 6.9 - Evaluation Strategies after using Goby

6.3.2.2.4 Conclusion From Analysis

Comparisons between the three groups were not significantly different for any of the metacognitive regulation factors. This indicates that there was no increase in the mean responses to the MAI from learners who participated in the Goby experiment. This implies that the current manifestation of ETTHOS in this way has not resulted in learners encoding the metacognitive strategies for use beyond the current learning environment.

6.3.2.3 Metacognitive Ability when Comparing Prior-Ability

Learners in the low (L) and high (H) prior-domain-ability percentiles[71] were compared to assess whether prior-ability influenced *change in metacognitive ability*[72]. The change in metacognitive ability was calculated for each of the five regulatory strategies (planning, information management, comprehension, debugging, and evaluation). An in depth examination of the analysis carried out is provided in Appendix M. In each case, learners with low and high ability were on par for metacognitive gain. While some of these tests were somewhat underpowered, the overall trends in the data suggested that prior ability did not influence the metacognitive results. During the initial analysis of metacognitive gain when comparing intervention groups above, there was no increase in the mean responses to the MAI from learners who participated in the Goby experiment. In creating learning interventions to support metacognitive strategies for use beyond the current

[71] C.f. Section 6.2.3.3 above for a description on how this breakdown was carried out.
[72] Post metacognitive ability – Pre metacognitive ability. Initial analysis of this change and the influence of the intervention groups were previously discussed in Section 6.3.

learning environment, the consideration of prior ability will still be important as this can effect the amount of cognitive resources required by learners to complete the learning tasks.

6.3.2.4 Conclusion from Analysis

This section has examined metacognitive change from the perspective of metacognitive gain, changes between metacognitive groups, and prior-domain-ability. In each case, the results suggest that there is no increase or decrease in metacognitive awareness for each factor across each of the groups after interacting with Goby. In these experiments, neither intervention nor prior-ability appears to have been correlated with changes in metacognitive ability. This implies that the current manifestation of ETTHOS in this way has not resulted in learners encoding the metacognitive strategies for use beyond the current learning environment. The improvement of metacognition beyond the learning environment to enable these skills to be transferred to other learning contexts is one of the more ambitions goals of metacognitive tutoring systems (Koedinger et al., 09). There are two goals that are prerequisite of this transfer – the first goals that need to be achieved is altering the learner's metacognitive approach in the context of the learning environment. The second goal is an improvement in the educational or learning outcomes as a result of the change in strategy. Although the metacognitive supports can be a useful tool for modelling learner metacognition, this means that the metacognitive model could benefit from being used to trigger richer support tools (e.g. digital sketchpad, goal setting functionality) to support each regulatory factor. Despite the lack of correlation with prior-domain-ability, the addition of these rich tools would still need to consider prior-ability carefully to avoid overloading novice or lower ability learners.

6.3.3 Analysis of Learners' Qualitative Responses to Goby [R1.2, R4.2]

Previously, it was shown that participants in the experimental groups displayed greater educational improvements than their peers in the control group. However, these results must be considered with caution because of the interaction of prior-ability and the small number of participants that were examined when accounting for these prior-ability effects. An analysis of qualitative reports is outlined in this section in order to assess the extent to which learners perceived the metacognitive prompts as suitable and beneficial for the learning context.

6.3.3.1 Overview

The two experimental groups were asked to complete a questionnaire when they completed the course. This questionnaire (available in Appendix L) explores the assumption that dialog can trigger metacognitive activities during learning, by assessing qualitative responses that learners gave after engaging in the learning environment. This section looks at questions that related to three categories:

- Motivation and learning support
- Relevancy of the prompts/questions to learning
- Prompt/question interaction workload

The first, *motivation and learning support* comprises of a number of questions on the perceived help offered, motivation gained, support for organising the learning time, and level of thought or reflection provided (or inhibited in each case) through the metacognitive dialog supports in Goby. The second set of questions is related to *relevancy* - here, the relevancy of the supports was assessed in terms of their relevancy to learning, to computer science, and to wider domains. Participants were also ask about how well the supports matched the learning objects and how this relevancy changed over time due to the user model. Finally, the last set of questions relate to the perceived effects of the metacognitive supports on the *workload*. This set of questions examines how the supports were perceived in terms of: adding to the workload, interrupting the learning, or adding time to the learning experience.

6.3.3.2 Test Setup and Analysis Method

Participants were asked to complete a questionnaire at the end of the Goby experiment, sought to gather feedback on the perceived accuracy and benefits from Goby. All of the participants from Group A (n = 17) and Group B (n = 16) completed the questionnaire (n = 33). They were asked to rate a number of statements on a 5-point scale (1 strongly disagree to 5 strongly agree). The figures in this section represent the number of response on this scale, with each response being assigned a colour. For example, in the key illustrated in Figure 6.10 on the right, a response of '*strongly disagree*' is 1 on the scale and will be highlighted in a green colour.

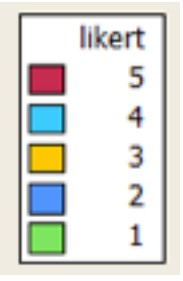


Figure 6.10 - Likert Key

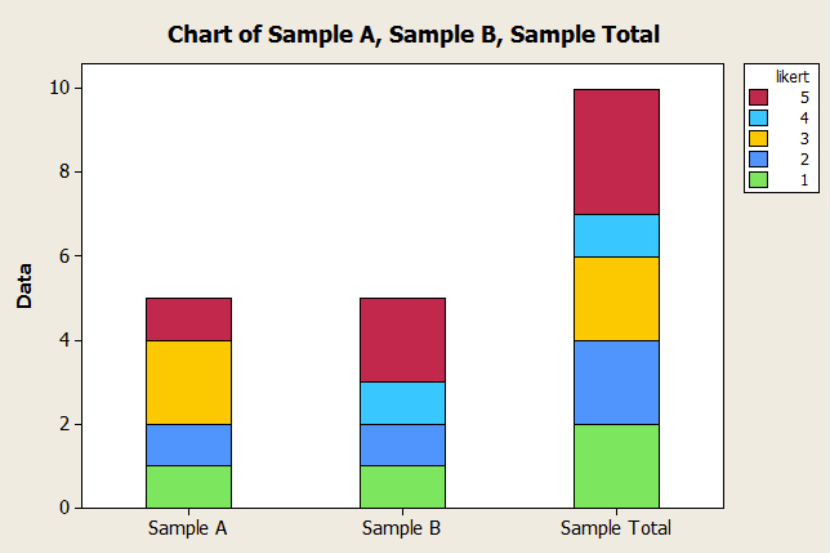


Figure 6.11 - Sample Bar Chart Figure

In the sample bar chart illustrated in Figure 6.11 above, there have been 5 response from the first group (Sample A) and five from the second (Sample B). A total bar (Sample Total) is also presented in order to give an overview of the responses from all participants. This means that it is easy to quickly examine a visual overview of the relative distribution of responses both within groups, and for the overall cohort. Here, in 'Sample A' one participant has responded as '*strongly disagree*' or 1, one participant has responded as '*disagree*' or 2, two have responded '*neither agree nor disagree'* or 3, and one has responded '*strongly agree*' or 5.

Participants were also given the option to leave a comment on each question. This feedback was subject to qualitative analysis for recurring themes. Each participant was given a unique an anonymous key – those in Group A were identified as Px and Group B were identified as Qx, with x being a unique number. Thematic analysis is a foundational method for qualitative data analysis; whereby responses are encoded with an identifying descriptor, in order to capture important results and make meaning within the data set (Braun & Clarke, 06). In this case, responses for each question were encoded into three main categories – positive responses, negative responses, and aside (where a response does not directly relate to the question) to ensure that the analysis was carried out in line with the Likert response. This approach makes it possible to organise the responses into manageable tables. In displaying the responses to each question, an example of both positive and negative categories is reported, where present. This combined with the visual overview of the responses given on the Likert scale provides an accurate overview of the responses

reported. Once the positive/negative/aside categories were created, individual questions were analysed for similarities and differences in the responses, breaking up the text from the participant's response to each question if necessary. For instance, this is exemplified in some questions where participants related their experiences back to time e.g. multiple participants reported that they thought about the dialog initially, but did so less over time. The following section outlines the Likert responses, summary statistics and discussion, and exemplary quotations from participants for each of three question categories. Each of these is analysed by reviewing the questions related to the category and then providing an overall analysis of the category. During this analysis, learner responses are also considered from the perspective of how prior-ability influenced learner impressions or opinions on the Goby learning environment. This has been possible because the responses from learners were also grouped according to prior domain ability percentile[73]. Here, interesting results and quotes are included when comparing low and high ability learners. For in depth analyses see further Appendix M, which includes discussion, descriptive statistics, and data plots that describe the categorisation of learners' responses into low and high prior-ability.

6.3.3.3 Results and Summary Graphs

6.3.3.3.1 Motivation and Learning Support

Participants were asked, "*Were you motivated by the popup content?*" Figure 6.12 below shows the responses from Group A (motPop A; M = 3.118, Mdn = 4, *SD* = 1.219), Group B (motPop B; M = 3.067, Mdn = 3, *SD* = 1.223), and overview of the responses from the two groups (motPop Total). It can be seen here that while some students disagreed, participants mostly agreed that the popup content motivated them while engaged with the learning environment.

[73] Here, quotes from learners who have been categorised into these percentiles (using the same data analysis method as described in Section 6.3.3) and participants are identified using their anonymised ID and a percentile identifier. The letter L (low) and H (high) have been provided to identify whether they fell within the low or high prior-ability percentile. For example (Px, H) indicates that the learner was in Group A and the higher percentile.

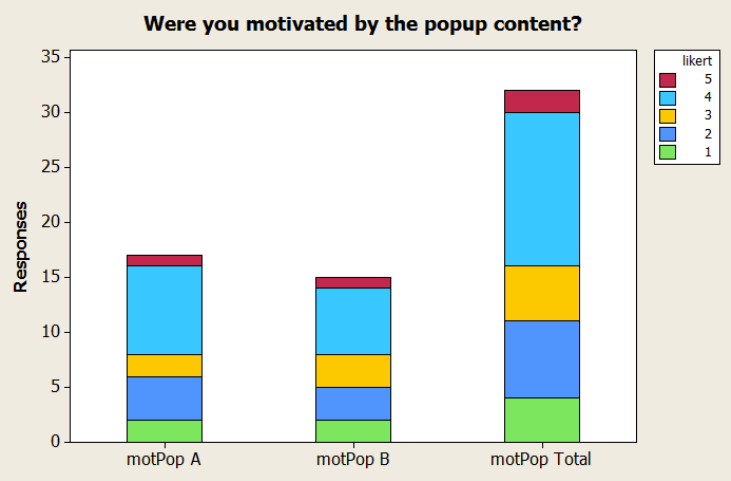


Figure 6.12 - Were you motivated by the popup content?

This was reflected in the responses from participants. Participants in Group A reported that even though the prompts weren't necessarily motivational, they were helpful; "*Got me thinking, but wouldn't describe it as motivational*" – (P13), "*Didn't really make a difference although the yes/no Q's were good to remind you important things*" (P3), and "*Only as far as breaking information down and diagrams*" (P14). However, others responded that it was motivational; "*Yes. It made me look again at what I was reading & offered suggestions to help in certain sections*" (P6), "*It kept me on track and kept me aware of my objectives*" (P7), and *"Yes. They do give the impression of a personal touch*" (P15). There was a mix of responses from Group B. Several participants responded that they were motivated "*most of the time"* (Q9). However, there were "*too many, it distracted a bit from the material as there was one per slide"* (Q14). Q8 replied that there was "*No use as a mature student"* but there could be "*potential uses elsewhere"*

Responses to the question, "*Did the Goby prompts/questions help you while learning?*" are illustrated in Figure 6.13 below. There is mixed agreement with this statement in Group A (M = 3.118, Mdn = 3, *SD* 0.928) and Group B (M = 3.4, Mdn = 4, *SD* = 1.183).

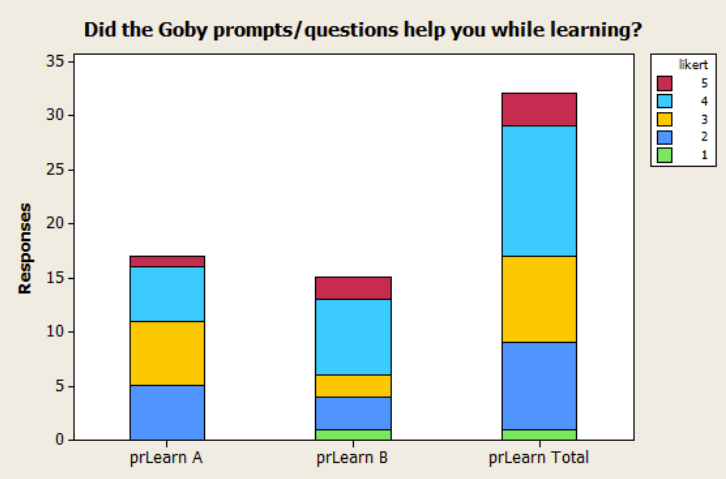


Figure 6.13 - Did the Goby prompts/questions help you while learning?

Participants agreed that "*Yes they provided a good interactive feature which helped me keep on track*" (P7), and "*gave intervals to reconsider and absorb what you were learning*" (P15). There was a comment that the amount of prompts/questions "*was not nessessary (sic)*" (P3), and that they should be "*more relevant and precise*" (P8). Group B responded positively that "*yes*" (Q14) "*the tips were good*" (Q9), with one participant commenting that "*not overtly*" (Q8).

Participants were asked; "*Did you think about the prompts and questions?"* As illustrated in Figure 6.14 below, there was agreement with this statement in Group A (M = 3.647, Mdn = 4, *SD* = 0.606) and Group B (M = 3.667, Mdn = 4, *SD* = 0.724).

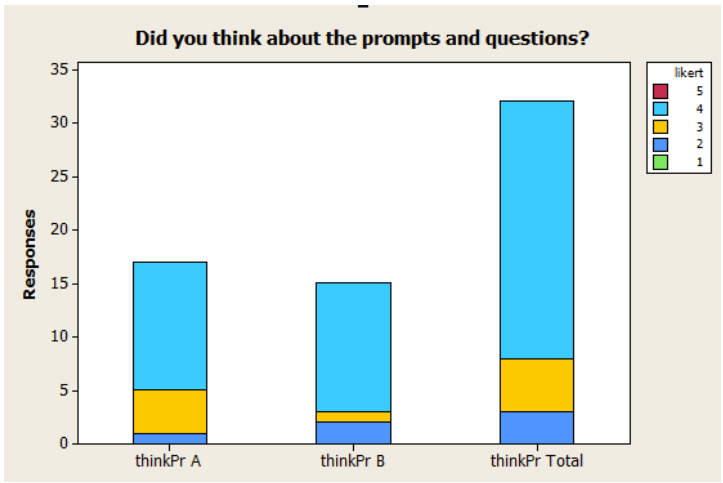


Figure 6.14 - Did you think about the prompts and questions?

The majority of respondents in Group A reported that they did at the start, but that this "*effect varied over time*" (P16), in particular, "*less so, towards the end*" (P4), or if they "*were inappropriate or unnecessary*"(P8) they "*tuned out*"(P8). Some "*stop(ed) and reasssess (sic) … learning after reading the prompts & questions*"(P6) and "*tried to use the methods the prompts suggested at all time*"(P7). Responses from Group B were

comparable; participants thought about "*most of them*", or "*initially I did*" (Q6) "*although towards the latter sections I started paying less attention as I had seen the same ones so many times and started clicking the answers without really considering the prompts fully*" (Q14). Prompts did not require as much attention, however "*questions got my full attention*" (Q11).

One of the strategies in successful moderation of learning is the ability to organise your time. Participants were asked; *"Did you feel as though you used the prompts and questions to help you organise your time?"* Most participants in Group A (M = 2.765, Mdn = 3, *SD* = 0.97) and Group B (M = 2.733, Mdn = 3, *SD* = 1.033) disagreed or were neutral on statement as can be seen in Figure 6.15.

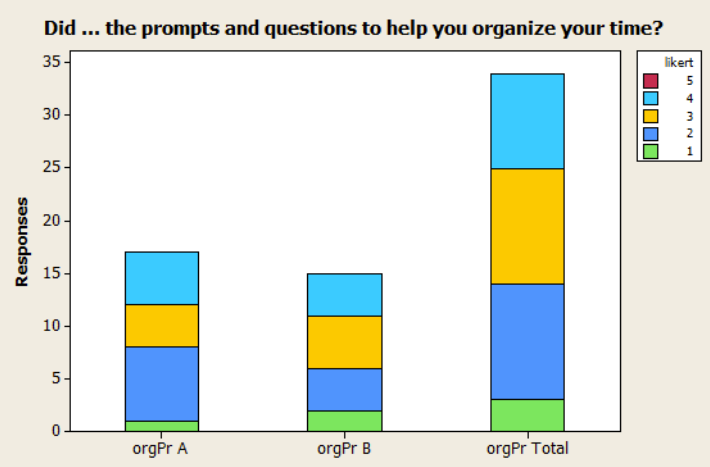


Figure 6.15 - Did the prompts and questions help organise your time?

One participant in Group A responded that "*The prompts & questions did not offer suggestions on how to better organise my time just asked me if I thought about doing so. I had.*" (P6). This is representative of the feedback from this group. While "*Sometimes the prompt did suggest 'taking stock' - this was useful*" (P16), there would have to be further support than just prompts/questions to support the development of this skill. A number of participants in Group B responded negatively, for example "*No I considered some briefly but it did not help to organise me - I can organise myself*" (Q8).

6.3.3.3.2 Comparison and Analysis of Motivation and Learning Support when Considering Prior-Ability

When examining *motivation and learning support*, participants overall reported that the popup content got them thinking about the strategies that they could use while learning. Some participants didn't feel the dialog was beneficial; however most found it a positive addition to the learning environment. The dialog got them thinking about

breaking down the information; kept them on track and aware of their objectives; and helped them to stop and reassess their progress.

The qualitative response from the learners were similar across the low and higher ability learners – the dialog got them thinking about breaking down the information; kept them on track; helped them to stop and reassess their progress. The comments suggested that they got them "*thinking, but wouldn't describe it as motivational*" – (P13, H). Thus, learners may have different needs when it comes to creating motivation metacognitive supports. Lower ability learners' overall perceived the supports as more *beneficial*, suggesting that *"they served as little pauses in the information and refresh the learning process"* - (P6, L). There was a tendency for lower ability learners to *think about the supports*, whereas half of those with greater prior ability were indifferent or did not. This may be as a result of their own awareness of their novice capabilities, which meant that they tried to help themselves while learning by attending to the supports. Also, regardless of the group or ability, the attention to the support can be *time* dependent as many participants started to pay less attention later on. Thus, it is not enough to simply map the content of the dialog to the status of the learner within their task (e.g. evaluation supports towards the end). Any additional supports that are provided alongside this dialog may be faded as control is given over to the learner in order to manage their own learning experience. Overall, regardless of group and prior ability, a range of supports are needed for different learners – in particular, the type and functions of these supports can benefit from changing over time as the learner becomes familiar with the regulatory strategies that the system is trying to support.

6.3.3.3.3 Relevancy of the Prompts/Questions to Learning

Participants were asked on their perception on the relevancy of the prompts and questions. There was a positive response to the first question; "*Were the prompts and questions relevant to learning SQL?"* As illustrated in Figure 6.16 below, the majority of participants in Group A (M = 3.353, Mdn = 4, *SD* = 0.932) and B (M = 3.437, Mdn = 4, *SD* = 1.183) tended to agree with this statement.

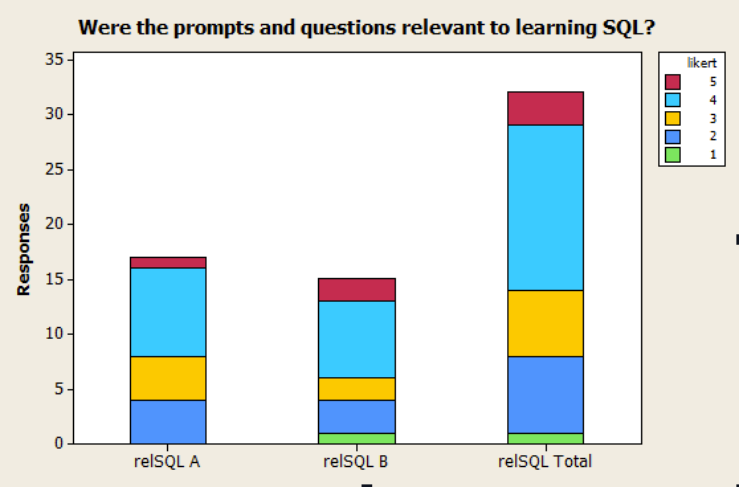


Figure 6.16 - Were the prompts and questions relevant to learning SQL?

The following quotes are representative of the response from Group A – "*Well the same prompts could be used for any learning, not just SQL*" (P15), "*some were to (sic) general and could be used in any learning setup*" (P14). P4 responded that the prompts/questions were "*Usually relevant. Sometimes pointless*"(P4). One participant in Group B believed that "*learning to learn and learning SQL are 2 unrelated topics that did not mix well for me*" (Q8). However, others were positive, for example Q9 "*yes most of them*" and Q10 "*yes, thought (sic) a little abstract.*"

Respondents were asked; "*Were the prompts and questions relevant to learning Computer Science?"* Responses from Group A (M = 3.413, Mdn = 4, *SD* = 1.004) and Group B (M = 3.438, Mdn = 4, *SD* = 1.209), as illustrated in Figure 6.17 below, shows an inclination toward agreement with this statement.

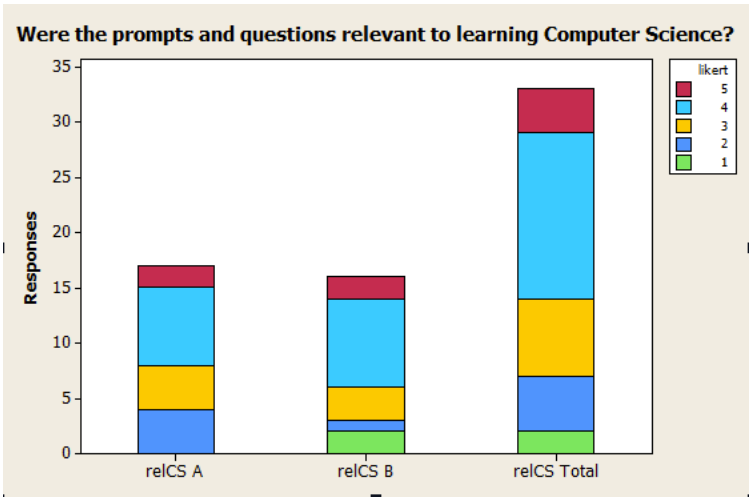


Figure 6.17 - Were the prompts and questions relevant to learning CS?

Only one participant in Group A has a particularly strong negative reaction to this question, stating "*not really no*" (P4). The rest of the responses exhibited a more

positive reaction. For example, "*Drawing diagrams & real life applications were relevant*" (P6), "*they brought home good thinking techniques*" (P16), and "*could be used for any learning, not just SQL*" (P15). We can see a trend appearing, that participants believed that the prompts/questions were broad enough as to be relevant to other CS domains outside SQL. Similar responses were gathered from Group B; "*they were more general learning tips but they were still helpful*" (Q14).

Figure 6.18 below illustrates whether participants believed; *"Were the prompts and questions relevant to the right section?"* Group A (M = 3.412, Mdn = 3, *SD* = 0.618) and B (M = 3.733, Mdn = 4, *SD* = 0.961) were neutral or agreed that prompts/questions were relevant. Group A responded "*yes*" (P2), "*usually, sometimes not*" (P4). "*Most were relevant, very few were not*" (P6). Although they were often relevant, "*sometimes they did not seem relevant*" (P8). This reveals that they were often relevant, but not always. This mix was also illustrated in the "*yes and no*" (Q9) responses from Group B.

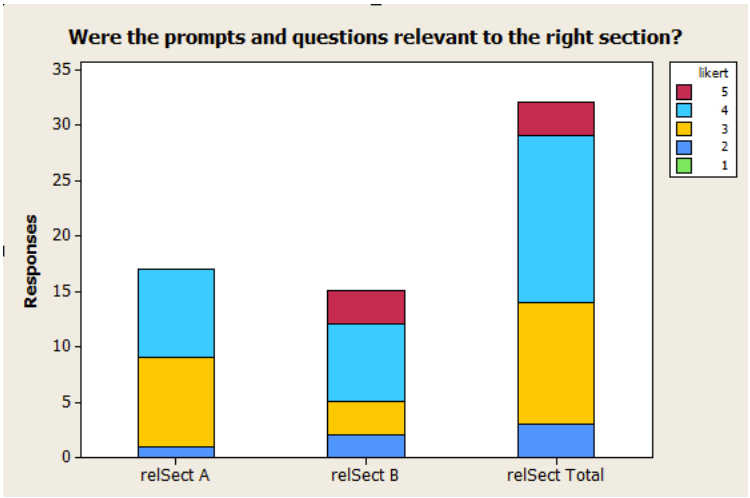


Figure 6.18 - Were the prompts and questions relevant to the right section?

Participants were conversely asked; *"Were there many times where the prompt/question was not relevant?"* Group A (M = 2.765, Mdn = 3, *SD* = 1.091) and B (M = 3, Mdn = 3, *SD* = 1) displayed both agreement and disagreement to this statement, as shown in Figure 6.19.

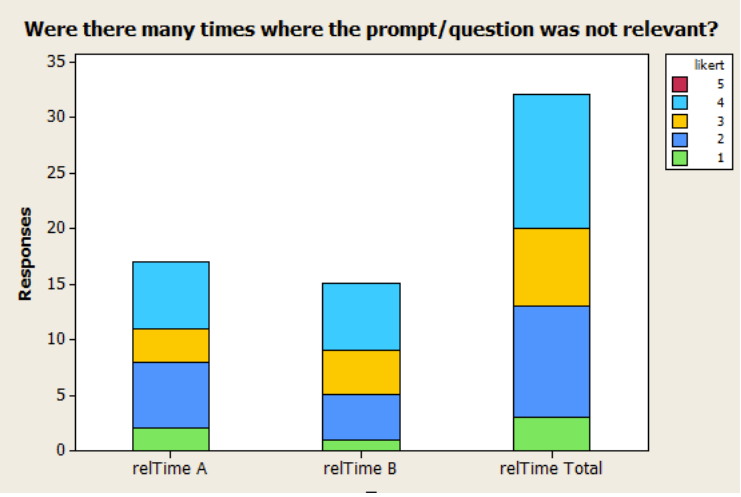


Figure 6.19 - Were there many times where the prompts/questions were not relevant?

This is expected considering the results of the previous question. Prompts and questions were usually relevant, but there were times that they were not. Group A responded in varying levels of agreement - "*never*" (P2), "*a couple of times*" (P4), "*very few*" (P6), or "*once or twice*" (P7). One participant responded, "*some of the prompts were to (sic) general and did not seem relevant*" (P14). Responses from Group B reflected this - responses were not relevant "*sometimes*" (Q11), "*no not many*" (Q9). "*They seemed OK*" (Q8). While some were not relevant, this was not the norm – "*yes, but probably not as much as they were relevant*" (Q14). Comments revealed that the method of using a question with only a Yes/No answer had it's limitations, as there was "*no distinct yes or no answer to the question*." (Q10).

Participants were asked, "*Did you feel as though the Goby interactions were more relevant over time?"* Group A (M = 2.941, Mdn = 3, *SD* = 1.144) and Group B (M = 3, Mdn = 3, *SD* = 1.134) disagreed or responded neutrally to this questions as shown in Figure 6.20.

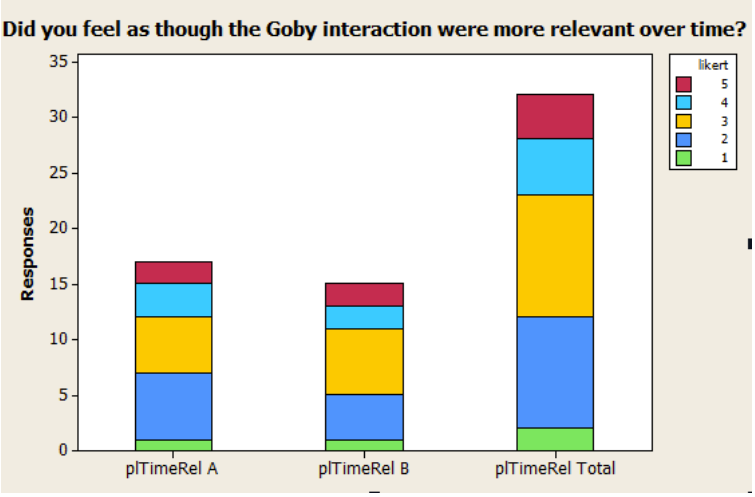


Figure 6.20 - Did you feel as though the Goby interactions were more relevant over time?

Group A, in general "*didn't get that feeling*"(P15), instead believing that "*they seemed relevnt all the way throught (sic)*" (P2), and that "*the relevance was fairly consistent*" (P7). One participant thought they were "*less relevant over time*" (P8) whereas P6 said, "*yes*" they were more relevant over time. Comparatively, Group B though that "*yes, I think this was because I gave more heed to them*" (Q9), "*it did feel less invasive over time, I think if I got used to it it (sic) would be very useful*" (Q11).

This question was opened up to the broader area of Computer Science. As participants were/could have been at the early stages of a Computer Science degree, we are interested in assessing whether they would see any benefit to using Goby outside of the Database course. Participants were asked, "*Would Goby be useful while learning other Computer Science modules?*" Overall, as illustrated in Figure 6.21, participants agreed that the Goby service would be useful for the delivery of other modules.

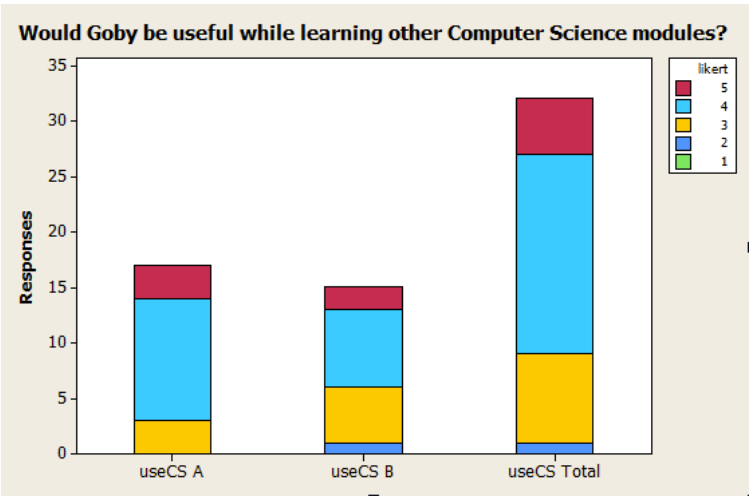


Figure 6.21 - Would Goby be useful while learning other CS modules?

Results from Group A were predominantly positive; for example, "*Please design a software engineering and web development course*" (P1), and "*Provides a good new dimension to learning I hadn't experienced before*" (P7). However, "*it would have to be tailored to the different modules*" (P14). The use of Goby outside of an experimental setting would mean that there could be less prompts/questions as the learner will get to access the system over a longer period of time. This is reflected in the response: "*toned down a bit when there is no advantage to displaying a popup*" (P4). Group B similarly though "*yes*" (Q6), "*it has the potential very much so, but needs refining*" (Q8). "*I imagine, if refined it would be. I really liked that it kept you aware of the extent of your learning, this added an engaging dimension*" (Q14).

What about other domains that Computer Science? Figure 6.22 is interested in whether the participants perceived benefits of Goby in a non-CS domain. The learners were asked, "*Would Goby be useful for other domains?*" Responses for Group A (M = 3.882, Mdn = 4, *SD* = 0.781) and Group B (M = 3.867, *SD* = 0.639) show that participants agreed that it would be a useful service that could be applied in other domains outside of CS.

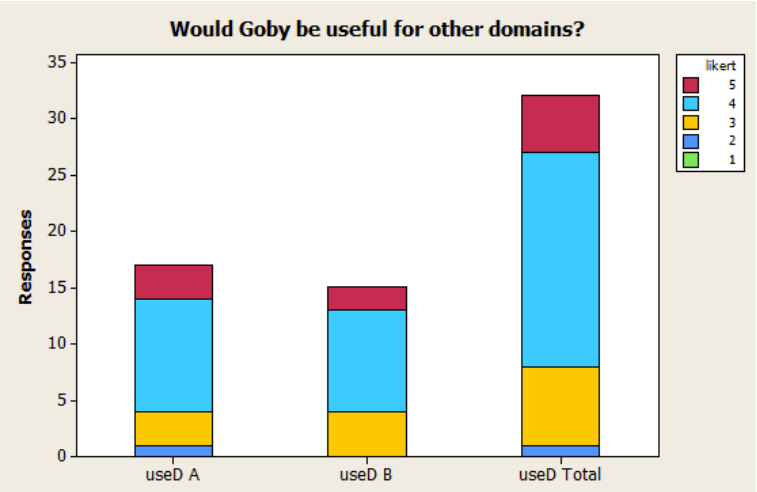


Figure 6.22 - Would Goby be useful for other domains?

Group A though that it "*would be useful in any learning situation*" (P6). "*It could be developed for most subjects*" (P7) "*with some tweaks*" (P8). "*It would be good for revision purposes, or maybe as a reference guide*" (P15). "*Goby should be part of the moodle course offerings*" (P1). One of the respondents in Group B though that Goby was not so useful for SQL as it could be as a general education tool – "*To learn stuff like SQL, no, as an educational tool - yes.*" (Q8). However, most responses in Group B thought Goby would be beneficial, and have "*potential very much so*" (Q9) in other

domains; "*Yes, I think it helped me aware of the approaches I was adopting and encouraged me to engage more with the material*" (Q14).

6.3.3.3.4 Comparison and Analysis of the Relevancy of the Prompts/Questions to Learning when Considering Prior-Ability

When asked about the *relevancy to the prompts/questions to learning,* participants mostly saw the dialog as relevant; however there were times the dialog was too general or abstracted from the learning content. The dialog was mostly relevant to the right section, however sometimes they were not explicit enough for the particular learning object. However, in general this dialog helped learners to be aware of the approaches they were adopting, usually at suitable points in the course, in order to encourage them to engage with the material more successfully. Although the dialog content would benefit from being more precise the underlying message was beneficial. The supports were perceived as highlighting some good techniques that could be used for learning in computer science or other domains.

On examination of the boarder relevancy of Goby for use with other modules both within and outside of the Computer Science domain, there was no difference between the initial analysis (between groups) and the comparison of learners with different prior abilities. Here, many of the participants saw the "*the potential, very much so*" – (Q8, L) and benefit of developing Goby further to work with other learning material, suggesting that it would need to "*be tailored for different modules*" (P14, L) or learning contexts. Overall, regardless of group or percentile, participants saw the benefit of developing and refining Goby further to work with other learning material.

6.3.3.3.5 Prompt/Question Interaction Workload

The prompts/questions were incorporated with the learning material in a non-invasive way, and although learners could ignore them, they were still asked to interact with them. The next set of questions investigates whether participants believed these prompts added to the workflow or broke the learning flow. First, Figure 6.23 illustrates responses to; "*Did you feel that the Goby prompts added to the workload?"* Group A (M = 3.176, Mdn = 4, *SD* = 1.074) and B (M = 3.267, Mdn = 4, *SD* = 0.961) mostly agreed with this statement.

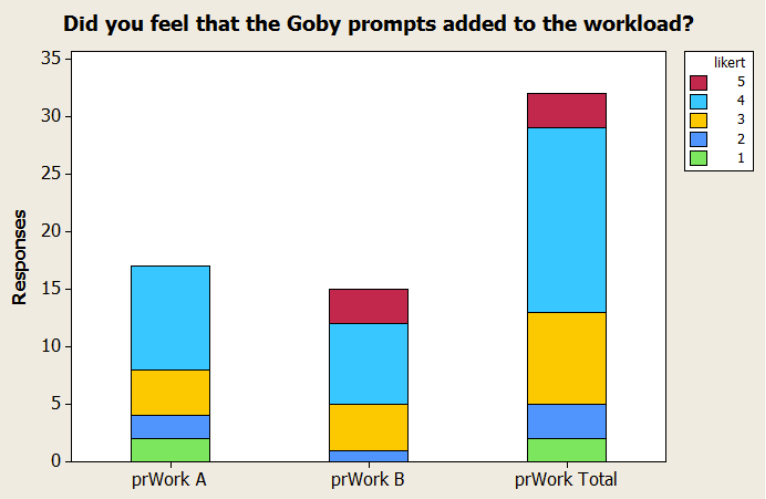


Figure 6.23 - Did you feel that the Goby prompts added to the workload?

Group A thought that it did, "*a little bit, especially if you drew a diagram every time it said to*" (P3). However, the "*pop ups were optional so you could choose to do them or not*" (P2). For the most part, they were seen as a useful addition – "*I agree slightly but in a good way. It slowed you down but it did get you to focus on specific parts*" (P4). Group B believed the prompts "*interrupted flow of thought at times*" (Q10), especially as there "*is a pop-up on every page you are always aware of the process*" (Q11).

Participants were also asked about the effect of questions on the workload: "*Did you feel that the Goby questions added to the workload?*" The results for Group A (M = 3.176, Mdn = 3, *SD* = 0.882) and B (M = 3.267, Mdn = 4, *SD* = 0.961) are illustrated in Figure 6.24 below.

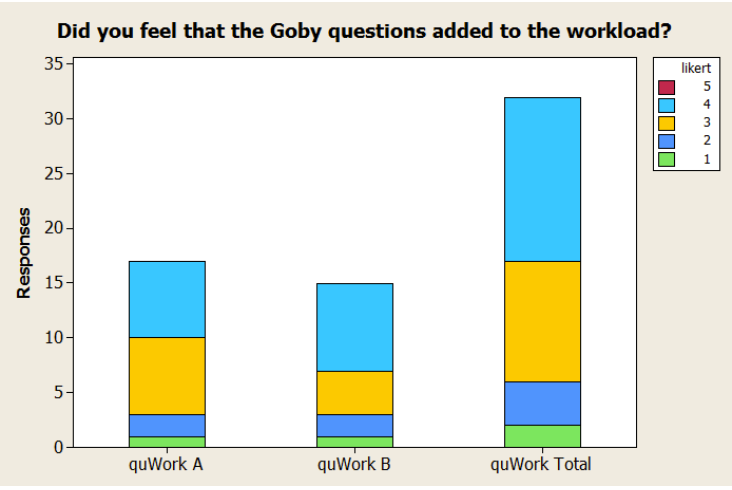


Figure 6.24 - Did you feel that the Goby questions added to the workload?

Group A "*agree(d) slightly. Sometimes it added to the workload without any benefit*" (P4). Although they added to the workload, "*in many cases*" (P13), the "*positives balanced out the negatives*"(P7).

Participants were asked, *"Did you feel that the Goby prompts interrupted the flow of the work?"* There was a mixed response from Group A (M = 3.294, Mdn = 3, *SD* = 1.358) and B (M = 3.571, Mdn = 4, *SD* = 1.352), as illustrated in Figure 6.25.

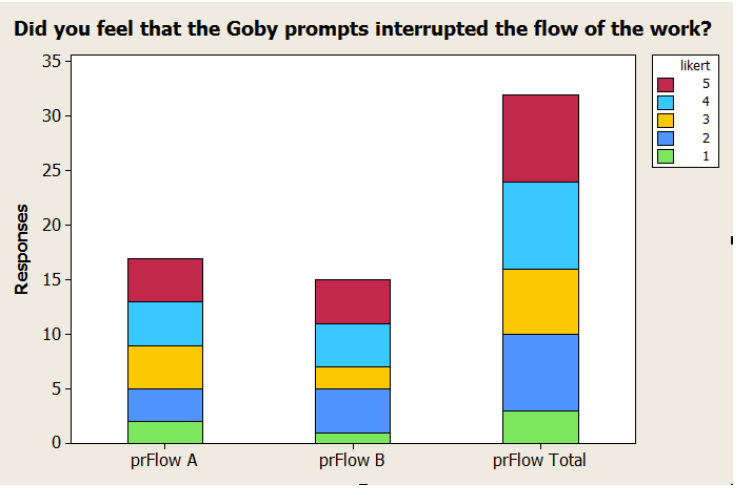


Figure 6.25 - Did you feel that the Goby prompts interrupted the flow of the work?

Group A believed that "*there were too many popups*" (P4), but that they helped "*prompt the user to question what they had just seen*" (P1) and that "*they were part of the learning process*" (P14). The positioning of the popups was debatable, some reported that as they "*were optional so you could choose to do them or not*"(P2) or "*just a glance and confirmation*" (P6). However, others though "*they distracted the eye towards the bottom of the screen*" (P16). Response from Group B indicated that prompts interrupted the flow "*somewhat due to the quantity … but they were also helpful and helped pacing and encouraging contemplation*" (Q14).

Next, they were asked, "*Did you feel that the Goby questions interrupted the flow of the work?"* The responses are illustrated in Figure 6.26 below for Group A (M = 3.353, Mdn = 3, *SD* = 1.169) and B (M = 3.533, Mdn = 4, *SD* = 1.302). Once again, there was a mixed response to this question. Participants in Group A indicated that, "*at first I (they) did as I tried to answer everything as applicable to the section I was reading. After time I took them to serve as reminders and used them as needed (sic)*" (P6). Since the "*pop ups were optional so you could choose to do them or not*" (P2). However, P3 felt they "*could have gotten through each section quicker without so many of them*". Similarly, a participant in Group B felt this repetition was "*not needed (although this may work for other people)*" (Q8). Workflow was increased for Q 6 "*when I (they) don't understand a particular question.*"

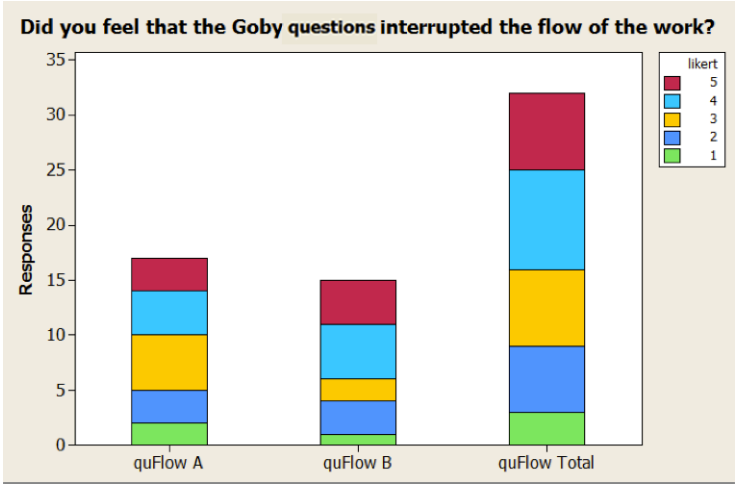


Figure 6.26 - Did you feel that the Goby questions interrupted the flow of the work?

Participants were questioned, *"Did interactions with the Goby popup box add time to the learning task?"* Group A (M = 3.647, Mdn = 4, *SD* = 0.862) and B (M = 4, Mdn = 4, *SD* = 1.183) responses are illustrated in Figure 6.27.

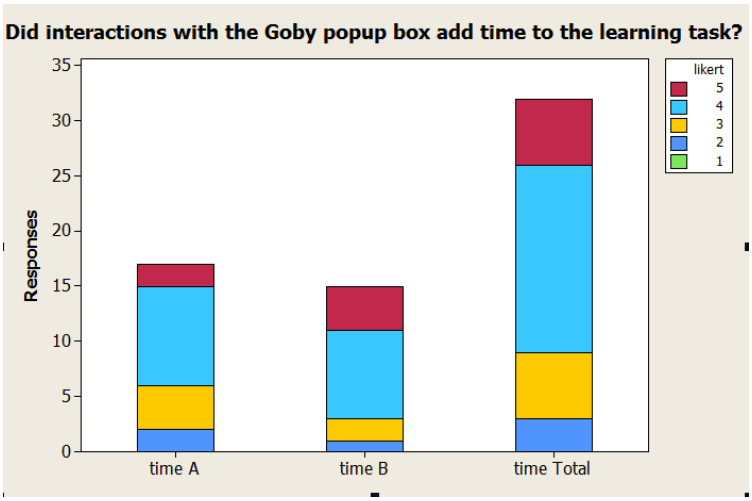


Figure 6.27 - Did interactions with the Goby popup box add time to the learning task?

The majority of respondents agreed that interacting with Goby added time to the learning activity. Respondents in Group A indicated that they did, but that "*it was time well spent*" (P1). Time was added "*only as the popup suggestions made me study the information more and in different ways*" (P7). "*Not a lot of time*" (P11) was added, but it could be a "*distraction*" (P11). Group B though the popup was a "*distraction*" (Q8), "*because it was another task to complete on every page*" (Q11). However, according to Q14, this was "*not to a large extent and it didn't really bother me.*"

6.3.3.3.6 Comparison and Analysis of the Prompt/Question Interaction Workload when Considering Prior-Ability

Responses to questions about the *prompt/question interaction workload* were also similar in the analysis of experimental groups and the learner percentiles. Some learners believed that prompts added to the workload, but were a useful addition, whereas others did not as they though that "*prompts did not interrupt me as there was no deciding process required, just a glance and confirmation*"- (P6, L). Since they were optional, the learner had control over how much they added to the workload. Initially, participants responded to questions, which would have interrupted the flow of the database coursework, however they learned to ignore the dialog over time. The qualitative results point to the fact that the learner still took control of their own metacognitive learning, choosing which strategies to implement or when to ignore Goby. As the dialogs did add an extra element to the learning environment, it is expected that this type of add-on can create interruptions to the flow in the work.

Regardless of the prior ability the timing and type of support offered is of importance. When asked whether the *prompts* or *questions interrupted the flow of work*, higher ability learners tended to see these supports as interrupting the workflow. Overall, there was agreement that time was added, particularly when attending to the questions. However, the supports were generally not seen as negative additions and in some cases were seen as added benefit because they were *"a bit distracting from time to time but the positives balance out the negatives*" – (P7, L). This suggests that there is potential for future uses of these types of metacognitive supports, however their integration may be used in alternative ways to better suit the preferences of the learner.

6.3.3.4 Final Remarks from Participants

Finally, participants were asked to, "*Describe your impressions of the Goby service."* Table 6.25 below shows that participants were very positive about the possibilities of the metacognitive support service. There were trends of agreement that suggested that there were too many popups and that there should be even more assistance to put the suggestions into practice.

Group A	P1 - Very intuitive and easy to get used to. P2 - it seems to be a good learning tool if it is applied to the right modules and subjects … P3 - … asked too many pop-up questions. P4 - Lots of potential. Slightly annoying and should be curtailed and made slightly more relevant. P5 - clear and to the point! P6 - A helpful and easy to use tool to assist with learning. Some people my find it second nature to either draw diagrams, associate information to real life situations, re-read important sections or take the general meaning from complicated/detailed section. But most of us will lack one or more of these techniques and as we take in more information these good learning practices may slip. I found Goby to be an ever-present tutor helping me to help myself through the learning process. P7 - It was a helpful and innovative service, which I found useful, as you're never truly taught how to learn. It was especially good as you were being taught how to learn, as you learned. This meant I could put it into practice immediately. P8 - It's a good idea but it needs to be slightly better written and allow the user to put knowledge into practice. P9 - Could be useful for students who were new to a subject. … P11 - Overall it was very good but the popups were a distraction P12 - Very useful tool for students to have and access over time. P13 - A bit basic. A lot of overkill. Fairly static. P14 - … The prompts and questions … could have been more detailed to each particular topic. P15 - An interesting experiment in online learning. It is interactive, but in a sort of impersonal way. More work and development needed to make it more user friendly as a learning vehicle P16 - User friendly
Group B	Q1 - I'm not a big fan of the pop up boxes Q2 - Very helpful Q3 - It's a good service. I think the pop up boxes were distracting at times. Q6 - it was a good learning test and experience that i have learned some new things from it. Q8 - Looks professional, potential to be a very good educational on line model but just needs a little more tweaking …The audience is there you just need to get it! Q10 - Very interesting idea, nice design.

Table 6.25 - Participants impressions of the Goby service

These issues represent a number of limitations with the Goby study. Since participants would only be using the service for a number of hours rather than for an entire semester, it was necessary to deliver a popup at almost every step in the learning environment. This shows that they learned to ignore the prompts and focus on the content, occasionally returning to respond to a prompt or question. However, the potential benefits are clear – Goby can act as an ever-present tutor who will suggest new techniques or remind them to use techniques that they already knew but

were simply not activating. In the future, when Goby is released as a real learning tool, it would be possible to reduce the frequency of the prompts and add supporting materials such as multimedia, sample tasks, or video.

6.3.3.5 Conclusion from Analysis

There were three categories of question under investigation in this qualitative analysis. The first was *motivation and learning support.* The qualitative response from the learners were similar across the low and higher ability and between groups – the dialog got them thinking about breaking down the information; kept them on track; helped them to stop and reassess their progress; however these effects varied over time as many initially paid attention but did so less over time. While many participants reported that the dialog supports got them thinking, there were some who did not find the supports as beneficial. Learners who had lower prior abilities tended to think more about the dialog supports and saw them as more beneficial to the learning than their high ability counterparts. However, regardless of group and prior ability, a range of supports are needed for different learners – in particular, varying levels of scaffolds to better motivate and support the learner when engaged in the learning environment. The type and functions of these supports could benefit from changing over time as the learner becomes familiar with the regulatory strategies that the system is trying to support.

The second category of question was *relevancy of prompts/questions to learning.* . The dialog was typically relevant to the right section, however sometimes they were not linked sufficiently to the learning content. These metacognitive supports were seen as a helpful tool to help learners to be aware of the approaches they were adopting, usually at suitable points in the course, in order to encourage them to engage with the material more successfully. Although the metacognitive supports would benefit from being more precise they were perceived as highlighting some good techniques that could be used for learning in computer science or other domains. Overall, regardless of group or percentile, participants saw the benefit of developing and refining Goby further to work with other learning material and different subject domains.

Finally, participants were also asked about the effect of the *prompt/question interaction on their workload.* Responses were mixed, as some learners believed that

prompts added to the workload, but were a useful addition. Conversely, others did not think that they added because they could address the prompts/questions very quickly. Since they were optional, the learner had control over how much they added to the workload. Regardless of prior ability and group, the timing and type of support offered is of important. Initially, participants responded to questions, which would have interrupted the flow of their coursework, however they learned to ignore the dialog over time. Interestingly, higher ability learners tended to see these supports as interrupting the workflow more so than lower ability learners. This may be because they were confident in the area, and did not want to have to complete the extra work involved in attending to metacognitive supports. This suggests that there is potential for future uses of these types of metacognitive supports, however their integration may be used in alternative ways to better suit the preferences of the learner. Although the dialog could be ignored, a more comprehensive interface whereby the learner can control whether or not they appear, or indeed what type of support is offered (such as extra learning tools that can better support metacognitive training) could result in better learner satisfaction.

Finally, the learner's overall impression of Goby was that it served as a helpful assistant or ever-present tutor that assisted with learning to learn. They were able to put the suggestions into practice immediately, however some participants felt that they would like richer support for improving their metacognitive abilities.

6.3.4 Log Data Analysis to Examine Learner Behaviour and the Influence of Prior Ability

This section provides a discussion and overview of the interesting results found through further analysis of the Goby log data to analyse learner behaviour. In-depth log data analysis reports are provided in Appendix M, which provides effects, interaction, and value plots with discussions of the statistical tests and power analyses carried out. In each of the analyses, the learners were categorised into percentiles using the pre-test SQL quiz. Also, overall analysis of the *intervention* was possible by comparing results from the experimental groups are combined in order to compare those who received metacognitive intervention (denoted by M) with the control group (denoted by C). A number of analyses have been possible on learner behaviour, including examination of:

1. Time taken - Examined with *overall learning time* and *time on page* as well as considering the *number of pages visited*.
2. Learning efficiency.
3. Responses to metacognitive dialog - Including *response rate*, or number of metacognitive dialogs responded to in comparison to the amount of dialogs sent and the *response time* taken in responding to the dialogs.

6.3.4.1 Time Taken

Time taken was examined through analyses of the overall learning time, number of pages visited, and amount of time taken on page. These data were analysed by a general linear model, using as indicators learner percentile (for prior-domain ability), intervention and the interaction between percentile and intervention. The *overall learning time* (in seconds s, mean 5734s[74]) model was a poor fit (R-Sq adj = 25.27%), but the relationship with intervention was significant ($F(1,21) = 7.04$, $p = 0.015$) indicating that the addition of the metacognitive dialog increased the learning time. Although percentile and interaction were not significant, lower ability learners tended to have higher learning time scores than high ability learners (M diff = 1980s (95% CI (-5145s, 1185s)). Although the intervention test was significant and others were not, these results must be considered with caution, as it was not sufficiently powered to assess short time differences between groups and such a range of responses within the groups (SD 3712s). Also, while no difference was revealed in this data between the high and low ability learners, this does not mean that the dialog did not slow the higher ability cohort. The addition of dialogs may have slowed this group and the interaction may not have been revealed because of lack of power in the tests carried out. Nonetheless, it is reasonable to consider that these data indicate that the addition of the metacognitive dialogs created extra workload for the learners. This is not necessarily a negative finding, because it implies that the learners in the metacognitive group interacted with the dialog supports. However, because of the range of responses reported in both intervention and percentile, there are most likely a range of other variables which also influence learning time, such as motivation, interest, or their individual reading strategies (e.g. ability to skim the dialog/learning content). One consideration is that the learners in the metacognitive intervention visited more pages that the control.

[74] 5734s is just over 1.5 hours

In analysis of the *number of pages visited*, there was no difference between the intervention groups, learner percentile or the interaction between intervention and percentile[75]. Given that this was a short course (three sessions with an extra fourth optional session, compared to a traditional semester long module which may have between 11 and 13 sessions), the tests were somewhat underpowered[76] to assess small differences between alternative groups. Several of the learners (n = 13) accessed over the total number of pages suggesting that they reviewed previous work already complete before completing the final quiz. There was also a large variance in the total number of pages visited (SD 91). These results indicate that regardless of prior ability or intervention, learners accessed a range of pages. Once again, there are most likely confounding variables that also influence the number of pages visited (such as the learners study style, interest, or motivation before completing the final SQL quiz). Considering that the intervention resulted in greater overall learning time and that this group did not appear to visit a greater number of pages, the amount of time spent on page was examined.

On analysis of the *amount of time on page* (in seconds s) the general linear model was not a good overall fit (R-Sq adj = 28.04%) suggesting that there were confounding influences, however the intervention was significant ($F(1,22) = 5.19$, $p = 0.033$). On examination of learners' percentile, a range of time was spent per page, regardless of prior ability. While there were a sufficient number of results to assay a difference of 20s, learners' prior ability does not appear to be correlated with time on page. As with overall learning time, this may be as a result of other factors, such as motivation, interest, reading strategies such as the ability to skim, etc. There was a range of responses within the control group (C) clustered at the lower end of the time scale, whereas the intervention group (M) had a larger range of responses, with an overall significantly higher mean time on page (t=--2.3, p=0.03 M diff = -8.38 (95% CI (-15.88, -0.87)). Interestingly, some of the learners in the metacognitive support group took similar time as their control group peers. This may be because they learned to quickly

[75] The overall mean number of pages visited was 254.8. There were 258 pages in the total course. In the three sections (for their three days of study) that the learners were requested to complete, there was a total of 133 pages. The fourth section was optional, and contained 125 pages.
[76] By one or two learners when individual t-tests for intervention and percentile were carried out.

attend to or ignore the metacognitive dialog (as was reported in qualitative feedback).

6.3.4.2 Learning Efficiency

Analysis of *learning efficiency* was carried out to compare the learning results (*post-test score*) to the amount of time taken on task. Here, learner percentile influenced the learning efficiency score ($F(2,23) = 4.2$, $p = 0.028$), whereas intervention and the interaction between did not. However, these metrics only explain a small amount of the variation in the data (R-Sq adj = 19.62%), meaning that there are most likely other influential factors that affect the learning efficiency. On examination of the percentile plots, low ability learners cluster towards the lower end of the learning efficiency scale with high ability learners clustered at both the low and high end of the scale (t=2.60, p=0.019 M diff = 0.633 (95% CI (0.116, 1.150)). The large deviations in learning efficiency reported by the higher ability group also indicate that prior ability may not be the only factor that affects learning efficiency. In the case of experimental intervention, the test was somewhat underpowered and the estimated difference between the two groups was small. On examination of the intervention data, it appears that both groups are more evenly distributed with the control group having a slightly better (but not significant) learning efficiency overall. Despite the addition of the metacognitive dialog supports, learners were not overburdened to the extent that they reported a large decrease in learning efficiency. Although this analysis would benefit from a larger sample size in order to further examine the interaction of learner ability, interventions, and their interaction the addition of the metacognitive dialog supports did not overburdened learners to the extent that they reported a large decrease in learning efficiency.

6.3.4.3 Responses to Metacognitive Dialog

Response rate and response time were assessed to examine whether there was a difference in the response behaviour evident when comparing the learners' prior ability, metacognitive group[77] (A vs. B), or the interaction between percentile and metacognitive group. *Response rate* was examined to assess the ratio of the responses

[77] Here, no comparison of the control group was possible because the control did not receive any metacognitive dialog supports. Instead, in this case, we examine the metacognitive groups.

to the number metacognitive dialog supports sent[78]. Overall, the mean response rate was 59.5%. On examination of the data, the model did not reflect the variation in the data and no significant results were found. There was a large amount of variation seen within these groups (SD 25), suggesting that the response rate was not dependent on prior ability (M diff = -4.9 (95% CI (-33.4, 23.7)) or metacognitive group (M diff = -5.69 (95% CI (-23.04, 11.66)). Despite the greater amount of questions delivered to Group B, the two groups appeared to be on par. *Response time* was analysed by comparing the amount of time (mean 16.18s) taken by learners to respond to a metacognitive dialogs. There was a large range of variability in response time (SD 6.5s), however no significant differences were found in any of the tests. Regardless of prior ability or group, learners reported a range of average response times to the metacognitive dialog indicating that other factors may be at play when considering response time. As these analyses were carried out on a small number of participants, further analysis would be required with a sufficiently powered test to investigate this area further. In particular, examination of other factors that may influence response rate and response time (e.g. interest, motivation, level of engagement, metacognitive ability, future tools that may be used to prompt specific metacognitive supports) would be useful in future use of dialog supports to help learners attend to the suggestions as needed.

6.3.4.4 Conclusion from Analysis

Interaction with metacognitive supports resulted in the learners in the Goby experiment spending more time on page and more time on the overall learning experience. The increase in time is not necessarily a negative finding, because it indicates that the learners in the metacognitive group interacted with the dialog supports. This analysis of the log data (time on page, learning time) is similarly reflected in the qualitative feedback from learners, where learners reported that responding to the questions in particular added to the workload. Interestingly, there was a range of learning time and time on page for all learners. This may be because some learned to quickly attend to or ignore the metacognitive dialog, as was indicated in the qualitative feedback. The range of responses reported in both intervention and percentile, suggests that there are most likely a range of other variables which also influence learning time, such as motivation, interest, their individual reading

[78] This metric was calculated by dividing the number of responses by the number of metacognitive dialogs sent.

strategies (e.g. ability to skim the dialog/learning content), or even their prior ability (as the tests on learning time were not sufficiently powered to assess short time differences between groups). Although higher ability learners tended to report that the dialog interrupted the flow of the work, this was not reflected in these time measurements. As suggested by the qualitative feedback, the timing and type of support offered is of importance and should be considered further. However the inclusion of supports that are richer that simple dialog prompts would no doubt result in an increase in even greater time spent. It would be important to ensure that the curriculum is given priority and that metacognitive supports do not overtax learners' cognitive resources.

Regardless of prior ability or intervention, learners accessed a range of pages, with a large variance in total number of pages visited but no significant differences found between these groups. These variables did not explain this data well, meaning that there are most likely other influential factors at work. Considering that the mean number of pages visited was 254.8 (SD 91) and that there were 258 pages in total, this suggests that many learners were motivated to engage with a large proportion of the course. This tends to suggest that the extra workload created by the addition of the metacognitive dialog did not have negative effects in terms of the number of pages visited. These additions did not result in learners stopping their learning experience early due to the additional time and cognitive resources required of them.

Learner percentile influenced the learning efficiency score, however, the model suggested that other variables are also at play. Previously, it was shown that learners with lower ability had greater learning gains. Here learning efficiency was calculated using the post-test score rather than the gain score. Although higher ability learners were more efficient, there were large deviations in learning time reported in the higher ability group. Despite the addition of the metacognitive dialog supports, learners in the experimental interventions were not overburdened to the extent that they reported a large decrease in learning efficiency. Thus, further analysis with greater power and examination of other confounding or influential variables and their interaction would be needed to examine metacognitive dialog and learning efficiency.

There were no differences between learners for response rate or time to respond to the metacognitive dialog supports. However, this test suffered from being underpowered and further analysis would be needed to explore these metrics. In qualitative feedback, learners indicated that they did think about the dialog, however many learners also suggested that the extent to which they attended to them varied over time. It was repeatedly reported that although they responded to questions, they learned to quickly attend to them and even began to ignore the prompts. Response rate and response time are also most likely dependent on a number of other factors, such as motivation, interest, level of engagement with the main learning material, and perceptions about the usefulness of the dialog. Overall, in examining learner behaviour, the data suggested that prior-ability influenced learning efficiency and that intervention influenced the time taken by learners. There are also most likely a number of other factors that influenced learner behaviour.

6.4 Approach Taken to Implement ETTHOS

The second set of analyses was carried out to assess the extent to which the approach taken to implement ETTHOS in Goby was successful. This addresses the second aim of this research: *What approach can be taken to integrating this model with a TEL system?* The ETTHOS model provides a technological approach to model, trace, and subsequently foster metacognitive competencies – one of the core facets of the successful lifelong learner. The development of successful lifelong learning with the aid of TEL presents two significant challenges – how to support the learning skills and how to develop an ever-present aid that will travel and grow with the learner without requiring too much time or too many cognitive resources. This section evaluates how ETTHOS has addressed the challenge of how to develop a cognitive modelling service that can travel and grow with the learner without requiring a large amount of the learner's resources.

There are two analyses described here. The first relates to the cold-start issue - whereby systems need to gather sufficient data to initialise the user model. Current approaches have influenced and informed the implementation of ETTHOS. The second analysis takes the form of a critical analysis of Goby in comparison to the architectural requirements and the features from which they stem.

6.4.1 Comparison of the Baseline Model to Goby Participants [R6]

6.4.1.1 Overview

The study of Goby incorporated a new approach to initialise the user model – a baseline model of metacognitive values was used to create their learner profile. In AEH systems, it is common that systems require learners to complete surveys to initialise the user model, however this can take time and frequent surveys can result in survey fatigue. The baseline model approach was carried out to investigate whether it would be possible to initialise the user model in a new non-invasive manner and overcome the cold-start problem. The user model for Group B (the stereotype group) was initialised using the population standard rather than the individual survey results from each user. Using the pilot study, a stereotypical metacognitive model was generated. This was based on the assumption that a survey of the target population of 100+ participants would provide an accurate representation of learners – this assumption was ratified by a comparative analysis of factors in the baseline model with a model that would have been generated from participants who signed up to the Goby experiment. In Goby, the user model metrics are given a lower confidence rating for group B. Consequently, the Goby service engages in more questions with these participants until the confidence increases. This baseline model is then updated over time through interactions with the learner to form a more precise representation of the learner. This means that in the future, learners would not need to fill out surveys, and this would contribute to solving the problem of survey fatigue. In the Goby experiment, over 150 participants signed up initially and completed the same MAI inventory. This study investigates whether the baseline model generated in the earlier pilot study would be equivalent to a baseline model of the learners who signed up to Goby.

6.4.1.2 Test Setup

Metacognitive awareness was initially sampled from 101 participants (male 67, female 34, age 18 to 50) using the MAI. The mean was calculated for each item on the MAI to create the metacognitive user model. During the Goby experiment, metacognition was assayed from 154 participants (male 112, female 43, age 18 to 64, mean age 32). The premise to be tested here whether the baseline model generated from the pilot study would match a baseline model generated from participants who

signed up to the Goby online course. Thus the null hypothesis is that there is no difference in long run means between the two groups.

Ho: μ1 (Baseline MAI model) = μ2 (Goby participants model) = μ
H_1: μ1 ≠ μ2 ≠ μ

A *t*-test for independent samples was carried out to assess whether measures departed from the null hypothesis. The probability chosen to define an exceptional outcome was significance level α=0.05.

6.4.1.3 Test Results and Summary Statistics

	Mean	StDev	SE Mean
Baseline	3.164	0.321	0.12
Goby	3.258	0.221	0.084

Table 6.26 – Initialising the User Model - Planning

For planning in Table 6.26, the test statistic was t=-0.64, *p*=0.539 (95% CI (-0.422,0.234)). This means there was no real difference between the two planning models so the two can be considered equal.

	Mean	StDev	SE Mean
Baseline	3.735	0.405	0.13
Goby	3.457	0.268	0.085

Table 6.27 - Initialising the User Model - Information Management Strategies

For information management strategies as shown in Table 6.27, the test statistic was t=1.81, *p*=0.091 (95% CI (–0.049,0.604)). There was no significant difference between the two models meaning the two can be considered on par.

	Mean	StDev	SE Mean
Baseline	3.392	0.228	0.086
Goby	3.190	0.117	0.044

Table 6.28 - Initialising the User Model - Comprehension

For comprehension, as in Table 6.28, the test statistic was t=2.08, *p*=0.071 (95% CI (–0.0215,0.4247)). Again, there is no difference between the two models so the pilot study model and Goby participants' model would be considered on par for comprehension.

	Mean	StDev	SE Mean
Baseline	3.986	0.373	0.17
Goby	3.765	0.272	0.12

Table 6.29 - Initialising the User Model - Debugging

For debugging, as shown in Table 6.29, the test statistic was t=1.07, *p*=0.319 (95% CI (–0.267,0.709)) which indicates no significant difference. The pilot study model can be considered as equal to the model that would be generated from the participants who signed up to Goby.

	Mean	StDev	SE Mean
Baseline	3.289	0.343	0.14
Goby	3.288	0.140	0.057

Table 6.30 - Initialising the User Model - Evaluation

For evaluation, as is Table 6.30, the test statistic was t=0.01, *p*=0.995 (95% CI (–0.369,0.371)) meaning there was no difference between the mean evaluation model. Again, the pilot study model and the Goby model would be considered on par.

6.4.1.4 Conclusion From Analysis

The null hypothesis can be accepted for each of the evaluations above. This means that it can be concluded that there is no evidence to suggest that the baseline model generated in the pilot study would differ significantly from a model generated out of the responses from participants who signed up to Goby. This baseline model is specific to the target population – subjects who would satisfy the criteria to be submitted to an introductory computing course. Accordingly, the stereotype metacognitive user model implemented in Goby was sufficient for use by the decision engine. This alone is not enough to suggest whether this approach can be used to inform how the learning system should interact with the learner. However, when analysed in the context of previous evaluation on knowledge gain and qualitative responses this approach is very promising. In the experimental setting, all participants were required to complete a pre-test to inform the analysis. In light of these results, future personalised learning environments or the Goby metacognitive service could use a baseline model to overcome the cold-start problem.

6.4.2 Approach Taken to Implement ETTHOS - Requirements and Features [R4.1 R4.3]

A number of requirements describe the approach with which ETTHOS was to be implemented and are examined here to assess the extent to which they were successfully implemented in the Goby environment. These relate to the use of the service-oriented architectural pattern to allow metacognitive support be delivered as a service [R4.1] and the creation of an interface to ensure that the learning environment and metacognitive support can be delivered as a cohesive system [R4.3]. This section discusses these requirements and the extent to which they have been applied to sufficiently implement Goby. The first is that TEL environments emulate the role of the tutor by providing dynamic assessment of capabilities, and the support of a range of knowledge (declarative, procedural and metacognitive) for a range of learners and their individual differences [F7]. Another important feature is that learning is that it should be situated within a particular learning context [F10]. In separating the modelling and support from the learning environment, this means delivering metacognitive support and learning support as separate services, but providing the two as a cohesive learning experience.

6.4.2.1 Service-Oriented Architectural Pattern [R4.1]

TEL services have allowed for the delivery of distributed learning components over they web. Discrete components such as personalised content, tutoring services, and quizzes can be managed independently, to allow for reuse and interoperation with each other. The multi-model approach has resulted in better decomposition of adaptation by making logical separation of the various models with which the learner is represented. The centralised user modelling approach (e.g. Sosnovsky et al., 09; Kay, Kummerfeld & Lauder, 06) has implications for the lifelong learner because it means that the model can travel and grow with the learner. The benefit is that several adaptive educational systems can draw from and report to the server. However, it is still necessary for each of the services to perform their own reasoning about the user model before reporting to the server and there is no explicit model to define cognitive competencies that are complementary to learning. The logical integration of services requires agreed mechanisms of communication. In current systems, the implicit and explicit rules that are used to inform the user modelling process are usually tightly tied into the system, which limits their reuse. The Goby service has been similarly

distributed using the SOA architectural pattern. However, the task model in ETTHOS is used by Goby to infer the current state of the learner. This means that Goby is able to work in symbiosis (through loose coupling) with the APeLS learning environment to deliver a mashup learning application that combines a database course with suggestions on useful metacognitive strategies.

6.4.2.2 Cohesion between Metacognitive Support and Learning Context [R4.1]

Regulation of cognition comprises of general abilities that are useful across multiple learning tasks. However, in order to contextualise supports, harnessing of metadata standards in describing LOs (the current learning object or web page) can be used to create simple dynamic prompts. In tutoring systems, skills are often represented as their component parts or tasks that need to be completed (Heffernan & Koedinger, 02; Koedinger et al., 97). There is a similar decomposition of learning objects in AEH services – the content is broken into a set of nodes or webpages. AEH can also incorporate interactive tasks or problems for the learner to complete. In ETTHOS, the cognitive traits are represented using psychometric inventories. This means that the regulatory metacognitive skills that are supported in Goby have been broken into a set of five factors: planning, information management strategies, comprehension, debugging, and evaluation. Each factor is represented with a number of items – it is these items from which suggestions for the learner are generated. The prompts and questions generated are then contextualised using the LO metadata, which describe the current page the learners is on. In the qualitative analysis the supports were largely perceived as relevant to the correct sections. Also, the initial user-centric design (described in Chapter 5) approach taken included a pilot study to ensure that the mashup combined the two services (metacognitive and learning) as a cohesive application.

6.5 ETTHOS Design

The final set of analyses compares ETTHOS to the design requirements that are assessed through implementation and the measures of accuracy for the current Goby implementation at modelling metacognition. This address the third aim of the thesis Can ETTHOS be considered as an *appropriate design* for a cognitive model? The aim behind the development of ETTHOS was to provide a mechanism to model, track, and

subsequently foster metacognitive abilities. This means that future developers or course authors can use ETTHOS as a blueprint with which to implement cognitive support services. It has already been shown that this approach can be realised to motivate learners, to make them aware of strategies that they can use or to help to create new ones. Although no lasting metacognitive change was reported, participants who engaged with the Goby supports reported positive learning outcomes (although this learning gain analysis was carried out on a small subsection of the overall cohort). This set of evaluations examines the accuracy of Goby service at measuring metacognitive awareness. The user model comprises of items from the MAI – these are persisted over time, and are used to inform the decision-making and support processes. An analysis is also carried out to examine the extent to which technological ETTHOS design requirements were successfully implemented in Goby.

6.5.1 The Accuracy of Goby Modelling [R1, R1.2]

6.5.1.1 Overview

This evaluation analyses the accuracy of the Goby service at measuring metacognitive awareness. Subsequently, a comparative analysis of the accuracy of Goby at modelling individual metacognitive awareness is carried out. In this set of evaluations, two groups are examined: Group A (cold start group) and Group B (stereotype group).

6.5.1.2 Test Setup

This test compares the metacognitive user model calculated in the Goby service to self-reports from the participants. The learners reported metacognitive awareness was assessed with a post-test MAI survey. The hypothesis to be tested here is that each factor modelled by the Goby service will have the same mean values as the participants' self-reports. Basically, this involves comparing the model that the Goby service has generated versus the learners post-test MAI. Thus the null hypothesis is that there is no difference between the system and the survey reposes. The alternative hypothesis is that both sets of metrics have different long run mean.

H_o: $\mu 1$ (system calculated metrics) = $\mu 2$ (survey response) = μ

H_1: $\mu 1 \neq \mu 2 \neq \mu$

A *t*-test for independent samples was carried out to assess whether measures departed from the null hypothesis. The probability chosen to define an exceptional outcome was significance level $\alpha=0.05$.

6.5.1.3 Test Results and Summary Statistics Group A

An AD test for normality was carried out on each sample and any outliers removed if necessary.

	N	Mean	StDev	SE Mean
Survey	17	3.303	0.647	0.16
System	17	3.751	0.486	0.12

Table 6.31 - Group A: Comparison of Goby and user reported Planning

For planning, the test statistic was t(29)=-2.29, p=0.03 (95% CI (-0.85,-0.047)). Table 6.31 reports a difference in means of almost .5, which can be considered significant. This means that there was a difference between the system and learners' self-reports. The variation (SD = 0.647) in the survey responses is quite large, indicating that participants reported a range of results around the mean. However, the difference in the means is still within 1 point on the 5-point scale.

	N	Mean	StDev	SE Mean
Survey	17	3.594	0.53	0.12
System	17	4.385	0.271	0.066

Table 6.32 - Group A: Comparison of Goby and user reported Information Management

For information management strategies, as shown in Table 6.32, the test statistic was t(23)=-5.48, p=0.000 (95% CI (-1.089,-0.492)), which shows a significant difference. There was a difference between the system and the learners' self-reports. The mean difference is over 1 point on the 5-points scale, indicating that Goby had too much confidence in the participants' information management strategy ability.

	N	Mean	StDev	SE Mean
Survey	17	3.412	0.434	0.11
System	15	3.633	0.399	0.1

Table 6.33 - Group A: Comparison of Goby and user reported Comprehension

For comprehension, as shown in Table 6.33, the test statistic was t(29)=-1.5, p=0.143 (95% CI (-0.523,0.080)). There is no significant difference between the two sets of results, indicating the Goby model of comprehension is on par with the learners self-report.

	N	Mean	StDev	SE Mean
Survey	17	3.812	0.885	0.21
System	17	4.331	0.329	0.080

Table 6.34 - Group A: Comparison of Goby and user reported Debugging

For debugging, as in Table 6.34, the test statistic was t(20)=-2.27, p=0.035 (95% CI (-0.997,-0.042)). Here, there is a significant difference between the reports – there is a mean difference of around .5 with large variation in the learners' self-reports.

	N	Mean	StDev	SE Mean
Survey	17	3.49	0.406	0.098
System	17	3.688	0.501	0.12

Table 6.35 - Group A: Comparison of Goby and user reported Evaluation

For evaluation, as shown in Table 6.35, the test statistic was t(30)=-1.26, p=0.217 (95% CI (-0.517,0.122)). In this case there is no difference in the long-run means – the Goby model and participants self-reports are on par.

6.5.1.3.1 Conclusion From Analysis

Previous analysis of the two-sample *t*-tests revealed that the null hypothesis was rejected in the case of planning (p=0.03), information management (p=0.00), and debugging (p=0.035). Thus, in the case of these factors, there is a significant difference between the system and learner survey. However, in the case of comprehension (p=0.143) and evaluation (p=0.217) the null hypothesis can be accepted. In these cases there is no evidence to suggest that the model generated in Goby differed significantly from self-reports from participants after competing the database course.

6.5.1.4 Test Results and Summary Statistics Group B

Once again, an AD test for normality was carried out on each sample, outliers were removed to normalise the survey. However in this case too many values would have had to been removed to normalise the system data. Since the data looked close to normal with some skewing towards the tails, the *t*-test was carried out. A Man-Whitney test for nonparametric data was carried out, to ensure accuracy, with similar results. These results are included in Appendix K.

	N	Mean	StDev	SE Mean
Survey	16	3.38	1.01	0.25
System	16	3.747	0.278	0.069

Table 6.36 - Group B: Comparison of Goby and user reported Planning

For, planning the test statistic was t(17)=-1.42, *p*=0.173 (95% CI (-0.923,0.180)). In Table 6.36 the mean planning results can be said to be on par because of the non-significant difference between them

	N	Mean	StDev	SE Mean
Survey	16	3.637	0.799	0.20
System	16	4.679	0.387	0.097

Table 6.37 - Group B: Comparison of Goby and user reported Information Management

For, information management the test statistic was t(21)=-4.69, *p*=0.000 (95% CI (-1.503,-0.580)). The mean difference reported in Table 6.38 is greater than 1 and can be considered significantly different.

	N	Mean	StDev	SE Mean
Survey	16	3.571	0.677	0.17
System	16	3.801	0.217	0.054

Table 6.38 - Group B: Comparison of Goby and user reported Comprehension

For comprehension, the test statistic was t(16)=-1.26, *p*=0.227 (95% CI (-0.618,0.158)). The mean comprehension in Table 6.38 can be said to be on par.

	N	Mean	StDev	SE Mean
Survey	15	4.040	0.596	0.15
System	16	4.501	0.266	0.066

Table 6.39 - Group B: Comparison of Goby and user reported Debugging

For debugging, the test statistic was t(19)=-2.79, *p*=0.012 (95% CI (-0.818,-0.116)). The difference between the debugging means in Table 6.39 is almost .5. In this case the difference is significantly different between the Goby model and the learners' self-reports, however the difference is not too great.

	N	Mean	StDev	SE Mean
Survey	16	3.593	0.905	0.23
System	16	3.771	0.201	0.050

Table 6.40 - Group B: Comparison of Goby and user reported Evaluation

For evaluation, the test statistic was t(16)=-0.81, p=0.431 (95% CI (-0.678,0.304)). There is no significance reported, thus the evaluation results in Table 6.40 can be said to be on par.

6.5.1.4.1 Conclusion From Analysis

Analysis of the independent samples for each of the factors revealed that the null hypothesis could be rejected in the case of information management (p=0.00), and debugging (p=0.012). In the case of information management the mean difference was greater than 1, indicating the Goby model had attributed too much confidence in the learners information management abilities. For debugging the difference was less than .5, which is closer to agreement but still significantly different. The null hypothesis was accepted for planning (p=0.173), comprehension (p=0.227), and evaluation (p=0.431). In these cases, it can be concluded that the representation Goby had of the learner was par with learners' self-reports.

6.5.1.5 Conclusion

The data show that the system and the learner self-reports are on par in many cases. Although some of the factors calculated by the Goby service were not accurate, there were only 2 out of the ten conditions where there was a difference of slightly greater than 1. Group B, which was initialised using the baseline MAI study, had results that were on par for three factors: planning, comprehension, and evaluation. Group A was the same for two of the factors: comprehension and evaluation. There was a general tendency for increased accuracy in the stereotype group. In the previous evaluation, which assessed the metacognitive gain of learners immediately after the Goby experiment, there was no significant improvement to metacognitive awareness. It was theorised that the prompts and questions would have an impact on the learner's metacognition not only during, but also after the learning experience. In the implementation of Goby this meant that the metrics used to track the items were updated over time. This metric is useful as it demonstrates how frequently the learner was supported for a particular item. In the case of Group A, the learner model was initialised by the learner and subsequently the post-test revealed that this group only accurate in two cases. In Group B however, the baseline model initialised the learner model and this model was more accurate after the Goby study. This suggests the prompts were given too much weight when updating the learner trait model and that questions can provide a better assessment tool.

This indicates that Goby can be successful at measuring the learner's cognition, but that metacognition in this environment is slow to change in nature. The benefit of this approach is that it shows how the use of the structure of a psychometric can be used as a way to model the learner. However, this model cannot be considered a psychometric after it has been used in this temporal manner, instead it should be referred to as a learner trait model in ETTHOS. This is a powerful asset since it can be used to track the support and response from the learner and inform future support. Psychometric inventories should have strong test-retest reliability for aspects of a learner that are not expected to change (e.g. personality). However, the thesis in this research is only interested in the changing nature of cognition and supporting the development of strategies that are complementary to learning. Some of the characteristics are still accurate – for example the cognitive model is univariate since it measures one aspect of the learners cognition – for this reason the learner trait model can be considered as having internal consistency since each item measured is created with only one goal. Since the MAI has already been assessed for validity, the constructs represented in the learner trait model can also be considered valid – however the specific metrics gathered to describe the learner as yet cannot be considered accurate in all cases. However, ETTHOS has been useful in demonstrating some predictive power – the model can be used to inform the decision-engine on what items could be suitable considered the state of the learner's abilities. As we have seen, this approach can significantly improve educational benefits for the learner. Overall, it can be said that ETTHOS has made a key contribution in that it has demonstrated that it can be used as a tool to understand individual differences in metacognition. It has shown that it can be useful as a model with which to assess the learner over time in order to trigger suitable metacognitive support.

6.5.2 Design of ETTHOS – Features and Requirements [R1.2, R1.3, R3]

Here, ETTHOS design requirements, which can be assessed through their technical implementation, are reviewed in order to provide a brief synopsis of how they were instrumental in the implementation of the Goby environment. An in depth discussion of the implementation of these requirements was previously provided in Chapter 5. These include the modelling of cognition in a structured, measurable way that is trait-neutral by using psychometric inventories to inform the technical architecture [R1.2];

the capture of a temporal and progressive view of each learners' metacognitive model [R1.3]; and modelling learner cognition in a manner analogous to schema theory [R3].

6.5.2.1 Psychometric Inventory to Structure the Technical Model [R1.2]

The quantification of cognitive and metacognitive competencies is possible through the use of inventories [F6]. Inventories are regularly used in TEL research and have been used to generate initial user model data (Brown et al., 06; Moore et al., 03; Conlan & Wade, 04). Metacognitive inventories in particular have recently been used at the start of the adaptation process to generate personalised support (e.g. Cannella et al., 10). Systems that have used inventories to generate a user model in TEL environments can model, prompt, and support the learner's cognitive processes [F5]. However, these inventories are typically used as static pre-test models to categorise learners, the items addressed are not explicitly fostered, and cannot be tracked over time. The current manifestation of ETTHOS has been implemented to model metacognition – in particular it models the regulatory cognitive processes that can be described with the MAI. ETTHOS provides a mechanism to assess, track, model and subsequently provide personalised cognitive support over time This is achieved in Goby using pseudo-dialog prompts/questions that update the learners model and track their progression over time. From this perspective, ETTHOS provides a mechanism to model and foster metacognitive and regulatory facets of a learner's cognition – as long as these elements are described using psychometric inventories. The limitation of this is that it does not model knowledge that is better described as a set of concepts, actions or constraints such as conceptual or procedural knowledge.

6.5.2.2 Temporal and Progressive Metacognitive Model [R1.3]

User models in TEL environments enable intelligent adaptation to suit the needs of the learner as an individual [F12]. The changing nature of learners' abilities and cognition are often modelled and measured with dynamic models of the learner through explicit and inferred assessment of their interactions [F11]. A unique user model is therefore required for learners to represent their individual metacognitive abilities. This means that the supports provided can be personalised for that learner and that the model can be updated as a result of the response for the learner. A temporal, real-time and progressive view is thus needed of the learner's metacognitive model [R1.3]. This is achieved through interactions with the learner

and the tracking of their interactions with both he learning environment and the metacognitive dialogs. A unique XML model is created for each learner and updated over time to influence future interactions and keep track of their progress.

6.5.2.3 Technical Model Analogous to Schema Theory [R3]

Mental models represent information that is related to other information, has a changing nature, and is used to attend to and respond to our immediate environment. Schema theory is a useful mechanism with which to describe how our cognition is stored and processed in our mind and how triggers can activate prior information that we have available to us [F15]. From this perspective, the ETTHOS model represents learner cognition in a manner analogous to schema theory, in order to define the items, factors and traits, as well as the activities and tasks [R3]. These are described as objects or components using objected-oriented programming techniques to describe how objects are related to each other and are activated in order to reason over them and respond to learners.

6.6 Research Limitations

The ETTHOS model and Goby service have provided metacognitive modelling within the context of a cognitive support service. However, it was necessary to limit the scope of the research undertaken in a number of discrete ways. This section discusses the main limitations.

6.6.1 Task Model Limitations

The task model proposed in ETTHOS is a summary list of the cognitive activities undertaken by the successful reader. The main limit of this model is that it is constrained to the activities undertaking by individuals who are engaged with reading material (including tables, illustrations, figures, references, etc.). This model is overlaid on the modules in the learning environment to estimate the stage at which a learner is. However, the activities in the task model will not be suitable or beneficial for all learners in all contexts. Also, as individuals learn new procedures and become more expert they become progressively automatic. This modelling approach cannot read the state of mind of the learner. Instead it provides a mechanism to estimate the stage the learner should be at and a method with which to step through each of the activities that a learner should carry out as they address academic material. This

means that the task model is not as specific as tightly coupled rules that are tied to each learning activity. This model was identified as suitable for AEH systems that deliver academic reading material, however it does not deal with other tasks such as practical course work, practical examples, or engagement in dialog.

6.6.2 Trait Model Limitations

The trait model is a limited representation of the learner. In Goby, metacognitive factors (from the MAI) that are important for the regulation of cognition are modelled. The trait model cannot be considered an inventory because it does not demonstrate the same predictions as the inventory on which it was based. Instead, the learner trait model can trace the learner over time and is used to reason about suitable support. Understanding modelling, and support of multiple aspects of the learner's cognitive repertoire will be important in future. This is because successful students characteristically possess numerous learning strategies that are suitable for a variety of contexts and situations. They change their responses to the task depending on the learning context, as well as other constructs such as their own motivational, affective, and social states.

6.6.3 Limitations of the Experiments Performed

The experiment carried out with the Goby service was designed for power in relation to measuring differences and accuracy of metacognitive regulatory strategies. There were good responses to the metacognitive and qualitative aspects of this experiment, however the learning gain component had a poor response rate. This is probably because participation in the experiment was voluntary and the database quiz was more taxing than the other parts of the survey. The subsequent analysis using learner's prior-ability, experimental interventions, and the interaction between percentile and intervention using general linear models were also limited in the amount of data available. This meant that examinations of these variables on metacognition, learning, and learning behaviour were underpowered in cases where there were relatively small differences or large deviations within the data and made it difficult to examine interaction effects.

The results gathered were also from a specific target population – subjects who would satisfy the criteria to be submitted to an introductory computing course.

Accordingly, the baseline metacognitive user model implemented in Goby was sufficiently accurate for use by the decision engine for participants in this category. However this baseline model could vary for different groups. For example, young people might be in the process of developing higher-order cognition, whereas participants from other demographic backgrounds would be stronger in certain factors. Nonetheless, it can be said that this baseline model was suitable for people who would be admitted to a third-level undergraduate computing course.

Qualitative reports also suggested that learners engaged more with questions than prompts. Also, the pseudo-dialog approach taken in the Goby experiment was probably not rich or interactive enough to sufficiently engage the learner. The use of ETTHOS could be more effective if matched with more engaging material. The underlying model does not need to change to include this enrichment – other forms of metacognitive support such as triggering suitable multimedia or simulations would most likely benefit the learner.

6.7 Requirements Traceability Table

Table 6.41 provides a brief synopsis of the requirements derived from the research question and the state of the art analysis, how these requirements were addressed and subsequently evaluated. Some requirements are addressed with through the successful implementation approach (e.g. successful implementation using the SOA architectural approach), whereas the levels of success for other requirements are addressed with the evaluations described previously (e.g. examination of the results of learning supports on domain/metacognitive ability).

Run	*Main Related Feature*	*(R) Description*	*Addressed By*	*Evaluated With*	*Result*
R1		Model learner ***traits*** - metacognition		R1.1, R1.2, and R1.3	
R1.1	- Scaffold metacognition to support domain learning (F2) -Explicit metacognitive modelling (F1) - Prioritise domain learning when offering metacognitive supports (F14)	- Improve the educational gains for the learner by delivering personalised support.	Learner trait model and subsequent learner support	Evaluation of knowledge gain, metacognitive gain, and qualitative response to metacognitive hints.	Potential educational benefit No direct increase in MC after the course Perceived metacognitive benefit

R1.2	- Quantification of cognitive and metacognitive competencies is possible through the use of inventories (F6) - Model, prompt, and support the learner's metacognitive and self-regulatory processes (F5)	- Model cognition in a structured, measurable way that is trait-neutral by using psychometrics.	Psychometric – MAI regulation of cognition – factors and items	Implementation Modelling Accuracy	Implemented over SOA Model accurate in a large number of factors
R1.3	- Learners' metacognition modelled and measured with dynamic models (F11) - Enable intelligent adaptation and to suit the needs of the learner as an individual (F12)	- Capture a temporal, view of the learner	Persisted in learner models over time	Implementation	Temporal log of user progress/ responses
R2	- Address timing of these scaffolds is also important (F9) - Metacognitive strategies are important when engaged in academic reading (F4)	- Shall model learner conduct, via a ***task***/activity model.	Descriptive and learner task model to describe learners activities	Qualitative response regarding suitability of metacognitive hints.	Dialog usually accurate and consistently so
R3	- Schema signals can activate prior information available. - Schema theory itself provides a useful mechanism with which to describe how our cognition is stored and processed (F15)	- Model analogous to ***schema*** theory.	Activation and update of the learner model	Implementation	Activation, alteration, and focusing on weaker items
R4		- Work in ***symbiosis*** with a TEL system.		R4.1, R4.2, R4.3	
R4.1	- Metacognition supports be situated within a particular context or suitable learning environment (F10) - Emulate the role of the tutor in providing supports for a range of knowledge (F7)	- Employ the SOA pattern for integration and consumption of functionality.	Integration of cognitive support system with TEL system.	Implementation	Cohesive experience in implementation (user-centric design)
R4.2	- Metacognition supports be situated within a particular context or suitable learning environment (F10) - Emulate the role of the tutor in providing supports (F7) - Address timing of these scaffolds is also important (F9)	- Mapping between trait and task model.	Trait-task model used to inform decision-making	Qualitative responses	Dialog usually accurate and consistently so.

R4.3	- Metacognition supports be situated within a particular context or suitable learning environment (F10) - Emulate the role of the tutor in providing supports for a range of knowledge (F7)	- The metacognitive scaffolds should be contextualised.	Dialog chunks from MAI and LO metadata used to generate prompt/questions	Educational outcomes Qualitative responses	Potential for educational benefit Perceived metacognitive benefit
R5	- Dialog approaches have been used in TEL emulate role of tutor (F3) - Scaffolds are determined from user model and adaptation characteristics (F9) – feedback from dialog can be used to update the learner model	- Interactions with the learner will be provided in a non-invasive pseudo-***dialogic approach***.		Educational outcomes Qualitative responses	Potential for educational benefit Perceived metacognitive benefit
R6	- Learners begin their learning experiences with prior knowledge and abilities – both cognitive and metacognitive (F13) - Quantification of prior metacognitive competencies is possible through the use of inventories (F6)	- Initialise user model with a ***baseline*** model		Compare baseline model to Goby model	Goby model on par with baseline model

Table 6.41 – Requirements Traceability Table

6.8 Conclusion and Discussion

This chapter described the evaluations and analyses carried out to assess the extent to which ETTHOS and its manifestation in the Goby service provide a mechanism for discrete cognitive modelling. An initial evaluation of the target population carried out on over 100 participants informed the setup and sample size requirements of the experiment on Goby. The mean score for each of the items was also used during implementation of Goby in order to initialise the baseline trait model. This model is included in Appendix E. The Goby system was implemented to work in symbiosis with the APeLS learning service in order to deliver an AEH databases course with metacognitive support.

Participants were assigned to one of three groups – the experimental groups interacted with the Goby metacognitive dialog with the aim to model and foster metacognition. Group A, the cold start group completed a pre-test MAI in order to initialise their learner trait model. The second group - Group B the stereotype group, had their cognitive model initialised using the baseline metrics. Finally, Group C, the

control group completed the surveys but their metacognition was not modelled or fostered. Results from participants were also examined through comparison of their prior-ability (low vs. high), examination of the intervention as a whole (Results combined from Group A and Group B) compared to the control, and the intervention between prior-ability and intervention. This section concludes with discussion of the extent to which Goby supported the learner, the approach taken to implement ETTHOS and the design of ETTHOS.

6.8.1 Supporting the Learner

The overarching goal for designing a model to describe learner cognition in TEL is to foster and support the development of learner strategies that are antecedent to positive lifelong learning and better can improve educational results. The first question that was addressed was to what extent does this approach result in ***educational benefits*** for knowledge gain and cognitive awareness? Goby aimed to achieve three of the goals of metacognitive tutoring – to change the learners metacognitive behaviour in the supported environment; to subsequently promote domain learning; and finally to improve future metacognitive behaviour.

Qualitative analysis and examination of the log data was undertaken to examine how learners' ***behaviour*** varied within the learning environment. Interaction with metacognitive supports resulted in the learners in the Goby experiment spending *more time* on page and more time on the *overall learning* experience. However, this is not necessarily a negative finding, because it indicates that the learners in the metacognitive groups interacted with the dialog supports. This is similarly reflected in the qualitative feedback from learners, where learners reported that responding to the questions in particular added to the workload. These qualitative responses were mixed, as some learners believed that prompts added to the workload, but were a useful addition. Conversely, others did not think that they added because they could address the prompts/questions very quickly or because they were simply seen as part of the learning process.

Interestingly, learners with higher prior-domain ability tended to view the dialog as interrupting the workflow more so than lower ability learners. This may be because they were confident in the area, and did not want to have to complete the extra work

involved in attending to metacognitive supports. Overall, learners reported a range of learning time and time on page. Based on qualitative feedback, this is most likely because some learned to quickly attend to or ignore the metacognitive dialog. There are most likely a number of other variables that also influence learning time, such as interest, their individual reading strategies (e.g. ability to skim the dialog/learning content) or motivation. This suggests that future uses of these types of metacognitive supports could benefit from giving the learner more control over the dialog interaction. Although the supports could be ignored, specific functionality to control the extent to which the metacognitive supports are provided may improve learner perception. As suggested by the qualitative feedback, the timing and type of support offered is of importance and should be considered further. However the inclusion of supports that are richer than simple dialog would no doubt result in further increases in the amount of time required by learners.

Regardless of prior ability or intervention, learners accessed a *range of pages*, with a large variance in total number of pages visited but no differences found between these groups. Overall, learners accessed a large proportion of the overall course, suggesting that they were motivated sufficiently to make a good attempt at the course. On examination of *motivation,* qualitative response from the learners were similar across the low and higher ability and between groups – the dialog got them thinking about breaking down the information; kept them on track; helped them to stop and reassess their progress; however these effects varied over time as many initially paid attention but did so less over time. Learners who had lower prior abilities indicated that they thought more about the dialog supports and saw them as more beneficial to the learning. Although extra workload was created by the addition of the metacognitive dialog, these additions did not result in learners stopping their learning experience early due to the additional time and cognitive resources required of them.

Learner percentile was highlighted as having influenced *learning efficiency.* These results must be considered with caution because there was limited data available when comparing intervention, prior-ability and their interaction. Here, higher ability learners were more efficient, but there were large deviations in learning time reported in the higher ability group. These deviations, combined with the small

coefficient of determination suggested that there were other influential factors also at play. Nevertheless, despite the addition of the metacognitive dialog supports, learners in the experimental interventions were not overburdened to the extent that they reported a large decrease in learning efficiency.

There were no differences between learners for *response rate* or *time to respond* to the metacognitive dialog supports. In the qualitative feedback, learners (particularly learners with low prior-ability) indicated that they thought about the content of the dialog. However, many also suggested that the extent to which they attended to them varied over time. It was repeatedly reported that although they responded to questions, this effect varied over time and they learned to quickly attend to them and some began to ignore the prompts. This examination of metacognitive dialog responses suffered from being underpowered - further analysis would be needed to explore these metrics and examine their influences.

On analysis of ***learning gain***, it appeared that learner prior-domain-ability; the intervention as a whole; and the interaction between prior ability and intervention were influential. Prior-domain ability influenced the subsequent learning gain found in learners – here, the higher ability learners reported significantly less gains, most likely as a result of celling effects and lower ability learners reported greater gains, most likely because they had the larger ranges within which to improve. When comparing the intervention overall with the control, greater learning gains were also found in the experimental groups. Also, on comparison of all of the groups, learners in Group B reported the highest gains. However, this group also had the lower prior-ability. In an attempt to separate this effect from the influences of prior-ability the results were broken down into separate percentile populations to compare high ability learners and lower ability learners separately. In this experiment, high ability learners who received metacognitive supports had greater learning gains than high ability learners who did not receive the metacognitive support. Low ability learners who received the metacognitive supports also had slightly better (non-significant) learning gains than low ability learners in the control. However, these comparisons of individual percentile populations were underpowered. Nevertheless, the results show that participants in this data set reported greater learning gains when in the intervention group, regardless of prior-ability and point to the benefit of future use

and in particular examination and evaluation of how metacognitive supports in this manner can benefit the learner.

Although learners' prior-metacognitive-ability was not correlated with the learning gain in this experiment, this does not mean that metacognitive ability does not influence learning gain. The MAI has been shown to correlate better with broad measures of academic achievement such as overall course scores rather than specific quizzes. In these cases, there are most likely other confounding issues. Nonetheless, the results presented are promising and point to the benefit of future use and evaluations. Indeed, it is probable that prompts and questions are not sufficient – while they are useful in gathering information about the learner to build the metacognitive model other richer supports could better benefit the learner.

A number of analyses were carried out to examine the extent to which the Goby experiment influenced learner ***metacognition***. Learner groups were on par and there was no significant improvement between the pre and post-test MAI scores. On analysis of learners according to intervention, prior-domain-ability and interaction between intervention and prior-ability, there was no influence on metacognitive change. This indicates that the metacognitive behaviour patterns of the learner did not change directly after the experiment. This is one of the more difficult goals for metacognitive tutoring systems to achieve. Although the qualitative feedback indicated that some learners changed their metacognitive strategies in situ, these supports were not sufficient to result in sustained changes in metacognitive ability. Feedback from the learners indicates that this might be because there was insufficient support to practise these skills. Also, this experimentation was carried out over a short number of sessions, which is most likely not sufficient to sustain metacognitive behavioural change. Nonetheless, the qualitative responses are promising – they indicate that the learners saw benefit in the dialog and that it could enable them to activate learning strategies or apply new strategies during the learning experience.

6.8.2 Approach taken to implement ETTHOS

The ***approach*** taken to use the ETTHOS model in the development of a metacognitive support system has been examined through analysis of the baseline

modelling approach and analysis of the extent to which the architectural requirements have been achieved. With logical separation between learning systems and cognitive support systems, learners may be required to complete multiple surveys or inventories on registration. The baseline user modelling approach undertaken has been used in order to examine whether the cold-start problem associated with personalised services can be addressed by providing learners with reasonable defaults on registration with new cognitive support services. An evaluation was carried out to compare the baseline model created with the earlier study to the model that would have been generated using the 150 participants who signed up to Goby. The two models were on par for each of the factors indicating that the baseline model sufficiently represented the Goby population.

A service-oriented architectural approach was taken to enable metacognitive support be delivered as a service and a technical interface created to ensure that the learning environment and metacognitive support could be delivered as a cohesive system In separating the modelling and support from the learning environment, this meant delivering the metacognitive support service and learning service as a single mashup web application. The learner needs not know that the underlying architecture comprises of separate services that are owned and managed independently. The incorporation of this type of support with a TEL environment means that it has been possible for Goby to deliver personalised support for the learner that was delivered on a case-by-case basis in the form of pseudo-dialog prompts and questions. These have been contextualised using the metadata associated with each of the LOs in the learning environment. Responses to these dialog interactions enabled the metacognitive support service to update the metacognitive model and subsequently inform further reasoning about their status.

6.8.3 ETTHOS Design

On examination of the ***design*** of ETTHOS as a cognitive model, an evaluation was carried out on the modelling accuracy and comparative analysis of the design requirements that were tested through implementation of ETTHOS in Goby. The evaluation of the accuracy of Goby in modelling metacognitive factors revealed that Goby was accurate half of the time. In the cold start group, factors were on par for comprehension and evaluation. However, the stereotype group who received more

questions was more accurate – factors were on par for planning, comprehension, and evaluation. This suggests that the prompts were given too much influence when updating the learner trait model and that questions could provide a better assessment tool. Nonetheless, this level of accuracy was sufficient to deliver suitable prompts and qualitative analysis indicates that learners considered their metacognitive strategies in response to the support. In the qualitative analysis, items chosen were also typically perceived as being suitable for the content. This modelling approach can therefore satisfice the needs of the learner by making the best possible decision with limited information.

The design requirements of ETTHOS that were assessed through their technical implementation in Goby included; the use of inventories as the basis of technical models, the inclusion of a temporal and progressive metacognitive user model, and the use of schema theory as an analogy with which to describe how the ETTHOS model should be used when implementing a support service. Using the structure of inventories (traits, which comprise of a number of related by individual factors, each of which are assessed through a number of observable items) has been successfully used as a basis for describing the MAI and subsequently tracking learners' metrics over time. While this means that the metacognitive model cannot be considered to be a psychometric inventory, this structure has provided a useful approach with which to model, trace and quantify learner competencies and cognitive capabilities. The use of the schema analogy provides a useful mechanism with which to describe how the learner traits, and the cognitive tasks are represented using object-oriented techniques.

6.8.4 Final Evaluation Remarks

The results of these analyses and evaluations can be used as the basis for suggestions for future implementations of ETTHOS and subsequent evaluations. There is strong pedagogical motivation behind supporting metacognition and self-regulated learning strategies – in developing these aspects of the learner's cognitive repertoire they are enabled to monitor and take control of their own learning. With the use of ETTHOS, Goby can prompt learners to periodically plan, activate their prior knowledge, and engage in metacognitive processes. Goby uses dynamic scaffolds to serve as ever-

present reminders as to how they can activate effective learning strategies and better achieve their learning goals.

Overall, in examining the learner behaviour and educational outcomes, these have been influenced by prior-ability, intervention, and their interaction. However, there are also most likely a number of other factors that influence learner behaviour which need to be considered in the implementation and provision of metacognitive supports. Regardless of group and prior ability, a range of supports are needed for different learners – in particular, varying levels of scaffolds to better motivate and support the learner when engaged in the learning environment. The type and functions of these supports could benefit from changing over time as the learner becomes familiar with the regulatory strategies that the system is trying to support.

Also, although the dialog interactions may be useful for gathering information about the learner to inform their user model, they are not necessarily sufficient to support the learner. The underlying model does not need to change to include the provision of additional rich supports – other forms of metacognitive support such as triggering suitable multimedia, simulations, task setting functions, digital sketchpads, etc. would most likely benefit the learner if they could be successfully aligned with the metacognitive factors. However, in the addition of these types support, they would most likely require more cognitive resources from the learners. It is particularly important to ensure that the curriculum is given priority and that metacognitive supports do not overtax learners' cognitive resources.

This chapter has outlined the analyses and evaluations of the ETTHOS model. It described details of each of the analyses undertaken, the data gathered, and findings that resulted. The application of ETTHOS within the Goby system was has been examined to ratify how the design and approach requirements were implemented and assess the extent of the educational, metacognitive, and behavioural changes. The following chapter discussed these results within the wider context of TEL and makes suggestions for future developments.

Chapter 7 Conclusion

To date, TEL approaches have not yet adequately addressed the modelling of higher-order cognitive competencies. This work presents an innovative TEL solution to augment learning environments in the form of the ETTHOS model. This thesis has detailed the mechanisms of ETTHOS including the underlying cognitive and metacognitive theories, a discussion on features and mechanisms in TEL environments that informed the ETTHOS requirements, the cognitive and metacognitive components that are modelled, traced, and subsequently supported, and the approach with which it is implemented, as well as the multifaceted evaluations undertaken to ratify its success.

TEL systems that adapt to the learner need not only promote the acquisition of knowledge but also have the potential to foster metacognition, an essential higher-order skill that is part of successful self-regulation and is antecedent to positive lifelong learning. Current systems that support self-regulation or metacognition often do so indirectly through dialog and open models, and those that support these skills directly are implemented in a manner that is tightly tied to the domain learning. Despite the promising work in the area of TEL, researchers have not yet fully explored how to describe cognitive concepts as a discrete model that is separate from the learning environment. An agreement is needed on how to represent abstract cognition in a manner that can be codified in a support service and can be reasoned upon in order to deliver personalised assistance. Without such an understanding, it will not be possible to adequately model, trace, and subsequently foster cognitive competencies as a TEL service. This research remedies this gap in the state of the art by providing a model that describes learner cognition in a traceable and actionable manner. This chapter concludes the work presented by reviewing the original objectives and describing the contributions and limitations of the work. It also makes suggestions for how the results and insights can be used to fuel future work.

7.1 Review Against Original Objectives

Four objectives were identified in pursuit of answering the research question:

> *How and to what extent can the cognitive aspects of a learner be modelled to support learning with TEL?*

This thesis is now reviewed against each one of these objectives, as follows:

1. Research and analyse cognitive and metacognitive aspects of learning. In particular investigate the architectures, models, and the theory behind adaptive TEL, highlighting the strengths and problems that need to be overcome for successful cognitive modelling.

An analysis was carried out regarding the psychological and pedagogical theories that underpin our understanding of learning, cognition and metacognition. This analysis was carried out in order to explore the role of metacognition in learning and examine the learning theories within which it has significance. An understanding of the mechanisms with which metacognition can be modelled; the cognitive strategies undertaken when reading; and the schema construct have each directly influenced the requirements in defining the model of cognition developed in this thesis. This analysis of the underlying learning theories was also necessary in order to examine how they have influenced TEL development. The mechanisms of user modelling and adaptation were examined in order to assess approaches to modelling learner cognition, the mechanisms and functions with which they are updated, the characteristics of the personalised support provided, as well as particular consideration of distributed user modelling approaches. A specific examination of TEL environments that model and/or support metacognition was also carried out in order to examine how and the extent to which they provide this support. This analysis of TEL features and their psychological and pedagogical underpinnings, in the context of the research question has informed the second thesis objective:

2. Formulate a set of requirements to inform the design of a model of learner cognition that can be implemented in a service that delivers metacognitive support.

Analysis of the literature and the research question informed the development of a number of research requirements, practical requirements and subsequent system requirements. The research requirements specify the main components of the ETTHOS model: these include traits, tasks, and the mapping between traits and tasks, as well as how schema theory influenced the technological implementation. ETTHOS makes use of web-based architectural patterns meaning that it is possible to make a logical separation between the cognitive support and domain learning services. The approaches and issues that are reported in current personalised web-based learning systems informed the practical requirements. The key practical requirements are that ETTHOS is used in conjunction with a decision engine to enable reasoning about the state of the learner and in order to subsequently trigger suitable metacognitive support. Also, the cognitive support and domain learning should be delivered to the learner as a holistic learning application. The requirements were derived in order to inform the design and implementation of a cognitive support service that meets the third objective:

3. Provide a high quality, innovative, and supportive approach to modelling learner metacognition.

The quality in this research arises out of the rigour and analyses carried out in defining the pedagogical, psychological, and technological features and functionality that characterise ETTHOS as well as the subsequent evaluations undertaken to assess its success. ETTHOS is innovative since it applies best practice in the adaptive TEL domain as well as contributing a new model and new methods. ETTHOS provides a mechanism with which to support TEL services that deliver domain learning because it describes cognitive strategies in a traceable way. The result is that the learner's model can be used to inform the reasoning and assistance provided by a cognitive support service. The Goby service was developed in order to test the ETTHOS model and is specifically designed to model, trace, and subsequently foster metacognitive regulatory components. The extent to which ETTHOS provides a solution for modelling has been assessed through evaluations on the Goby service and is addressed in the final objective:

4. Evaluate the extent of the success of this approach within a real system, and thereby assess its effectiveness to model, track, and foster learner cognition.

In answering the research question, three *goals* were identified – what is (i) an appropriate *design* for a cognitive model that may be separate while still aligned with TEL systems; that will result in (ii) *educational benefits* for knowledge gain and cognitive awareness; and describe (iii) the architectural *approach* that needs to be taken to integrate this model with a TEL system for a successful learning experience. The implementation of ETTHOS in Goby was evaluated in relation to these three goals. This meant comparing Goby to technological requirements, analysing the qualitative responses and log data of learners who engaged in the environment, and the completion of a series of quantitative analyses.

In assessing the *educational benefits,* knowledge gain, metacognitive gain, and learner behaviour and perceptions were examined. The experimental intervention resulted in learners spending more time on page and more time on the overall learning experience. Interestingly, learners with higher prior-domain ability tended to view the dialog as interrupting the workflow more so than lower ability learners. Overall, learners reported a *range of learning time* and time on page. Based on qualitative feedback, this is most likely because some learned to quickly attend to or ignore the metacognitive dialog. Regardless of prior ability or intervention, learners accessed a *range of pages*, with a large variance in total number of pages visited but no differences were found between these groups. The learners accessed a large proportion of the overall course, suggesting that they were motivated sufficiently to make a good attempt at the course. Qualitative analysis of motivation indicated that many participants saw the dialog as a useful addition, seeing Goby as an ever-present tutor, however learners who had lower prior-ability indicated that they thought more about the dialog supports and saw them as more beneficial to learning.

Although there was no change in regulatory *metacognition* directly after the Goby experiment, there was an increase in *learning* gain reported for participants in the metacognitive interventions. There are issues with this finding, because there were interaction effects between the intervention and the prior-ability of learners. The data suggest that regardless of prior ability, learners in the metacognitive intervention had greater learning gain than those in the control. However, these results must be considered with caution because the analysis of the learning gain with consideration for prior-ability was underpowered. Nonetheless, the results point

to the potential for further investigation and suggest that the dialog approach undertaken is not yet sufficient for learning and metacognitive gain. The findings that Goby can act as a modelling tool and that many learners believed that Goby acted as an ever-present tutor have important consequences for the broader domain of TEL because it points to the suitability of this approach for modelling and the potential for fostering metacognition if richer supports were provided.

The *approach* taken to implement ETTHOS was to logically separate models and reasoning, and to deliver metacognitive support as a service. This approach was assessed in relation to the architectural requirements. This logical separation has been influenced by web-based applications, which distribute the components over service-oriented architectures. Goby and the APeLS course are discrete services that work together to deliver course content with metacognitive support. To facilitate cohesion between the metacognitive support service and the learning service an interface was designed to enable the two to be delivered as a mashup application. Through decomposition of the learning objects in the learning environment and the component metacognitive factors in the support service, it was possible to create dialog supports that were contextualised. Another facet of this logical separation was the inclusion of a baseline model generated from the target population, which made it possible to initialise the learner model with reasonable default values.

Examination of the effectiveness of the *design* of ETTHOS was undertaken through comparison with design requirements that were evaluated through implementation as well as a quantitative analysis of the accuracy of the Goby service. The accuracy of modelling afforded by ETTHOS in the Goby service was mixed. There was agreement for half of the factors, more so where the participants were asked more questions. ETTHOS advances current modelling and support features characteristic of adaptive TEL by defining the core structure and approach needed in a successful cognitive modelling system. This success is evident in the implementation of ETTHOS in Goby, the ability to model and track metacognition in a technical architecture, and subsequent ability to reason about how to deliver support delivered to the learner.

7.2 Contribution of this Research

This section outlines the main contribution of this work and the secondary contributions that have arisen as a result of the approach and design decisions taken.

7.2.1 Main Contribution

The main contribution of this work is ETTHOS (Emulating Traits and Tasks in Higher-Order Schemata), which provides a mechanism with which to model and trace learner metacognition in collaboration with a TEL environment. This model can be used as the basis from which to provide personalised supports with the goal of improving metacognitive behaviour, promoting better domain learning, and improving subsequent metacognitive capabilities. TEL research has moved towards personalisation and adaptation in response to learners' unique dispositions and individual differences. The work presented in this thesis is an important contribution to the state of the art because it has been demonstrated that ETTHOS can be used as a tool to reason about individual differences within the context of TEL. In particular, it has been manifest in the Goby service in order to model and foster metacognitive strategies. While the main contribution of the thesis is the development of a model to describe learner metacognition, the motivation behind such a model is to support learning. Although results from examination of the educational benefits were mixed, they point to the benefit of future use and examination of how ETTHOS can be harnessed to better support metacognitive and learning gain. Areas of future work and research directions are described in Section 7.3.

The core aspects of the ETTHOS model are the trait component, the task component, and the mapping between traits and tasks. Learner metacognition is represented with the factors and items described in the MAI psychometric inventory, however this model changes over time in response to interactions with the learner. This means that the model cannot be described as an inventory; instead it provides a mechanism with the discriminatory power to reason about the learner and with which to trace learners' progress over time. The use of inventories means that the factors have an internal consistency – the items in the model measure specific and related factors that describe one aspect of cognition. The strength in this approach is that ETTHOS can be used as a representational tool, with which learner progress may be measured

over time. A high-level task model describes the cognitive activities undertaken when engaged with academic reading materials (e.g. figures, tables, and examples). Models are organised in a logical manner that is analogous with schema theory. This is realised in the object-oriented programming approach taken to implement ETTHOS in the Goby service. Goby was developed in order to evaluate ETTHOS and was specifically designed to capture and support metacognitive regulatory components in a web-based learning environment. Interactions with learners are interpreted through the activation and expansion of these models in a decision engine.

7.2.2 Secondary Contributions

A secondary contribution afforded by this research is the discrete delivery of ETTHOS as a separate service. The delivery of cognitive support as a service is a step towards developing modelling and support services that can travel and grow with the learner over time and between services. Cognitive supports need to be integrated with learning tasks as a cohesive learning experience. The learning objectives of the system work in tandem with the cognitive learning objectives – this means that the cognitive support system works in symbiosis with a TEL system. Goby is logically separated from the learning environment, but delivers support that is complementary and aligned with its goals. This means that the cognitive support service is owned and managed independently from the TEL service and could travel with the learner across multiple environments. The ultimate goal of this abstraction is to take a step towards integrating with a number of services, and to facilitate the creation of a long-term lifelong user model.

Another secondary contribution is the generalisability of the ETTHOS model. Although the MAI is modelled currently, alternative cognitive inventories could be used. Psychometrics and protocol analysis offer standardised methods for measuring and describing learner cognition. Since ETTHOS is abstracted to describe traits as their component factors and items, alternative inventories could possibly be used. The task model is similarly abstracted in that instead of modelling clicks, actions, and responses the cognitive reading tasks undertaken by a learner when attending to new academic information is modelled. Rather than write rules specific to the learning environment, the task model instead drives the reasoning about the state of the

learner. For example, during the planning reading phase, the metacognitive items that are highlighted as important will be triggered in Goby.

An additional contribution is the use of a baseline model in order to initialise the learner model. This work has also provided an initial starting point with which to deal with the cold-start problem whereby learners are required to complete surveys or tests in order to initialise learner models. The baseline model generated was on par with the community model that would have been generated from the cohort of participants who completed the Goby experiment. This alone is not enough to suggest whether this approach can be used to inform how the learning system should interact with the learner. However, the baseline modelling approach is promising for use in future TEL environments which would have previously required a learner to complete an inventory to initialise their user model.

7.3 Future Research Directions

The findings and insights resulting from this work have promise for informing and opening new avenues of research. This innovative modelling approach has advanced the state of the art and will contribute to the development of new TEL research endeavours. There have also been limitations to this work and new questions that have arisen which will need attention in future research. The following describes a number of areas in which this work can be further developed.

7.3.1 Rich Cognitive Support with Simulations

Although simple metacognitive dialog interactions can be useful for gathering information from the learner to update their user model, in Goby this approach is not sufficient to support learners or enable them to develop new metacognitive behaviours. The ImREAL (Immersive Reflective Experience-based Adaptive Learning) project (Moore, Conlan, Dagger, et al., 11; Hetzner, Steiner, Dimitrova, et al., 11) is working towards augmenting immersive simulation learning with affective and metacognitive scaffolding in order to prompt self-reflection and self-regulation (www.imreal-project.ue). The *affective metacognitive scaffolding* work package within this project will further develop ETTHOS as the underlying model for metacognitive scaffolding (Moore, Conlan, Dagger, et al., 11; Moore, Macarthur & Conlan, 2012). This means extending the simulators from ETU (www.etu.ie) with the ETTHOS model in

order to deliver rich metacognitive support and promote self-regulation. Rather than triggering dialog from the prompt and question model, an operational guide can be accessed in order to trigger training resources and simulations to promote metacognition and self-regulation.

7.3.2 Lifelong Centralised Modelling Services on the Cloud

The overarching goal for designing a model to describe learner cognition in TEL is to foster and support the development of learner strategies that are complementary to positive lifelong learning. However, if learning is considered lifelong, then another challenge for technology is to enable long-term learner modelling. This work has provided an innovative solution for modelling metacognitive facets of learner cognition and has shown how this model can be implemented in a service-oriented application on the web. This separation of cognitive support from domain knowledge delivery is a step towards long term cognitive modelling. Recent developments in cloud computing have meant that these types of server solutions are not limited by processing power or data storage. Cloud computing is a key technology that is being employed strategically by businesses to reduce their reliance on IT assets. Just as educational web based applications can benefit from enterprise application architecture such as SOA and SaaS, so too can adaptive TEL services benefit from the cloud. The benefits of cloud infrastructures are that they are provided on demand, with seemingly unlimited resources (storage, server time, processing, memory) and have broad access because they are available over the Internet (Mell & Grance, 09).

Personal user model clouds (Dolog, Kay & Kummerfeld, 09) have previously been proposed, which represent user model data from multiple sources – such as learners' achievements and activities over their lifetime e.g. modules or courses undertaken. This means that multiple models are used to represent distinct aspects of the learner. ETTHOS is specifically designed to represent the cognitive competencies and learner traits that can be described using psychometric inventories. The Goby service is owned and managed independently from the TEL service, which means that it could be useful across multiple learning environments. The ultimate goal of this abstraction is to take a step towards integrating with a number of services, and to facilitate the creation of a lifelong user model. Distribution of such a service over the cloud could

be the solution to delivering a scalable and elastic cognitive modelling service that has the ability to travel and grow with the learner during their lifetime.

7.3.3 Dealing with the Cold Start Problem

This work has also provided an initial starting point with which to deal with the cold-start problem whereby learners are required to complete surveys or tests in order to initialise learner models. Current approaches to dealing with this arise from the distributed nature of delivering a centralised user model on a server through a common description of the model or through the use of ontology. In the case of CUMULATE for example, the learner model can be reused for multiple learning services. However, this is only useful if the learner has already used a system or completed an initial modelling survey. With ETTHOS, the baseline model is generated from a survey carried out to assess the mean responses from the target community. Analysis of this model compared to the Goby participants revealed that the two groups were on par, meaning that the baseline model was an accurate representation of the community. This is a promising approach for use in future support services and these results can then be reused for subsequent students. This has implications for future user modelling because current systems rely on participants undertaking surveys or tests in order to initialise the user model metrics.

7.3.4 Temporal Open Learner Modelling

This work has made the assumption that providing the experimental participants with a visual OLM would motivate them to complete the course. This assumption was based on the literature that describes OLMs as motivators, as well as on the advice from early consultations during the user-centric design of Goby. OLMs can take advantage of the modelling and tracing abilities afforded by ETTHOS in order to display an overview of the data to the learner. The progressive modelling of the interactions with the learner over time means that the OLM provided could not only visualise an overview of their status but also give a temporal view of their progress and interactions with the system.

7.3.5 Modelling Other Traits

Psychometrics and protocol analysis offer a standardised method for measuring learner cognition. These approaches have influenced the ETTHOS model by providing

a structure with which to monitor and measure cognitive competencies that are beneficial to learning. Rather than describe a specific cognitive trait, it uses the structure of a psychometric inventory. Moreover, although the MAI is modelled currently, alternative cognitive inventories could be used in the future. There are over one hundred psychometric inventories are currently available for clinical, educational and organisational or occupational evaluations which assess constructs such as numerical ability, verbal ability, memory span, spatial relations, conformity, depression, anxiety, empathy, and metacognition (Kline, 95).

The acquisition of higher-order cognitive skills involves practice and automation in order to enable the learner to learn new strategies. In the future ETTHOS could model multiple traits – first supporting the learner to practice the essential skills and subsequently fostering other related cognitive strategies. The baseline model would go towards providing a solution for the survey fatigue issue, which would be especially important if there were many traits modelled. This could mean gathering data on the trends of abilities and weaknesses reported by different communities of learners for multiple traits.

7.3.6 Modelling Other Tasks

One of the limitations of the current implementation of ETTHOS is that it represents the cognitive activities undertaken when attending to academic text. This model is appropriate for web pages that are not rich or immersive. However, many TEL solutions make use of rich approaches such as immersive simulations, intelligent dialog support, and interactive puzzles to be solved. Suitable task models would need to be defined through protocol analysis in order to outline the cognitive activities that are undertaken in these scenarios. This would establish each of the key cognitive strategies a learner undertakes during a task or when solving a problem.

7.3.7 Multiple Models

Considering that ETTHOS could be employed in multiple scenarios and for a variety of traits a multi-model approach could be taken ($ET^{N}T^{N}HOS$). There is a range of cognitive competencies other than metacognitive strategies that drive self-regulation and influence learning that would be particularly suitable to model, including motivation and emotional intelligence. It is typically the learner's role to activate

useful and applied cognitive strategies to undertake a task. However this requires expert understanding of their own strategy repertoire and the most appropriate strategy for the task at hand. The benefits of a multi-model approach would be that it could support strategies that are prerequisite for optimal learning in particular tasks. In situations where learners' individual differences cannot be assessed using an inventory, a separate service would be needed to provide modelling and support. The interaction between the metacognitive or other cognitive support, additional modelling services, and the learning environment would require ETTHOS to be implemented with a suitable interface to connect to multiple types of services. Thus, alignment with the learning environment would be more complex, since the reasoning about the suitability of which strategies to support would require assessment of the learner's cognitive functioning and suitable weighting for the strategies that are prerequisite for optimal learning in a given context.

7.4 Final Remarks

The original contribution to knowledge presented in this thesis is the ETTHOS model, which has been used to augment TEL by modelling, tracing, and acting as a reasoning tool with which to select metacognitive supports. Metacognitive awareness is particularly important because it enables learners to make the most of their own cognitive abilities and regulate their responses to learning tasks. The features and limitations of adaptive TEL systems have influenced the design of ETTHOS. It also draws from pedagogical and psychological theories that help us to understand, represent, and activate learning, cognition, and higher-order cognitive strategies. ETTHOS provides an innovative mechanism with which to represent and reason about learner metacognition. The result is that it can effectively collaborate with a TEL environment to reason about how to support learners' metacognitive behaviour and has the potential to promote better domain learning with the addition of richer supports. This research, the resulting findings, and subsequent insights will contribute to better cognitive support in future TEL environments and metacognitive support systems. It is also expected that this work will encourage new debates on how to model, trace, and foster metacognitive and other cognitive competencies with TEL.

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An Approach to Modelling Learner Cognition for Technology Enhanced Learning

Appendices Volume

A thesis submitted to the
University of Dublin, Trinity College
for the degree of
Doctor of Philosophy
2013

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Appendix A Decision Making Techniques

Approaches to user modelling and subsequent adaptation are carried out with a number of AI and non-AI reasoning approaches. For instance, AI approaches include model tracing or production rule generation, constraint-based modelling, case-based reasoning, and Markov models. Non-AI approaches include algorithmic and rule-based decision engines. This appendix provides an overview of this reasoning intelligence. The rule-based algorithmic approach taken when implementing ETTHOS and the rationale for its selection are discussed in Chapter 4.

A.1 Model Tracing

Model tracing is an AI technique often used in ITS, in particular with Cognitive Tutors (Aleven et al., 06, Koedinger, 01), to compare the expected activity or 'procedure model' to the learner's actions. Production rules describe the general process that must be undertaken to solve a problem (Mitrovic et al., 03). This means that each target skill is decomposed into a number of component parts - support and instructions are authored for each of these. The production rules describe the target skill or learning objective. These rules are described in a manner similar to conditional IF-THEN statements; however the subject and objects of these statements can be complex. For example, 'IF the goal is to write a paragraph to explain model tracing, THEN write an description and get an example'. Anderson (1995) describes this approach to tutoring as *model tracing,* because it relates the behaviour of the learner's actions through a task to a sequence of cognitive procedures. Where there is ambiguity during inference of the current state of the learner, they can be presented with a disambiguation menu (Anderson et al., 95) to indicate what action they were carrying out. The combination of these approaches for inference meant that contextually representative help messages could be delivered.

Cognitive tutors often apply a complimentary modelling facility alongside model tracing called *knowledge tracing.* This was included in the LISP tutor (Anderson Anderson, Farrell & Sauers, 84; Anderson et al., 95), and PAT tutor (Koedinger et al., 97), both of which tracked a learner's progress through an exercise. These use a Bayesian procedure to estimate the probability that a learner had learned each of the

production rules in the cognitive model. This knowledge tracing approach is usually used to ensure that a learner has reached a suitable level of mastery before new skills or rules are introduced. Research has reported significant positive impact on the learners' achievement level (Anderson et al., 84; Koedinger et al., 01) and that knowledge tracing can be used to predict performance (Corbett & Anderson, 95).

A.2 Example-Tracing

Example-tracing (Aleven et al., 09, Razzaq et al., 09) tutors on the other hand have the rules that are automatically generated with Cognitive Tutor Author Tools (CTAT). These do not require programming/AI background, instead these tools help teachers to write assessments, and related hints, and sample solutions. CTAT records the demonstrated appropriate path through a problem or approach to solving a task these are recorded in a behaviour graph. This graph can be generalised using tools to indicate constraints or ordering formulas. The ASSISTment Builder (Razzaq et al., 09), for example, is a tool that assists educators develop these example-tracing tutors. This system provides functionality for a teacher by initially demonstrating a path and subsequently by providing associative appropriate formative and summative feedback. The resulting system is then capable of providing suitable scaffolds and hints throughout the course.

A.3 Curriculum Scripts

Curriculum scripts describe how learners can engage in dialog with the TEL environment. These are similar to production rules in the way that they are created. These follow an Expectation and Misconception Tailored (EMT) dialog by comparing learners' responses to a curriculum script (Graesser et al., 09). For example, AutoTutor's curriculum script includes expectations and misconceptions that are anticipated in response to a physics question (Graesser et al., 09). The model tracing approach models each step of an expert solution and can incorporate common mistakes that are taken by novice learners. However, it is possible that these approaches can sometimes ignore alternative solutions. Since the model typically represents the ideal path, the learner is required to follow a fixed path. This approach can be computationally taxing since it requires the system to compare the learner's most recent actions against the entire learner model.

A.4 Constraint-Based Modelling

An alternative AI approach, which is considered less taxing on system resources, is *Constraint-Based Modelling (CBM)* (Mitrovic et al., 03, Mitrovic et al., 07). In CBM each step in a task or in solving a problem is associated with a set of constraints. The CBM approach to student modelling was proposed by Ohlsson (1992), which accredited learners' mistakes to the fact that they have not yet related theory with practice. Through trial, error, and constructive feedback, the learner recovers from mistakes and can internalise new knowledge about the task. Over time, they make fewer mistakes. The premise behind CMB is that there does not have to be a specific path through a problem – learners are free to take whichever path they wish. However, if the learner violates a constraint then the system will intervene. The execution cycle (Ohlsson & Mitrovic, 07) for a CBM system is: First, match the relevance criteria of all constraints against the current world state. Secondly, for each constraint with a satisfied relevance, match their condition against the current world state. Thirdly, pass the constraint violations and satisfactions to a decision making function and deal with any violations. Finally, wait until the world state changes and then re-run the cycle. CBM requires course authors to define an execution cycle for comparing the state of the learner against the constraint violations and satisfactions (Ohlsson & Mitrovic, 07). This can result in a large number of explicit rules for a learning environment (e.g. SQL-Tutor contains 500+ constraints (Mitrovic & Martin, 07)).

A.5 Case-Based Reasoning

Another alternative AI reasoning approach is *Case-Based Reasoning (CBR)* (Ohlsson & Mitrovic, 07, Aleven, 03) which defines relationships between entities by modelling the structure of an exemplar solution. CBR does not model the production rules required to carry out the steps – instead computational models are created using previous knowledge, or example solutions in order to solve future problems (Aamodt & Plaza, 94). This approach is often used in ITS's that deliver legal studies learning by helping the learner find relevant legal findings to defend their case.

A.6 Algorithmic and Rule-Based Reasoning

Algorithmic and *rule-based reasoning* is another non-AI approach to user modelling and intelligent decision making that is commonly used in AEH systems. For example,

the APeLS system reasons over multiple models of the learner and their domains with an adaptive engine that is written in a rule-based language (Conlan et al., 02, Conlan & Wade, 04). The metrics that represent the user, domain, pedagogy or other models are persisted in relational or XML databases. The reasoning can then be carried out with normative decision-making rules (Kabassi & Virvou, 06), or with narrative rules (Conlan et al., 02) in order to link the learner's style or competencies to relevant learning objects. In the Web-F SMILE service (Kabassi & Virvou, 06), a multi-attribute decision engine calculates the relative utility of an option, in order to advise the system how to provide support to the learner. This is done by breaking each possible mechanism for support into its independent and weighted dimensions e.g. how recently it was supported or the learner's previous response to a similar support. The relative utility of each of these dimensions is weighed against each other. The optimum decision is the option with the highest expected utility – how well an outcome is expected to help the learner.

A.7 Statistical Modelling

Bayesian models such as the Hidden Markov Modelling (HMM) (Rabiner, 89, Beal et al., 07) are *statistical modelling* systems that have been used in ITS systems. For example, the Betty's Brain teachable agent (Kinnebrew et al., 11, Schwartz et al., 09) and AEH ARTS environment (Mettler et al., 11) both make use of HMH. In the case of Betty's Brain, data mining was used to analyse the log files of learners in order to automate the derivation of a HMM. HMM models the probabilities of transitioning between different aggregated choice states; *"For example, one student read the resources, and then made a number of edits to the map. Afterwards, the student submitted the map to a quiz, made some more edits, and then asked a pair of questions of the map. In raw form, the sequence can be overwhelming:* $R \rightarrow M \rightarrow M \rightarrow M \rightarrow A \rightarrow M \rightarrow M \rightarrow M \rightarrow M \rightarrow M \rightarrow M \rightarrow M \rightarrow M \rightarrow M \rightarrow Q \rightarrow M \rightarrow M \rightarrow A \rightarrow A$*"* (Schwartz et al., 2009). Aggregated choice states describe a pattern of activities and transitions from one activity to another. This means that common clusters of observable actions can then described as an overarching state or goal. These HMM model the probabilities of transitioning between different aggregated choice states (Rabiner, 89, Schwartz et al., 09). This pattern matching and level of probability is used to adapt the learning environment.

Appendix B Metacognitive Awareness Inventory - Regulation of Cognition

PLANNING --Planning, goal setting, and allocating resources *prior* to learning **INFORMATION MANAGEMENT STRATEGIES** --Skills and strategy sequences used to process information more efficiently (e.g., organising, elaborating, summarizing, selective focusing) **COMPREHENSION MONITORING** --Assessment of one's learning or strategy use **DEBUGGING STRATEGIES** --Strategies used to correct comprehension and performance errors **EVALUATION** --Analysis of performance and strategy effectiveness after a learning episode	**PLANNING** **M01.** They pace themselves while learning in order to have enough time. **M02.** They think about what they really need to learn before they begin a task. **M03.** They set specific goals before they begin a task. **M04.** They ask themselves questions about the material before they begin. **M05.** They think of several ways to solve a problem and choose the best one. **M06.** They read instructions carefully before they begin a task. **M07.** They organise their time to best accomplish their goals.

INFORMATION MANAGEMENT STRATEGIES	**COMPREHENSION MONITORING**
M08. They slow down when they encounter important information.	**M18.** They ask themselves periodically if they are meeting their goals.
M09. They consciously focus their attention on important information.	**M19.** They consider several alternatives to a problem before they answer.
M10. They focus on the meaning and significance of new information.	**M20.** They ask themselves if they have considered all options when solving a problem.
M11. They create their own examples to make information more meaningful.	**M21.** They periodically review to help their understanding of important relationships.
M12. They draw pictures or diagrams to help them understand while learning.	**M22.** They find themselves analyzing the usefulness of strategies while they study.
M13. They try to translate new information into their own words.	**M23.** They find themselves pausing regularly to check their comprehension.
M14. They use the organisational structure of the text to help them learn	**M24.** They ask themselves questions about how well they are doing while learning something new.
M15. They ask themselves if what they're reading is related to what they already know.	
M16. They try to break studying down into smaller steps.	**EVALUATION**
M17. They focus on overall meaning rather than specifics.	**M30.** They know how well they did once they finish a test.
	M31. They ask themselves if there was an easier way to do things after they finish a task.
DEBUGGING STRATEGIES	**M32.** They summarize what they've learned after they finish.
M25. They ask others for help when they don't understand something.	**M33.** They ask themselves how well they accomplish their goals once they are finished.
M26. They change strategies when they fail to understand.	**M34.** They ask themselves if they have considered all options after they solve a problem.
M27. They re-evaluate their assumptions when they get confused.	**M35.** They ask themselves if they learned as much as they could have once they finish a task.
M28. They stop and go back over new information that is not clear.	
M29. They stop and reread when they get confused.	

Table B.1 – MAI – Regulation of Cognition (from Schraw & Dennison, 94)

Appendix C Cognitive Task Model – Regulation of Cognition

Before

A. Before Task – Planning

1.	Constructing a goal
2.	Overview the learning object
3.	Decide to only do particular sections
4.	Decide to quit because content not relevant to goal
5.	Activate prior knowledge
6.	Summarize what was gained from preview
7.	Based on overview, generate initial hypothesis

During

B. Salient behaviours during initial reading

8.	General front to back interaction with a module
9.	Reading only some sections, ones believed to contain critical information based on prior knowledge about the structures used
10.	Skimming
11.	If easy, tackle using automatic processes
12.	Repeating/Restating module just read to hold in working memory
13.	Pausing to reflect on module
14.	Explicitly looking for related concepts or ideas and using them to construct a main idea, gist, or summary
15.	Resetting learning goals at a different level of understanding because module suggests there might be a more appropriate goal

C. Identifying Important Information

16.	Looking for information relevant to personal or professional goals or specific reading goals for this module
17.	Deciding which pieces of information I text are important
18.	Looking specifically for what is 'news' in the reading
19.	Dismissing information presented in content because it is not consistent with prior knowledge
20.	Looking for and acquiring key words
21.	Highlighting, underlining, circling, making notes, outlining or flagging important points in module
22.	Explicitly skipping examples because general points, which the reader is seeking are not provided in examples
23.	Adjusting importance ratings as additional text is encountered

D. Conscious Inference-Making

24.	Inferring the referent of a concept
25.	Inferring the connotations of concepts
26.	Relating information encountered in the content to prior knowledge
27.	Making inferences about the state of the state of the world depicted in the module
28.	Confirming/disconfirming an inference with information in subsequent content
29.	Stating/drawing of implied conclusion

E. Integrating Different Parts

30.	Explicitly attempting to get the 'big picture' of meaning before worrying about detail
31.	Holding representations of the ideas developed in text in working memory
32.	Combining structure and contextual clues to determine meaning
33.	Looking elsewhere in module for information related to a point currently being encountered

F. Interpreting

34.	Visualising concepts and relationships
35.	Instantiating prior knowledge that is activated by information in the

text
36. Constructing interpretive conclusions
37. Constructing interpretive categorizations
38. Physically or mentally doing what a test instructs
39. Constructing alternative interpretations
40. Constructing alternative perspectives
41. Pretending to deliberate with others while engaging in module

After

G. After Reading
42. Rereading after the first iteration
43. Constructing cohesive summary
44. Self-questioning, self-testing
45. Imagining how hypothetical situations may be viewed in light of information
46. Reflecting on information in module, with possibility of this reflection going on for a long period of time
47. Rereading parts of module following reflection in order to reconsider insights gained during reflection
48. Possibly reconstructing understanding of the module
49. Changing one's response to the module
50. Reflecting on module in anticipation of using it later

Table C.1 - Reading Protocols (from Pressly and Afflerbach, 95)

Appendix D Goby Web Application Storyboard

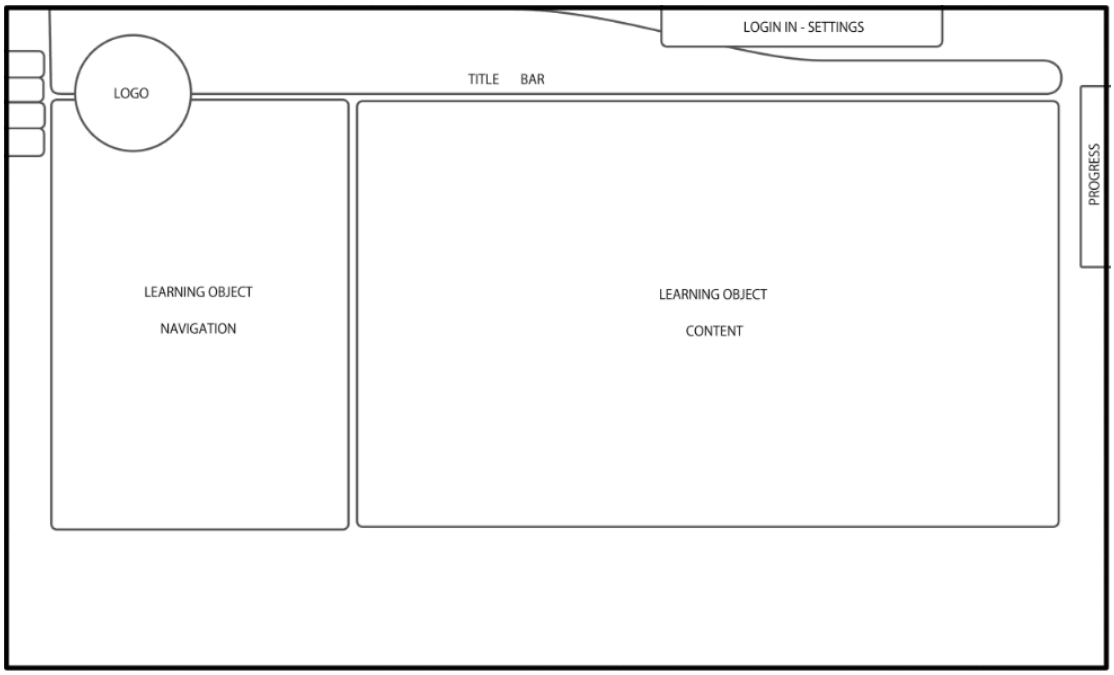


Figure D 1 - Goby Home Page

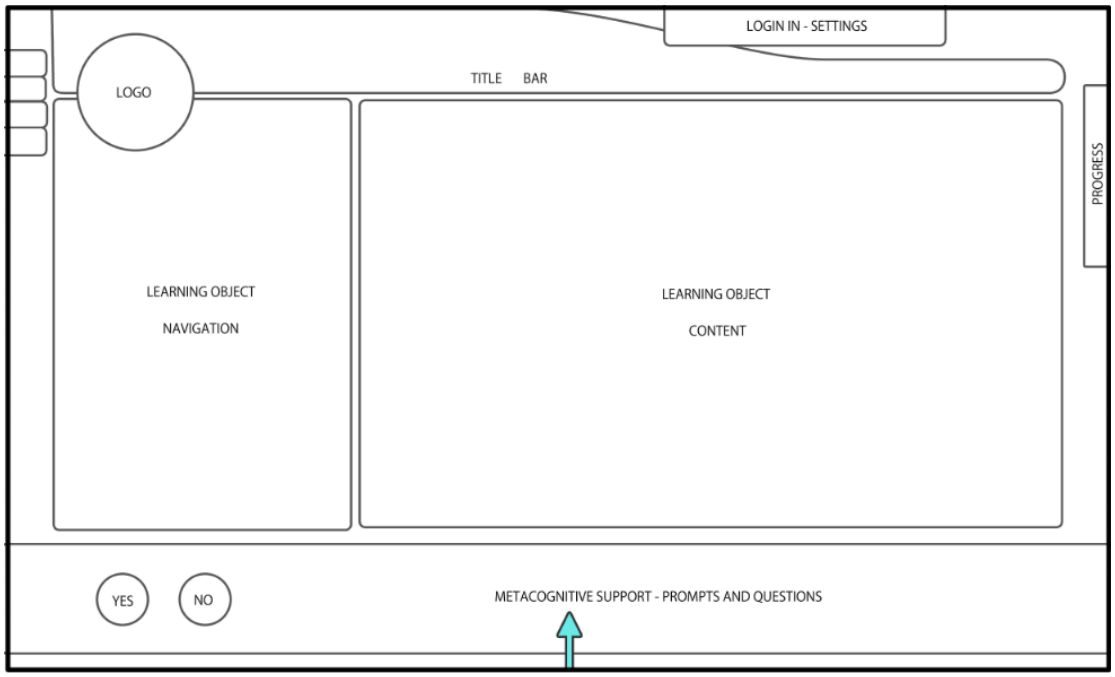


Figure D 2 - Metacognitive Support slides up as a panel on the bottom of the page

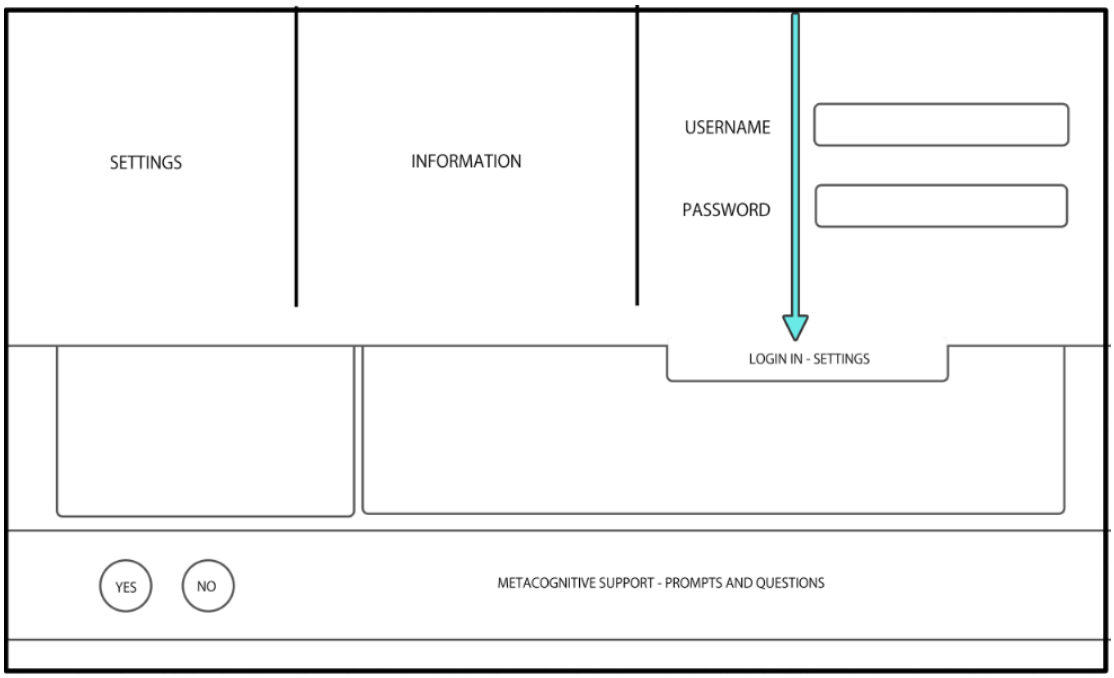


Figure D 3 - Extra related information and functionality is provided in a hidden panel on the top of the page

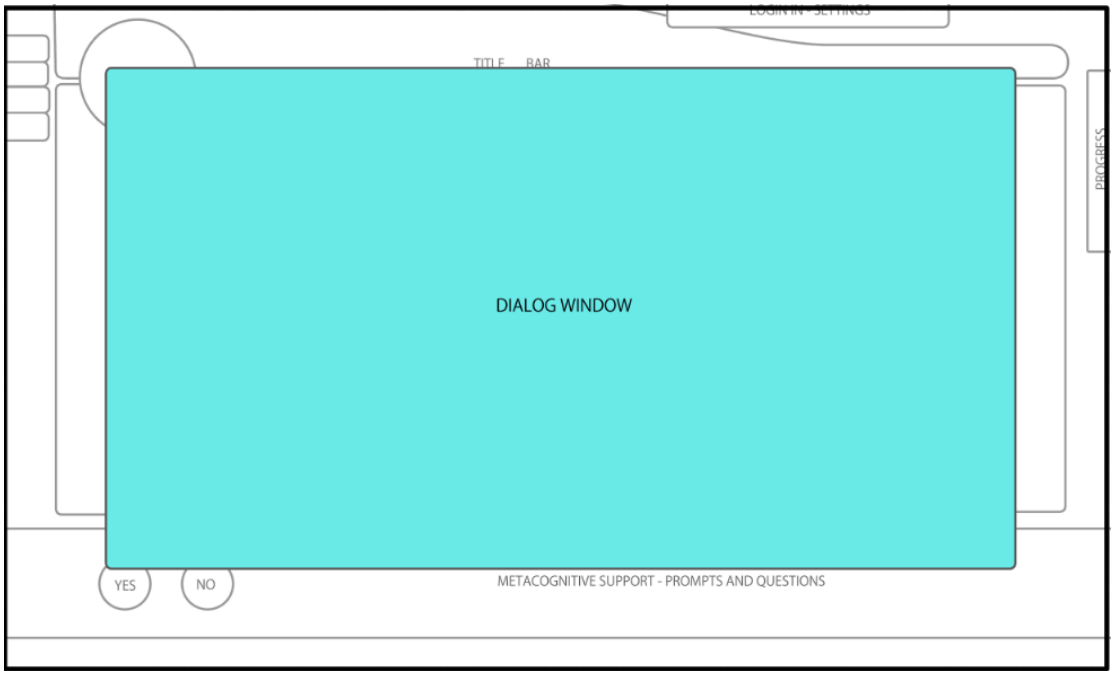


Figure D 4 - A dialog window presents secondary information

Appendix E Baseline Trait Model

```
<?xml version="1.0" encoding="UTF-8"?>
<collection>
    <description>
        Stereotypical values of the Metacognitive Awareness Inventory Factors (Only Planning and Information Management Strategies)
    </description>
    <factor id="trait_pln" name="Planning" confidence="1">
        <item name="plan_pace" desc="I pace myself while learning in order to have enough time" rating="2.871287129"/>
        <item name="plan_need" desc="I think about what I really need to learn before I begin a task" rating="3.227722772"/>
        <item name="plan_goal" desc="I set specific goals before I begin a task" rating="3.089108911"/>
        <item name="plan_quet" desc="I ask myself questions about the material before I begin" rating="3.03960396"/>
        <item name="plan_solv" desc="I think of several ways to solve a problem and choose the best one" rating="3.752475248"/>
        <item name="plan_inst" desc="I read instructions carefully before I begin a task" rating="3.356435644"/>
        <item name="plan_time" desc="I organise my time to best accomplish my goals" rating="2.811881188"/>
        <comment>

            Planning, goal setting and allocating resources prior to learning

        </comment>
    </factor>
    <factor id="trait_inf" name="Information Management Strategies" confidence="1">
        <item name="info_slow" desc="I slow down when I encounter important information" rating="4.138613861"/>
        <item name="info_infr" desc="I consciously focus my attention on important information" rating="3.861386139"/>
        <item name="info_mean" desc="I focus on the meaning and significance of new information" rating="3.910891089"/>
        <item name="info_exmp" desc="I create my own examples to make information more meaningful" rating="4.01980198"/>
        <item name="info_diag" desc="I draw pictures or diagrams to help" rating="3.633663366"/>
        <item name="info_word" desc="I translate new information into my own words" rating="4.01980198"/>
        <item name="info_stru" desc="I use the organisational structure of the text to help me learn" rating="2.712871287"/>
        <item name="info_rela" desc="I ask myself if what I'm reading is related to what I already know" rating="3.752475248"/>
        <item name="info_step" desc="I try to break studying down into smaller steps" rating="3.772277228"/>
        <item name="info_over" desc="I focus on the overall meaning rather than specifics" rating="3.524752475"/>
        <comment>

            Information Management Strategies are the skills and strategy sequences used to process information more efficiently
            e.g. organising, elaborating, summarizing, selective focusing

        </comment>
    </factor>
    <factor id="trait_cmp" name="Comprehension Monitoring" confidence="1">
        <item name="comp_goal" desc="I ask myself periodically if I am meeting my goals" rating="3.188118812"/>
        <item name="comp_ansr" desc="I consider several alternatives to a problem before I answer" rating="3.673267327"/>
        <item name="comp_prob" desc="I ask myself if I have considered all options when solving a problem" rating="3.673267327"/>
        <item name="comp_revu" desc="I periodically review to help me understand important relationships" rating="3.346534653"/>
        <item name="comp_strt" desc="I find myself analysing the usefulness of strategies while I study" rating="3.316831683"/>
        <item name="comp_paus" desc="I find myself pausing regularly to check my comprehension" rating="3.465346535"/>
        <item name="comp_qunu" desc="I ask myself questions about how well I am doing while learning something new"
rating="3.079207921"/>
        <comment>

            Assessment of own learning or strategy use

        </comment>
    </factor>
    <factor id="trait_dbg" name="Debugging Strategies" confidence="1">
        <item name="debg_help" desc="I ask others for help when I don't understand something" rating="3.732673267"/>
        <item name="debg_strt" desc="I change strategies when I fail to understand" rating="3.594059406"/>
        <item name="debg_revl" desc="I re-evaluate my assumptions when I get confused" rating="3.851485149"/>
        <item name="debg_ninf" desc="I stop and go back over new information that is not clear" rating="4.287128713"/>
        <item name="debg_cnfu" desc="I stop and reread when I get confused" rating="4.465346535"/>
        <comment>

            Strategies used to correct comprehension and performance errors

        </comment>
    </factor>
    <factor id="trait_evl" name="Evaluation" confidence="1">
        <item name="eval_well" desc="I know how well I did once I finish a test" rating="3.485148515"/>
        <item name="eval_easy" desc="I ask myself if there was an easier way to do things after I finish a task"
rating="3.811881188"/>
        <item name="eval_sumr" desc="I summarise what I've learned after I finish" rating="3.198019802"/>
        <item name="eval_goal" desc="I ask myself how well I accomplish my goals once I'm finished" rating="3.178217822"/>
        <item name="eval_optn" desc="I ask myself if I have considered all options after I solve a problem" rating="3.277227723"/>
        <item name="eval_lern" desc="I ask myself if I learned as much as I could have once I finish a task" rating="2.782178218"/>
        <comment>

            Analysis of performance and strategy effectiveness after a learning episode

        </comment>
    </factor>
</collection>
```

Appendix F Trait-Task mapping

```
<?xml version="1.0" encoding="UTF-8"?>
<relationships>
    <description>
        Each activity relates to a number of items on the MAI survey
    </description>
    <activity subActId="Before the Task" actId="start_1">
        <subActivity subActId="act_1_1" desc="Constructing a goal">
            <rel item="plan_need" importance="10"/>
            <rel item="plan_inst" importance="8"/>
            <rel item="plan_goal" importance="7"/>
        </subActivity>
        <subActivity subActId="act_1_2" desc="Overviewing the learning object">
            <rel item="plan_quet" importance="8"/>
            <rel item="info_diag" importance="6"/>
            <rel item="info_over" importance="7"/>
            <rel item="info_stru" importance="8"/>
        </subActivity>
        <subActivity subActId="act_1_3" desc="Decide only to do particular sections, and what sections">
            <rel item="plan_quet" importance="10"/>
            <rel item="info_mean" importance="5"/>
            <rel item="comp_goal" importance="7"/>
        </subActivity>
        <subActivity subActId="act_1_4" desc="Decide to quit because the content is not relevant to the goal">
            <rel item="info_rela" importance="6"/>
            <rel item="comp_goal" importance="10"/>
            <rel item="comp_strt" importance="9"/>
            <rel item="comp_qunu" importance="6"/>
        </subActivity>
        <subActivity subActId="act_1_5" desc="Activate prior knowledge and related knowledge">
            <rel item="info_mean" importance="4"/>
            <rel item="info_rela" importance="8"/>
            <rel item="info_word" importance="3"/>
        </subActivity>
        <subActivity subActId="act_1_6" desc="Summarize what was gained from previewing">
            <rel item="info_over" importance="8"/>
            <rel item="info_mean" importance="6"/>
            <rel item="eval_goal" importance="10"/>
        </subActivity>
        <subActivity subActId="act_1_7" desc="Based on overview, generate initial hypothesis">
            <rel item="info_infr" importance="8"/>
            <rel item="info_word" importance="7"/>
            <rel item="eval_goal" importance="4"/>
        </subActivity>
    </activity>
    <activity subActId="Sailent behaviours during initial reading of the learning object" id="during_1">
        <subActivity subActId="act_2_1" desc="General front ot back interaction of the LO">
            <rel item="plan_pace" importance="5"/>
            <rel item="plan_time" importance="6"/>
            <rel item="info_slow" importance="8"/>
            <rel item="info_step" importance="4"/>
        </subActivity>
        <subActivity subActId="act_2_2" desc="Reading only some sections, ones believed to contain critical information based on
prior knowledge about structures used">
            <rel item="info_infr" importance="10"/>
            <rel item="info_diag" importance="8"/>
            <rel item="info_stru" importance="6"/>
        </subActivity>
        <subActivity subActId="act_2_3" desc="Skimming">
            <rel item="info_over" importance="10"/>
        </subActivity>
        <subActivity subActId="act_2_4" desc="If LO is easy, tackle using automatic process with few intentional conscious strategies
aimed at meaning construction. Reliance on this automatic processes until something goes wrong (Feeling of miscomprehension)">
            <rel item="comp_goal" importance="6"/>
            <rel item="info_rela" importance="6"/>
            <rel item="debg_strt" importance="4"/>
        </subActivity>
        <subActivity subActId="act_2_5" desc="Repeating/Restating LO just read to hold in working memory">
            <rel item="info_step" importance="6"/>
            <rel item="info_word" importance="10"/>
            <rel item="info_diag" importance="5"/>
        </subActivity>
        <subActivity subActId="act_2_6" desc="Pausing to reflect on module">
            <rel item="eval_sumr" importance="7"/>
            <rel item="info_infr" importance="8"/>
            <rel item="debg_strt" importance="4"/>
            <rel item="debg_ninf" importance="6"/>
        </subActivity>
        <subActivity subActId="act_2_7" desc="Explicitly looking for related concepts or ideas and using them to construct a main
idea, gist, or summary">
            <rel item="info_stru" importance="8"/>
        </subActivity>
        <subActivity subActId="act_2_8" desc="Resetting reading/learning goals at a different level of understanding because LO
suggests there might be a more appropriate goal">
            <rel item="debg_ninf" importance="5"/>
            <rel item="comp_revu" importance="6"/>
            <rel item="debg_strt" importance="8"/>
        </subActivity>
        <comment>
            During the task
        </comment>
    </activity>
    <activity subActId="Identifying important information" id="during_2">
        <subActivity subActId="act_3_1" desc="Looking for information relevant to personal or professional goals or specific reading
goals for this LO">
            <rel item="plan_goal" importance="9"/>
```

```
            <rel item="plan_time" importance="6"/>
            <rel item="info_stru" importance="8"/>
        </subActivity>
        <subActivity subActId="act_3_2" desc="Deciding which pieces of information I text are important ">
            <rel item="info_infr" importance="9"/>
            <rel item="plan_step" importance="5"/>
        </subActivity>
        <subActivity subActId="act_3_3" desc="Looking specifically for what is ?news? in the reading">
            <rel item="info_stru" importance="10"/>
            <rel item="info_rela" importance="7"/>
        </subActivity>
        <subActivity subActId="act_3_4" desc="Dismissing information presented in text because it is not consistent with prior
knowledge">
            <rel item="debg_cnfu" importance="7"/>
            <rel item="info_rela" importance="6"/>
            <rel item="comp_prob" importance="4"/>
        </subActivity>
        <subActivity subActId="act_3_5" desc="Looking for and acquiring key words">
            <rel item="info_diag" importance="8"/>
            <rel item="info_infr" importance="8"/>
        </subActivity>
        <subActivity subActId="act_3_6" desc="Highlighting, underlining, circling, making notes, outlining or somehow flagging
important points in LO, including important examples">
            <rel item="info_infr" importance="8"/>
            <rel item="info_slow" importance="9"/>
        </subActivity>
        <subActivity subActId="act_3_7" desc="Explicitly skipping examples because general points, which the reader is seeking are
not provided in examples">
            <rel item="info_diag" importance="4"/>
            <rel item="info_infr" importance="7"/>
        </subActivity>
        <subActivity subActId="act_3_8" desc="Adjusting importance ratings as additional text is encountered ">
            <rel item="info_rela" importance="8"/>
            <rel item="comp_revu" importance="6"/>
        </subActivity>
        <comment>
            Identifying important information during the task
        </comment>
    </activity>
    <activity subActId="Conscious inference making" id="during_3">
        <subActivity subActId="act_4_1" desc="Inferring the referent of a concept">
            <rel item="info_diag" importance="10"/>
            <rel item="info_word" importance="8"/>
        </subActivity>
        <subActivity subActId="act_4_2" desc="Inferring the connotations of concepts">
            <rel item="info_word" importance="10"/>
            <rel item="info_diag" importance="8"/>
            <rel item="info_mean" importance="7"/>
        </subActivity>
        <subActivity subActId="act_4_3" desc="Relating information encountered in text to prior knowledge">
            <rel item="plan_quet" importance="5"/>
            <rel item="info_infr" importance="6"/>
            <rel item="info_rela" importance="10"/>
            <rel item="comp_revu" importance="4"/>
        </subActivity>
        <subActivity subActId="act_4_4" desc="Making inferences about the state of the world depicted in the learning object">
            <rel item="info_over" importance="10"/>
            <rel item="info_exmp" importance="6"/>
        </subActivity>
        <subActivity subActId="act_4_5" desc="Confirming an inference with information in subsequent text">
            <rel item="eval_optn" importance="8"/>
            <rel item="comp_ansr" importance="6"/>
        </subActivity>
        <subActivity subActId="act_4_6" desc="Stating or drawing of implied conculsions">
            <rel item="info_exmp" importance="8"/>
            <rel item="info_word" importance="6"/>
        </subActivity>
        <comment>
            Conscious inference making during the task
        </comment>
    </activity>
    <activity subActId="Identifying different parts" id="during_4">
        <subActivity subActId="act_5_1" desc="Explicitly attempting to get the 'big picture' of meaning before worrying about the
detail">
            <rel item="info_over" importance="8"/>
            <rel item="info_infr" importance="9"/>
        </subActivity>
        <subActivity subActId="act_5_2" desc="Holding representations of the ideas developed in text in working memory">
            <rel item="info_step" importance="5"/>
            <rel item="info_word" importance="8"/>
        </subActivity>
        <subActivity subActId="act_5_3" desc="Combining structure and contextual cues to determine meaning">
            <rel item="debg_revl" importance="5"/>
            <rel item="comp_revu" importance="6"/>
        </subActivity>
        <subActivity subActId="act_5_4" desc="Looking elsewhere in the learning object for information related to a point currently
encountered">
            <rel item="info_stru" importance="8"/>
            <rel item="info_slow" importance="5"/>
            <rel item="info_mean" importance="8"/>
        </subActivity>
        <comment>
            Conscious inference making during the task
        </comment>
    </activity>
    <activity subActId="Interpreting" id="during_5">
        <subActivity subActId="act_6_1" desc="Visualising concepts and relations">
            <rel item="info_stru" importance="4"/>
            <rel item="info_diag" importance="10"/>
        </subActivity>
        <subActivity subActId="act_6_2" desc="Instantiating prior knowledge schemata that are activated by information in the
learning object">
            <rel item="info_mean" importance="8"/>
```

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            <rel item="info_infr" importance="7"/>
        </subActivity>
        <subActivity subActId="act_6_3" desc="Constructing interpretive conclusions">
            <rel item="info_word" importance="10"/>
            <rel item="info_exmp" importance="8"/>
            <rel item="info_mean" importance="8"/>
        </subActivity>
        <subActivity subActId="act_6_4" desc="Constructing interpretive categorizations">
            <rel item="info_diag" importance="6"/>
            <rel item="info_infr" importance="8"/>
        </subActivity>
        <subActivity subActId="act_6_5" desc="Physically or mentally doing what the test instructs">
            <rel item="plan_inst" importance="8"/>
            <rel item="plan_time" importance="4"/>
        </subActivity>
        <subActivity subActId="act_6_6" desc="Constructing alternative interpretations">
            <rel item="plan_need" importance="6"/>
            <rel item="debg_help" importance="4"/>
            <rel item="info_mean" importance="6"/>
        </subActivity>
        <subActivity subActId="act_6_7" desc="Constructing alternative perspectives">
            <rel item="comp_prob" importance="5"/>
            <rel item="debg_ninf" importance="4"/>
            <rel item="info_infr" importance="8"/>
            <rel item="plan_solv" importance="6"/>
        </subActivity>
        <subActivityNOTRAIT subActId="act_6_8" desc="Pretending to deliberate with others while engaged with the learning object"/>
        <comment>
            Interpreting during the task
        </comment>
    </activity>
    <activity subActId="After Reading" id="end_1">
        <subActivity subActId="act_7_1" desc="Rereading after first iteration">
            <rel item="comp_prob" importance="6"/>
            <rel item="info_step" importance="7"/>
            <rel item="eval_sumr" importance="4"/>
        </subActivity>
        <subActivity subActId="act_7_2" desc="Constructing a cohesive summary">
            <rel item="info_diag" importance="7"/>
            <rel item="info_exmp" importance="4"/>
            <rel item="eval_goal" importance="5"/>
        </subActivity>
        <subActivity subActId="act_7_3" desc="Self-questioning, self-testing">
            <rel item="eval_well" importance="8"/>
            <rel item="eval_lern" importance="6"/>
            <rel item="eval_goal" importance="7"/>
        </subActivity>
        <subActivity subActId="act_7_4" desc="Imagining how hypothetical situations might be viewed in light of information in the
learning object">
            <rel item="info_exmp" importance="8"/>
            <rel item="info_infr" importance="6"/>
            <rel item="plan_inst" importance="4"/>
        </subActivity>
        <subActivity subActId="act_7_5" desc="Reflecting on information in the learning object">
            <rel item="info_over" importance="7"/>
            <rel item="plan_need" importance="6"/>
        </subActivity>
        <subActivity subActId="act_7_6" desc="Rereading parts of the learning object following reflection in order to reconsider
insights gained during reflection"/>
        <subActivity subActId="act_7_7" desc="Continually evaluating and possibly reconstructing understanding of the learning
object">
            <rel item="debg_help" importance="8"/>
            <rel item="debg_strt" importance="4"/>
            <rel item="debg_ninf" importance="8"/>
            <rel item="debg_revl" importance="3"/>
        </subActivity>
        <subActivity subActId="act_7_8" desc="Changing one's responses to the learning objects as understing is reconstructed">
            <rel item="eval_goal" importance="6"/>
            <rel item="comp_prob" importance="8"/>
            <rel item="plan_solv" importance="9"/>
        </subActivity>
        <subActivity subActId="act_7_9" desc="Reflecting on the learning object in anticipation of using it later">
            <rel item="eval_well" importance="8"/>
            <rel item="info_word" importance="9"/>
            <rel item="info_mean" importance="10"/>
        </subActivity>
        <comment>
            After reading the task, interpretation
        </comment>
    </activity>
</relationships>
```

Appendix G Sample Learner Model

The following learner trait model and progress model are extracts out of the model captured by one of the Goby participants.

Learner Trait Model


```
<?xml version="1.0" encoding="UTF-8"?>
<lnrTrait learnerId="x">
    <factor id="trait_pln" name="Planning">
        <item confidence="1" desc="I pace myself while learning in order to have enough time" name="plan_pace" rating="2.871287129"
timestamp="2010-11-09 01:14:41"/>
        <item confidence="1" desc="I think about what I really need to learn before I begin a task" name="plan_need"
rating="3.227722772" timestamp="2010-11-09 01:14:41"/>
        <item confidence="1" desc="I set specific goals before I begin a task" name="plan_goal" rating="3.089108911" timestamp="2010-
11-09 01:14:41"/>
        <item confidence="1" desc="I ask myself questions about the material before I begin" name="plan_quet" rating="3.03960396"
timestamp="2010-11-09 01:14:41"/>
        <item confidence="1" desc="I think of several ways to solve a problem and choose the best one" name="plan_solv"
rating="3.752475248" timestamp="2010-11-09 01:14:41"/>
        <item confidence="1" desc="I read instructions carefully before I begin a task" name="plan_inst" rating="3.356435644"
timestamp="2010-11-09 01:14:41"/>
        <item confidence="1" desc="I organise my time to best accomplish my goals" name="plan_time" rating="2.811881188"
timestamp="2010-11-09 01:14:41"/>
    </factor>
    <factor id="trait_inf" name="Information Management Strategies">
        <item confidence="1" desc="I slow down when I encounter important information" name="info_slow" rating="4.138613861"
timestamp="2010-11-09 01:14:41"/>
        <item confidence="1" desc="I consciously focus my attention on important information" name="info_infr" rating="3.861386139"
timestamp="2010-11-09 01:14:41"/>
        <item confidence="1" desc="I focus on the meaning and significance of new information" name="info_mean" rating="3.910891089"
timestamp="2010-11-09 01:14:41"/>
        <item confidence="1" desc="I create my own examples to make information more meaningful" name="info_exmp" rating="4.01980198"
timestamp="2010-11-09 01:14:41"/>
        <item confidence="1" desc="I draw pictures or diagrams to help" name="info_diag" rating="3.633663366" timestamp="2010-11-09
01:14:41"/>
        <item confidence="1" desc="I translate new information into my own words" name="info_word" rating="4.01980198"
timestamp="2010-11-09 01:14:41"/>
        <item confidence="1" desc="I use the organisational structure of the text to help me learn" name="info_stru"
rating="2.712871287" timestamp="2010-11-09 01:14:41"/>
        <item confidence="1" desc="I ask myself if what I'm reading is related to what I already know" name="info_rela"
rating="3.752475248" timestamp="2010-11-09 01:14:41"/>
        <item confidence="1" desc="I try to break studying down into smaller steps" name="info_step" rating="3.772277228"
timestamp="2010-11-09 01:14:41"/>
        <item confidence="1" desc="I focus on the overall meaning rather than specifics" name="info_over" rating="3.524752475"
timestamp="2010-11-09 01:14:41"/>
    </factor>
    <factor id="trait_cmp" name="Comprehension Monitoring">
        <item confidence="1" desc="I ask myself periodically if I am meeting my goals" name="comp_goal" rating="3.188118812"
timestamp="2010-11-09 01:14:41"/>
        <item confidence="1" desc="I consider several alternatives to a problem before I answer" name="comp_ansr"
rating="3.673267327" timestamp="2010-11-09 01:14:41"/>
        <item confidence="1" desc="I ask myself if I have considered all options when solving a problem" name="comp_prob"
rating="3.673267327" timestamp="2010-11-09 01:14:41"/>
        <item confidence="1" desc="I periodically review to help me understand important relationships" name="comp_revu"
rating="3.346534653" timestamp="2010-11-09 01:14:41"/>
        <item confidence="1" desc="I find myself analysing the usefulness of strategies while I study" name="comp_strt"
rating="3.316831683" timestamp="2010-11-09 01:14:41"/>
        <item confidence="1" desc="I find myself pausing regularly to check my comprehension" name="comp_paus" rating="3.465346535"
timestamp="2010-11-09 01:14:41"/>
        <item confidence="1" desc="I ask myself questions about how well I am doing while learning something new" name="comp_qunu"
rating="3.079207921" timestamp="2010-11-09 01:14:41"/>
    </factor>
    <factor id="trait_dbg" name="Debugging Strategies">
        <item confidence="1" desc="I ask others for help when I don’t understand something" name="debg_help" rating="3.732673267"
timestamp="2010-11-09 01:14:41"/>
        <item confidence="1" desc="I change strategies when I fail to understand" name="debg_strt" rating="3.594059406"
timestamp="2010-11-09 01:14:41"/>
        <item confidence="1" desc="I re-evaluate my assumptions when I get confused" name="debg_revl" rating="3.851485149"
timestamp="2010-11-09 01:14:41"/>
        <item confidence="1" desc="I stop and go back over new information that is not clear" name="debg_ninf" rating="4.287128713"
timestamp="2010-11-09 01:14:41"/>
        <item confidence="1" desc="I stop and reread when I get confused" name="debg_cnfu" rating="4.465346535" timestamp="2010-11-09
01:14:41"/>
    </factor>
    <factor id="trait_evl" name="Evaluation">
        <item confidence="1" desc="I know how well I did once I finish a test" name="eval_well" rating="3.485148515" timestamp="2010-
11-09 01:14:41"/>
        <item confidence="1" desc="I ask myself if there was an easier way to do things after I finish a task" name="eval_easy"
rating="3.811881188" timestamp="2010-11-09 01:14:41"/>
        <item confidence="1" desc="I summarise what I’ve learned after I finish" name="eval_sumr" rating="3.198019802"
timestamp="2010-11-09 01:14:41"/>
        <item confidence="1" desc="I ask myself how well I accomplish my goals once I’m finished" name="eval_goal"
rating="3.178217822" timestamp="2010-11-09 01:14:41"/>
        <item confidence="1" desc="I ask myself if I have considered all options after I solve a problem" name="eval_optn"
rating="3.277227723" timestamp="2010-11-09 01:14:41"/>
        <item confidence="1" desc="I ask myself if I learned as much as I could have once I finish a task" name="eval_lern"
rating="2.782178218" timestamp="2010-11-09 01:14:41"/>
    </factor>
    <factor id="trait_pln" name="Planning">
        <item confidence="2" desc="I think about what I really need to learn before I begin a task" name="plan_need"
rating="3.477722772" timestamp="2010-11-09 01:32:26"/>
```

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    </factor>
    <factor id="trait_evl" name="Evaluation">
        <item confidence="2" desc="I know how well I did once I finish a test" name="eval_well" rating="3.735148515" timestamp="2010-
11-09 01:34:48"/>
    </factor>
    <factor id="trait_evl" name="Evaluation">
        <item confidence="2" desc="I ask myself how well I accomplish my goals once I'm finished" name="eval_goal"
rating="3.428217822" timestamp="2010-11-09 01:35:41"/>
    </factor>
    <factor id="trait_dbg" name="Debugging Strategies">
        <item confidence="2" desc="I ask others for help when I don't understand something" name="debg_help" rating="3.982673267"
timestamp="2010-11-09 01:35:55"/>
    </factor>
    <factor id="trait_inf" name="Information Management Strategies">
        <item confidence="2" desc="I focus on the overall meaning rather than specifics" name="info_over" rating="3.774752475"
timestamp="2010-11-26 16:13:21"/>
    </factor>
    <factor id="trait_inf" name="Information Management Strategies">
        <item confidence="2" desc="I create my own examples to make information more meaningful" name="info_exmp" rating="4.26980198"
timestamp="2010-11-26 16:13:35"/>
    </factor>
    <factor id="trait_evl" name="Evaluation">
        <item confidence="2" desc="I ask myself if I learned as much as I could have once I finish a task" name="eval_lern"
rating="3.032178218" timestamp="2010-11-26 16:14:18"/>
    </factor>
    <factor id="trait_inf" name="Information Management Strategies">
        <item confidence="2" desc="I draw pictures or diagrams to help" name="info_diag" rating="3.883663366" timestamp="2010-11-26
16:14:48"/>
    </factor>
    <factor id="trait_cmp" name="Comprehension Monitoring">
        <item confidence="2" desc="I ask myself if I have considered all options when solving a problem" name="comp_prob"
rating="3.923267327" timestamp="2010-11-26 16:15:08"/>
    </factor>
    <factor id="trait_inf" name="Information Management Strategies">
        <item confidence="2" desc="I consciously focus my attention on important information" name="info_infr" rating="4.111386139"
timestamp="2010-11-26 16:15:57"/>
    </factor>
    <factor id="trait_inf" name="Information Management Strategies">
        <item confidence="2" desc="I focus on the meaning and significance of new information" name="info_mean" rating="4.160891089"
timestamp="2010-11-26 16:16:15"/>
    </factor>
    <factor id="trait_pln" name="Planning">
        <item confidence="2" desc="I read instructions carefully before I begin a task" name="plan_inst" rating="3.606435644"
timestamp="2010-11-26 16:16:47"/>
    </factor>
    <factor id="trait_inf" name="Information Management Strategies">
        <item confidence="3" desc="I draw pictures or diagrams to help" name="info_diag" rating="4.133663366" timestamp="2010-11-26
16:17:11"/>
    </factor>
    <factor id="trait_inf" name="Information Management Strategies">
        <item confidence="2" desc="I translate new information into my own words" name="info_word" rating="4.26980198"
timestamp="2010-11-26 16:17:56"/>
    </factor>
    <factor id="trait_inf" name="Information Management Strategies">
        <item confidence="3" desc="I consciously focus my attention on important information" name="info_infr" rating="4.361386139"
timestamp="2010-11-26 16:18:08"/>
    </factor>
    <factor id="trait_inf" name="Information Management Strategies">
        <item confidence="2" desc="I use the organisational structure of the text to help me learn" name="info_stru"
rating="2.962871287" timestamp="2010-11-26 16:18:40"/>
    </factor>
    <factor id="trait_inf" name="Information Management Strategies">
        <item confidence="2" desc="I slow down when I encounter important information" name="info_slow" rating="4.388613861"
timestamp="2010-11-26 16:18:48"/>
    </factor>
    <factor id="trait_dbg" name="Debugging Strategies">
        <item confidence="2" desc="I re-evaluate my assumptions when I get confused" name="debg_revl" rating="4.101485149"
timestamp="2010-11-26 16:19:15"/>
    </factor>
    <factor id="trait_inf" name="Information Management Strategies">
        <item confidence="2" desc="I try to break studying down into smaller steps" name="info_step" rating="4.022277228"
timestamp="2010-11-26 16:20:33"/>
    </factor>
    <factor id="trait_inf" name="Information Management Strategies">
        <item confidence="3" desc="I focus on the overall meaning rather than specifics" name="info_over" rating="4.024752475"
timestamp="2010-11-26 16:21:23"/>
    </factor>
    <factor id="trait_inf" name="Information Management Strategies">
        <item confidence="3" desc="I create my own examples to make information more meaningful" name="info_exmp" rating="4.51980198"
timestamp="2010-11-26 16:21:36"/>
    </factor>
    <factor id="trait_evl" name="Evaluation">
        <item confidence="2" desc="I ask myself if I have considered all options after I solve a problem" name="eval_optn"
rating="3.527227723" timestamp="2010-11-26 16:21:58"/>
    </factor>
    <factor id="trait_inf" name="Information Management Strategies">
        <item confidence="4" desc="I focus on the overall meaning rather than specifics" name="info_over" rating="4.149752475"
timestamp="2010-11-26 16:22:31"/>
    </factor>
    <factor id="trait_inf" name="Information Management Strategies">
        <item confidence="2" desc="I ask myself if what I'm reading is related to what I already know" name="info_rela"
rating="4.002475248" timestamp="2010-11-26 16:22:43"/>
    </factor>
    <factor id="trait_inf" name="Information Management Strategies">
        <item confidence="3" desc="I focus on the meaning and significance of new information" name="info_mean" rating="4.410891089"
timestamp="2010-11-26 16:22:56"/>
    </factor>
    <factor id="trait_inf" name="Information Management Strategies">
        <item confidence="4" desc="I draw pictures or diagrams to help" name="info_diag" rating="4.258663366" timestamp="2010-11-26
16:23:05"/>
    </factor>
    <factor id="trait_cmp" name="Comprehension Monitoring">
        <item confidence="2" desc="I periodically review to help me understand important relationships" name="comp_revu"
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rating="3.596534653" timestamp="2010-11-26 16:23:30"/>
    </factor>
    <factor id="trait_inf" name="Information Management Strategies">
        <item confidence="4" desc="I consciously focus my attention on important information" name="info_infr" rating="4.486386139"
timestamp="2010-11-26 16:23:38"/>
    </factor>
    <factor id="trait_inf" name="Information Management Strategies">
        <item confidence="3" desc="I slow down when I encounter important information" name="info_slow" rating="4.638613861"
timestamp="2010-11-26 16:23:49"/>
    </factor>
    <factor id="trait_inf" name="Information Management Strategies">
        <item confidence="5" desc="I draw pictures or diagrams to help" name="info_diag" rating="4.383663366" timestamp="2010-11-26
16:24:02"/>
    </factor>
    <factor id="trait_dbg" name="Debugging Strategies">
        <item confidence="2" desc="I stop and reread when I get confused" name="debg_cnfu" rating="4.715346535" timestamp="2010-11-26
16:24:11"/>
    </factor>
    <factor id="trait_inf" name="Information Management Strategies">
        <item confidence="3" desc="I use the organisational structure of the text to help me learn" name="info_stru"
rating="3.212871287" timestamp="2010-11-26 16:24:26"/>
    </factor>
    <factor id="trait_inf" name="Information Management Strategies">
        <item confidence="5" desc="I consciously focus my attention on important information" name="info_infr" rating="4.611386139"
timestamp="2010-11-26 16:24:36"/>
    </factor>
    <factor id="trait_pln" name="Planning">
        <item confidence="2" desc="I set specific goals before I begin a task" name="plan_goal" rating="3.339108911" timestamp="2010-
11-26 16:25:02"/>
    </factor>
    <factor id="trait_dbg" name="Debugging Strategies">
        <item confidence="2" desc="I stop and go back over new information that is not clear" name="debg_ninf" rating="4.537128713"
timestamp="2010-11-26 16:25:11"/>
    </factor>
    <factor id="trait_inf" name="Information Management Strategies">
        <item confidence="4" desc="I use the organisational structure of the text to help me learn" name="info_stru"
rating="3.337871287" timestamp="2010-11-26 16:25:18"/>
    </factor>
    <factor id="trait_evl" name="Evaluation">
        <item confidence="2" desc="I summarise what I've learned after I finish" name="eval_sumr" rating="3.448019802"
timestamp="2010-11-26 16:25:42"/>
    </factor>
    <factor id="trait_inf" name="Information Management Strategies">
        <item confidence="3" desc="I translate new information into my own words" name="info_word" rating="4.51980198"
timestamp="2010-11-26 16:26:00"/>
    </factor>
    <factor id="trait_cmp" name="Comprehension Monitoring">
        <item confidence="2" desc="I ask myself periodically if I am meeting my goals" name="comp_goal" rating="3.438118812"
timestamp="2010-11-26 16:26:08"/>
    </factor>
    <factor id="trait_inf" name="Information Management Strategies">
        <item confidence="5" desc="I focus on the overall meaning rather than specifics" name="info_over" rating="4.274752475"
timestamp="2010-11-26 16:26:15"/>
    </factor>
    <factor id="trait_inf" name="Information Management Strategies">
        <item confidence="6" desc="I draw pictures or diagrams to help" name="info_diag" rating="4.508663366" timestamp="2010-11-26
16:26:20"/>
    </factor>
    <factor id="trait_pln" name="Planning">
        <item confidence="2" desc="I pace myself while learning in order to have enough time" name="plan_pace" rating="3.121287129"
timestamp="2010-11-26 16:26:35"/>
    </factor>
    <factor id="trait_evl" name="Evaluation">
        <item confidence="3" desc="I ask myself how well I accomplish my goals once I'm finished" name="eval_goal"
rating="3.678217822" timestamp="2010-11-26 16:26:55"/>
    </factor>
    <factor id="trait_inf" name="Information Management Strategies">
        <item confidence="4" desc="I focus on the meaning and significance of new information" name="info_mean" rating="4.535891089"
timestamp="2010-11-26 16:27:03"/>
    </factor>
    <factor id="trait_inf" name="Information Management Strategies">
        <item confidence="3" desc="I ask myself if what I'm reading is related to what I already know" name="info_rela"
rating="4.252475248" timestamp="2010-11-26 16:27:12"/>
    </factor>
    <factor id="trait_cmp" name="Comprehension Monitoring">
        <item confidence="2" desc="I find myself analysing the usefulness of strategies while I study" name="comp_strt"
rating="3.566831683" timestamp="2010-11-26 16:27:26"/>
    </factor>
    <factor id="trait_pln" name="Planning">
        <item confidence="2" desc="I ask myself questions about the material before I begin" name="plan_quet" rating="3.28960396"
timestamp="2010-11-26 16:27:42"/>
    </factor>
    <factor id="trait_inf" name="Information Management Strategies">
        <item confidence="5" desc="I use the organisational structure of the text to help me learn" name="info_stru"
rating="3.462871287" timestamp="2010-11-26 16:27:52"/>
    </factor>
    <factor id="trait_pln" name="Planning">
        <item confidence="3" desc="I think about what I really need to learn before I begin a task" name="plan_need"
rating="3.727722772" timestamp="2010-11-26 16:28:08"/>
    </factor>
    <factor id="trait_evl" name="Evaluation">
        <item confidence="3" desc="I know how well I did once I finish a test" name="eval_well" rating="3.985148515" timestamp="2010-
11-26 16:28:19"/>
    </factor>
    <factor id="trait_pln" name="Planning">
        <item confidence="2" desc="I think of several ways to solve a problem and choose the best one" name="plan_solv"
rating="4.002475248" timestamp="2010-11-26 16:28:28"/>
    </factor>
    <factor id="trait_dbg" name="Debugging Strategies">
        <item confidence="2" desc="I change strategies when I fail to understand" name="debg_strt" rating="3.844059406"
timestamp="2010-11-26 16:28:36"/>
    </factor>
    <factor id="trait_inf" name="Information Management Strategies">
```

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        <item confidence="6" desc="I focus on the overall meaning rather than specifics" name="info_over" rating="4.399752475"
timestamp="2010-11-26 16:28:49"/>
    </factor>
    <factor id="trait_pln" name="Planning">
        <item confidence="3" desc="I read instructions carefully before I begin a task" name="plan_inst" rating="3.856435644"
timestamp="2010-11-26 16:28:56"/>
    </factor>
    <factor id="trait_pln" name="Planning">
        <item confidence="2" desc="I organise my time to best accomplish my goals" name="plan_time" rating="3.061881188"
timestamp="2010-12-10 17:51:49"/>
    </factor>
    <factor id="trait_inf" name="Information Management Strategies">
        <item confidence="6" desc="I consciously focus my attention on important information" name="info_infr" rating="4.736386139"
timestamp="2010-12-10 17:52:04"/>
    </factor>
    <factor id="trait_inf" name="Information Management Strategies">
        <item confidence="4" desc="I create my own examples to make information more meaningful" name="info_exmp" rating="4.64480198"
timestamp="2010-12-10 17:52:10"/>
    </factor>
    <factor id="trait_inf" name="Information Management Strategies">
        <item confidence="5" desc="I focus on the meaning and significance of new information" name="info_mean" rating="4.660891089"
timestamp="2010-12-10 17:52:15"/>
    </factor>
    <factor id="trait_inf" name="Information Management Strategies">
        <item confidence="7" desc="I draw pictures or diagrams to help" name="info_diag" rating="4.633663366" timestamp="2010-12-10
17:52:19"/>
    </factor>
    <factor id="trait_inf" name="Information Management Strategies">
        <item confidence="4" desc="I slow down when I encounter important information" name="info_slow" rating="4.763613861"
timestamp="2010-12-10 17:52:24"/>
    </factor>
    <factor id="trait_dbg" name="Debugging Strategies">
        <item confidence="3" desc="I re-evaluate my assumptions when I get confused" name="debg_revl" rating="4.351485149"
timestamp="2010-12-10 17:52:41"/>
    </factor>
    <factor id="trait_inf" name="Information Management Strategies">
        <item confidence="3" desc="I try to break studying down into smaller steps" name="info_step" rating="4.272277228"
timestamp="2010-12-10 17:52:51"/>
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timestamp="2010-12-10 17:52:57"/>
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    <factor id="trait_inf" name="Information Management Strategies">
        <item confidence="4" desc="I translate new information into my own words" name="info_word" rating="4.64480198"
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    </factor>
    <factor id="trait_cmp" name="Comprehension Monitoring">
        <item confidence="2" desc="I consider several alternatives to a problem before I answer" name="comp_ansr"
rating="3.923267327" timestamp="2010-12-10 17:53:10"/>
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    <factor id="trait_inf" name="Information Management Strategies">
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        <item confidence="4" desc="I ask myself if what I'm reading is related to what I already know" name="info_rela"
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    <factor id="trait_dbg" name="Debugging Strategies">
        <item confidence="3" desc="I stop and go back over new information that is not clear" name="debg_ninf" rating="4.787128713"
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    </factor>
    <factor id="trait_inf" name="Information Management Strategies">
        <item confidence="6" desc="I use the organisational structure of the text to help me learn" name="info_stru"
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    <factor id="trait_evl" name="Evaluation">
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Learner Progress Model

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    <nav name="dialogResp">
        <item courseName="SQL Course" lnrName="gobyCourse" pageNum="5" resp="no" sectionName="Creating a Database - Day 2"
subSectionName="DDL : Create Statement" timestamp="2010-11-26 16:21:58" trait="eval_optn"/>
    </nav>
    <nav name="newPage">
        <item courseName="SQL Course" lnrName="gobyCourse" pageNum="6" sectionName="Creating a Database - Day 2" subSectionName="DDL
: Create Statement" timestamp="2010-11-26 16:22:01"/>
    </nav>
    <nav name="dialogSent">
        <item courseName="SQL Course" lnrName="gobyCourse" pageNum="6" sectionName="Creating a Database - Day 2" subSectionName="DDL
: Create Statement" timestamp="2010-11-26 16:22:01" trait="info_over"/>
    </nav>
    <nav name="dialogResp">
        <item courseName="SQL Course" lnrName="gobyCourse" pageNum="6" resp="ok" sectionName="Creating a Database - Day 2"
subSectionName="DDL : Create Statement" timestamp="2010-11-26 16:22:31" trait="info_over"/>
    </nav>
    <nav name="newPage">
        <item courseName="SQL Course" lnrName="gobyCourse" pageNum="7" sectionName="Creating a Database - Day 2" subSectionName="DDL
: Create Statement" timestamp="2010-11-26 16:22:33"/>
    </nav>
    <nav name="dialogSent">
        <item courseName="SQL Course" lnrName="gobyCourse" pageNum="7" sectionName="Creating a Database - Day 2" subSectionName="DDL
: Create Statement" timestamp="2010-11-26 16:22:33" trait="info_rela"/>
    </nav>
    <nav name="dialogResp">
        <item courseName="SQL Course" lnrName="gobyCourse" pageNum="7" resp="yes" sectionName="Creating a Database - Day 2"
subSectionName="DDL : Create Statement" timestamp="2010-11-26 16:22:43" trait="info_rela"/>
    </nav>
    <nav name="newPage">
```

```
        <item   courseName="SQL   Course"   lnrName="gobyCourse"   pageNum="1"   sectionName="Creating   a   Database   -   Day   2"
subSectionName="Table Constraints" timestamp="2010-11-26 16:22:48"/>
    </nav>
    <nav name="dialogSent">
        <item   courseName="SQL   Course"   lnrName="gobyCourse"   pageNum="1"   sectionName="Creating   a   Database   -   Day   2"
subSectionName="Table Constraints" timestamp="2010-11-26 16:22:48" trait="info_mean"/>
    </nav>
    <nav name="dialogResp">
        <item  courseName="SQL  Course"  lnrName="gobyCourse"  pageNum="1"  resp="yes"  sectionName="Creating  a  Database  -  Day  2"
subSectionName="Table Constraints" timestamp="2010-11-26 16:22:56" trait="info_mean"/>
    </nav>
    <nav name="newPage">
        <item   courseName="SQL   Course"   lnrName="gobyCourse"   pageNum="2"   sectionName="Creating   a   Database   -   Day   2"
subSectionName="Table Constraints" timestamp="2010-11-26 16:22:58"/>
    </nav>
    <nav name="dialogSent">
        <item   courseName="SQL   Course"   lnrName="gobyCourse"   pageNum="2"   sectionName="Creating   a   Database   -   Day   2"
subSectionName="Table Constraints" timestamp="2010-11-26 16:22:59" trait="info_diag"/>
    </nav>
    <nav name="dialogResp">
        <item  courseName="SQL  Course"  lnrName="gobyCourse"  pageNum="2"  resp="ok"  sectionName="Creating  a  Database  -  Day  2"
subSectionName="Table Constraints" timestamp="2010-11-26 16:23:05" trait="info_diag"/>
    </nav>
    <nav name="newPage">
        <item   courseName="SQL   Course"   lnrName="gobyCourse"   pageNum="3"   sectionName="Creating   a   Database   -   Day   2"
subSectionName="Table Constraints" timestamp="2010-11-26 16:23:11"/>
    </nav>
    <nav name="dialogSent">
        <item   courseName="SQL   Course"   lnrName="gobyCourse"   pageNum="3"   sectionName="Creating   a   Database   -   Day   2"
subSectionName="Table Constraints" timestamp="2010-11-26 16:23:11" trait="comp_revu"/>
    </nav>
    <nav name="dialogResp">
        <item  courseName="SQL  Course"  lnrName="gobyCourse"  pageNum="3"  resp="yes"  sectionName="Creating  a  Database  -  Day  2"
subSectionName="Table Constraints" timestamp="2010-11-26 16:23:30" trait="comp_revu"/>
    </nav>
    <nav name="newPage">
        <item   courseName="SQL   Course"   lnrName="gobyCourse"   pageNum="4"   sectionName="Creating   a   Database   -   Day   2"
subSectionName="Table Constraints" timestamp="2010-11-26 16:23:32"/>
    </nav>
    <nav name="dialogSent">
        <item   courseName="SQL   Course"   lnrName="gobyCourse"   pageNum="4"   sectionName="Creating   a   Database   -   Day   2"
subSectionName="Table Constraints" timestamp="2010-11-26 16:23:32" trait="info_infr"/>
    </nav>
    <nav name="dialogResp">
        <item  courseName="SQL  Course"  lnrName="gobyCourse"  pageNum="4"  resp="ok"  sectionName="Creating  a  Database  -  Day  2"
subSectionName="Table Constraints" timestamp="2010-11-26 16:23:38" trait="info_infr"/>
    </nav>
    <nav name="newPage">
        <item   courseName="SQL   Course"   lnrName="gobyCourse"   pageNum="5"   sectionName="Creating   a   Database   -   Day   2"
subSectionName="Table Constraints" timestamp="2010-11-26 16:23:40"/>
    </nav>
    <nav name="dialogSent">
        <item   courseName="SQL   Course"   lnrName="gobyCourse"   pageNum="5"   sectionName="Creating   a   Database   -   Day   2"
subSectionName="Table Constraints" timestamp="2010-11-26 16:23:41" trait="info_slow"/>
    </nav>
    <nav name="dialogResp">
        <item  courseName="SQL  Course"  lnrName="gobyCourse"  pageNum="5"  resp="yes"  sectionName="Creating  a  Database  -  Day  2"
subSectionName="Table Constraints" timestamp="2010-11-26 16:23:49" trait="info_slow"/>
    </nav>
    <nav name="newPage">
        <item   courseName="SQL   Course"   lnrName="gobyCourse"   pageNum="6"   sectionName="Creating   a   Database   -   Day   2"
subSectionName="Table Constraints" timestamp="2010-11-26 16:23:51"/>
    </nav>
    <nav name="dialogSent">
        <item   courseName="SQL   Course"   lnrName="gobyCourse"   pageNum="6"   sectionName="Creating   a   Database   -   Day   2"
subSectionName="Table Constraints" timestamp="2010-11-26 16:23:51" trait="info_diag"/>
    </nav>
    <nav name="dialogResp">
        <item  courseName="SQL  Course"  lnrName="gobyCourse"  pageNum="6"  resp="ok"  sectionName="Creating  a  Database  -  Day  2"
subSectionName="Table Constraints" timestamp="2010-11-26 16:24:02" trait="info_diag"/>
    </nav>
    <nav name="newPage">
        <item   courseName="SQL   Course"   lnrName="gobyCourse"   pageNum="7"   sectionName="Creating   a   Database   -   Day   2"
subSectionName="Table Constraints" timestamp="2010-11-26 16:24:03"/>
    </nav>
    <nav name="dialogSent">
        <item   courseName="SQL   Course"   lnrName="gobyCourse"   pageNum="7"   sectionName="Creating   a   Database   -   Day   2"
subSectionName="Table Constraints" timestamp="2010-11-26 16:24:04" trait="debg_cnfu"/>
    </nav>
    <nav name="dialogResp">
        <item  courseName="SQL  Course"  lnrName="gobyCourse"  pageNum="7"  resp="yes"  sectionName="Creating  a  Database  -  Day  2"
subSectionName="Table Constraints" timestamp="2010-11-26 16:24:11" trait="debg_cnfu"/>
    </nav>
    <nav name="newPage">
        <item   courseName="SQL   Course"   lnrName="gobyCourse"   pageNum="8"   sectionName="Creating   a   Database   -   Day   2"
subSectionName="Table Constraints" timestamp="2010-11-26 16:24:13"/>
    </nav>
    <nav name="dialogSent">
        <item   courseName="SQL   Course"   lnrName="gobyCourse"   pageNum="8"   sectionName="Creating   a   Database   -   Day   2"
subSectionName="Table Constraints" timestamp="2010-11-26 16:24:14" trait="info_stru"/>
    </nav>
    <nav name="dialogResp">
        <item  courseName="SQL  Course"  lnrName="gobyCourse"  pageNum="8"  resp="no"  sectionName="Creating  a  Database  -  Day  2"
subSectionName="Table Constraints" timestamp="2010-11-26 16:24:26" trait="info_stru"/>
    </nav>
    <nav name="newPage">
        <item   courseName="SQL   Course"   lnrName="gobyCourse"   pageNum="9"   sectionName="Creating   a   Database   -   Day   2"
subSectionName="Table Constraints" timestamp="2010-11-26 16:24:28"/>
    </nav>
    <nav name="dialogSent">
        <item   courseName="SQL   Course"   lnrName="gobyCourse"   pageNum="9"   sectionName="Creating   a   Database   -   Day   2"
subSectionName="Table Constraints" timestamp="2010-11-26 16:24:28" trait="info_infr"/>
    </nav>
```

```
    <nav name="dialogResp">
        <item courseName="SQL Course" lrnName="gobyCourse" pageNum="9" resp="ok" sectionName="Creating a Database - Day 2"
subSectionName="Table Constraints" timestamp="2010-11-26 16:24:36" trait="info_infr"/>
    </nav>
    <nav name="newPage">
        <item courseName="SQL Course" lrnName="gobyCourse" pageNum="10" sectionName="Creating a Database - Day 2"
subSectionName="Table Constraints" timestamp="2010-11-26 16:24:38"/>
    </nav>
    <nav name="dialogSent">
        <item courseName="SQL Course" lrnName="gobyCourse" pageNum="10" sectionName="Creating a Database - Day 2"
subSectionName="Table Constraints" timestamp="2010-11-26 16:24:38" trait="plan_goal"/>
    </nav>
    <nav name="dialogResp">
        <item courseName="SQL Course" lrnName="gobyCourse" pageNum="10" resp="yes" sectionName="Creating a Database - Day 2"
subSectionName="Table Constraints" timestamp="2010-11-26 16:25:02" trait="plan_goal"/>
    </nav>
    <nav name="newPage">
        <item courseName="SQL Course" lrnName="gobyCourse" pageNum="11" sectionName="Creating a Database - Day 2"
subSectionName="Table Constraints" timestamp="2010-11-26 16:25:05"/>
    </nav>
    <nav name="dialogSent">
        <item courseName="SQL Course" lrnName="gobyCourse" pageNum="11" sectionName="Creating a Database - Day 2"
subSectionName="Table Constraints" timestamp="2010-11-26 16:25:05" trait="debg_ninf"/>
    </nav>
    <nav name="dialogResp">
        <item courseName="SQL Course" lrnName="gobyCourse" pageNum="11" resp="yes" sectionName="Creating a Database - Day 2"
subSectionName="Table Constraints" timestamp="2010-11-26 16:25:11" trait="debg_ninf"/>
    </nav>
    <nav name="newPage">
        <item courseName="SQL Course" lrnName="gobyCourse" pageNum="12" sectionName="Creating a Database - Day 2"
subSectionName="Table Constraints" timestamp="2010-11-26 16:25:14"/>
    </nav>
    <nav name="dialogSent">
        <item courseName="SQL Course" lrnName="gobyCourse" pageNum="12" sectionName="Creating a Database - Day 2"
subSectionName="Table Constraints" timestamp="2010-11-26 16:25:14" trait="info_stru"/>
    </nav>
    <nav name="dialogResp">
        <item courseName="SQL Course" lrnName="gobyCourse" pageNum="12" resp="ok" sectionName="Creating a Database - Day 2"
subSectionName="Table Constraints" timestamp="2010-11-26 16:25:18" trait="info_stru"/>
    </nav>
    <nav name="newPage">
        <item courseName="SQL Course" lrnName="gobyCourse" pageNum="13" sectionName="Creating a Database - Day 2"
subSectionName="Table Constraints" timestamp="2010-11-26 16:25:20"/>
    </nav>
    <nav name="dialogSent">
        <item courseName="SQL Course" lrnName="gobyCourse" pageNum="13" sectionName="Creating a Database - Day 2"
subSectionName="Table Constraints" timestamp="2010-11-26 16:25:20" trait="eval_sumr"/>
    </nav>
    <nav name="dialogResp">
        <item courseName="SQL Course" lrnName="gobyCourse" pageNum="13" resp="no" sectionName="Creating a Database - Day 2"
subSectionName="Table Constraints" timestamp="2010-11-26 16:25:42" trait="eval_sumr"/>
    </nav>
    <nav name="newPage">
        <item courseName="SQL Course" lrnName="gobyCourse" pageNum="1" sectionName="Creating a Database - Day 2" subSectionName="DDL
: Alter and Drop Statements" timestamp="2010-11-26 16:25:53"/>
    </nav>
    <nav name="dialogSent">
        <item courseName="SQL Course" lrnName="gobyCourse" pageNum="1" sectionName="Creating a Database - Day 2" subSectionName="DDL
: Alter and Drop Statements" timestamp="2010-11-26 16:25:54" trait="info_word"/>
    </nav>
    <nav name="dialogResp">
        <item courseName="SQL Course" lrnName="gobyCourse" pageNum="1" resp="yes" sectionName="Creating a Database - Day 2"
subSectionName="DDL : Alter and Drop Statements" timestamp="2010-11-26 16:26:00" trait="info_word"/>
    </nav>
    <nav name="newPage">
        <item courseName="SQL Course" lrnName="gobyCourse" pageNum="2" sectionName="Creating a Database - Day 2" subSectionName="DDL
: Alter and Drop Statements" timestamp="2010-11-26 16:26:02"/>
    </nav>
    <nav name="dialogSent">
        <item courseName="SQL Course" lrnName="gobyCourse" pageNum="2" sectionName="Creating a Database - Day 2" subSectionName="DDL
: Alter and Drop Statements" timestamp="2010-11-26 16:26:03" trait="comp_goal"/>
    </nav>
    <nav name="dialogResp">
        <item courseName="SQL Course" lrnName="gobyCourse" pageNum="2" resp="yes" sectionName="Creating a Database - Day 2"
subSectionName="DDL : Alter and Drop Statements" timestamp="2010-11-26 16:26:08" trait="comp_goal"/>
    </nav>
    <nav name="newPage">
        <item courseName="SQL Course" lrnName="gobyCourse" pageNum="3" sectionName="Creating a Database - Day 2" subSectionName="DDL
: Alter and Drop Statements" timestamp="2010-11-26 16:26:10"/>
    </nav>
    <nav name="dialogSent">
        <item courseName="SQL Course" lrnName="gobyCourse" pageNum="3" sectionName="Creating a Database - Day 2" subSectionName="DDL
: Alter and Drop Statements" timestamp="2010-11-26 16:26:10" trait="info_over"/>
```

Appendix H Dialog Models

Prompt Model

```
<?xml version="1.0" encoding="UTF-8"?>
<dialog>
    <description>
        Questions to gather user data and to trigger the user to be aware of their planning or information management strategies
    </description>
    <question>
        <trait id="trait_pln" name="Planning Prompts">
            <item name="plan_pace" pr="Pace yourself so that you have enough time"/>
            <item name="plan_need" pr="Think about what you really need to learn before you begin reading this page"/>
            <item name="plan_goal" pr="Remember to set a specific goal"/>
            <item name="plan_quet" pr="Ask yourself some questions about the material before you begin"/>
            <item name="plan_solv" pr="Think of several ways to approach the task, and choose the best one"/>
            <item name="plan_inst" pr="Read the instructions or material carefully before you begin the next page"/>
            <item name="plan_time" pr="Organise your time to best accomplish your goals"/>
        </trait>
        <comment>

            Questions to gather information. Planning relates to a number of Before tasks
            Planning, goal setting and allocating resources prior to learning

        </comment>
    </question>
    <question>
        <trait id="trait_inf" name="Information Management Strategies Prompts">
            <item name="info_slow" pr="Do not forget to slow down when you encounter important information"/>
            <item name="info_infr" pr="Remember to focus your attention on the important information"/>
            <item name="info_mean" pr="Focus on the meaning and significance of new information"/>
            <item name="info_exmp" pr="Try to create your own examples to make information more meaningful"/>
            <item name="info_diag" pr="Why not draw pictures or diagrams to help"/>
            <item name="info_word" pr="Try to translate new information into your own words"/>
            <item name="info_stru" pr="You can use the organisational structure of the text to help you learn"/>
            <item name="info_rela" pr="Remember to ask yourself if what you are reading is related to what you already know"/>
            <item name="info_step" pr="Try to break studying down into smaller steps"/>
            <item name="info_over" pr="Sometimes it's good to focus on the overall meaning rather than the specifics"/>
        </trait>
        <comment>

            Information Management Strategies are the skills and strategy sequences used to process information more efficiently
            e.g. organising, elaborating, summarizing, selective focusing


        </comment>
    </question>
    <question>
        <trait id="trait_cmp" name="Comprehension Monitoring">
            <item name="comp_goal" pr="Ask yourself periodically if you are meeting your goals" rating="3.188118812"/>
            <item name="comp_ansr" pr="Imagine the types of questions this page might be examined on. Try to consider several
alternatives to a problem before you answer" rating="3.673267327"/>
            <item name="comp_prob" pr="Imagine the types of questions this page might be examined on. You should ask yourself if you
have considered all options when solving a problem" rating="3.673267327"/>
            <item name="comp_revu" pr="Try periodically reviewing in order to help you understand important relationships"
rating="3.346534653"/>
            <item name="comp_strt" pr="Try to analyse the usefulness of strategies while you study" rating="3.316831683"/>
            <item name="comp_paus" pr="Remember to pause regularly to check your comprehension" rating="3.465346535"/>
            <item name="comp_qunu" pr="Ask yourself questions about how well you are doing while learning something new"
rating="3.079207921"/>
        </trait>
        <comment>


            Assessment of own learning or strategy use


        </comment>
    </question>
    <question>
        <trait id="trait_dbg" name="Debugging Strategies">
            <item name="debg_help" pr="Consult others for help when you don't understand something" rating="3.732673267"/>
            <item name="debg_strt" pr="Try changing strategies when you fail to understand" rating="3.594059406"/>
            <item name="debg_revl" pr="Sometimes you should re-evaluate your assumptions when you get confused"
rating="3.851485149"/>
            <item name="debg_ninf" pr="You should stop and go back over new information that is not clear to you"
rating="4.287128713"/>
            <item name="debg_cnfu" pr="Try to stop and reread when you get confused" rating="4.465346535"/>
        </trait>
        <comment>


            Strategies used to correct comprehension and performance errors


        </comment>
    </question>
    <question>
        <trait id="trait_evl" name="Evaluation" confidence="1">
            <item name="eval_well" pr="Imagine that you will be assessed on this material. Try to imagine how well you would do after
you finished the test" rating="3.485148515"/>
            <item name="eval_easy" pr="Try to ask yourself if there was an easier way to accomplishs your goals after you finish
reading this material" rating="3.811881188"/>
            <item name="eval_sumr" pr="You should try to summarise what you've learned after you finish" rating="3.198019802"/>
```

```
            <item name="eval_goal" pr="Try asking yourself how well you accomplished your goals once you've finished"
rating="3.178217822"/>
            <item name="eval_optn" pr="Consider all options after you solve a problem" rating="3.277227723"/>
            <item name="eval_lern" pr="Ask yourself if you learned as much as you could have once you finish reading this material"
rating="2.782178218"/>
        </trait>
        <comment>


            Analysis of performance and strategy effectiveness after a learning episode


        </comment>
    </question>
</dialog>
```

Question Model

```
<?xml version="1.0" encoding="UTF-8"?>
<dialog>
    <description>
        Questions to gather user data and to trigger the user to be aware of their planning or information management strategies
    </description>
    <question>
        <trait id="trait_pln" name="Planning Questions">
            <item name="plan_pace" qu="Have you thought about pacing yourself so that you will had enough time?"/>
            <item name="plan_need" qu="Did you think about what you really needed to learn before beginning this page?"/>
            <item name="plan_goal" qu="Have you a specific goal in mind?"/>
            <item name="plan_quet" qu="Did you ask yourself some questions about the material before you began?"/>
            <item name="plan_solv" qu="Have you thought of several ways to approach this course and choosen the best one?"/>
            <item name="plan_inst" qu="Did you read the instructions carefully before you began?"/>
            <item name="plan_time" qu="Have you organised your time to best accomplish your goals?"/>
        </trait>
        <comment>

            Questions to gather information. Planning relates to a number of Before tasks
            Planning, goal setting and allocating resources prior to learning

        </comment>
    </question>
    <question>
        <trait id="trait_inf" name="Information Management Strategies Questions">
            <item name="info_slow" qu="Do you slow down when you encounter important information?"/>
            <item name="info_infr" qu="Have you focused your attention on the important information?"/>
            <item name="info_mean" qu="Have you focused on the meaning and significance of new information?"/>
            <item name="info_exmp" qu="Do you create your own examples to make information more meaningful?"/>
            <item name="info_diag" qu="Have you thought about trying to draw pictures or diagrams to help?"/>
            <item name="info_word" qu="Have you tried to translate new information into your own words?"/>
            <item name="info_stru" qu="Would you try to use the organisational structure of the course to help you learn?"/>
            <item name="info_rela" qu="Have you asked yourself if what you are reading is related to what you already know?"/>
            <item name="info_step" qu="Did you try to break studying down into smaller steps?"/>
            <item name="info_over" qu="Do you focus on the overall meaning rather than the specifics?"/>
        </trait>
        <comment>

            ...

        </comment>
    </question>
    <question>
        <trait id="trait_cmp" name="Comprehension Monitoring">
            <item name="comp_goal" qu="Have you asked yourself if you are meeting your goals?"/>
            <item name="comp_ansr" qu="Imagine that the material in this section will be covered in an assesment. Would you consider
alternatives to the problem before you answered?"/>
            <item name="comp_prob" qu="Imagine how this content can be applied to a reall world problem. Would you consider all
options when solving a problem like this?"/>
            <item name="comp_revu" qu="Have you found yourself periodically reviewing the course to help yourself understand
important relationships?"/>
            <item name="comp_strt" qu="Do you find yourself analysing the usefulness of strategies while you study?"/>
            <item name="comp_paus" qu="Have you found yourself pausing regularly to check your comprehension?"/>
            <item name="comp_qunu" qu="Have you asked yourself questions about how well your are doing while learning new course
material?"/>
        </trait>
        <comment>


            Assessment of own learning or strategy use


        </comment>
    </question>
    <question>
        <trait id="trait_dbg" name="Debugging Strategies">
            <item name="debg_help" qu="Do you ask others for help when you don't understand something?" rating="3.732673267"/>
            <item name="debg_strt" qu="Have you had to change your strategies when you fail to understand?" rating="3.594059406"/>
            <item name="debg_revl" qu="Have you gotten confused and had to re-evaluate your assumptions?" rating="3.851485149"/>
            <item name="debg_ninf" qu="Have you needed to stop and go back over new information that was not clear?"
rating="4.287128713"/>
            <item name="debg_cnfu" qu="Do you stop and reread when you get confused?" rating="4.465346535"/>
        </trait>
        <comment>


            Strategies used to correct comprehension and performance errors

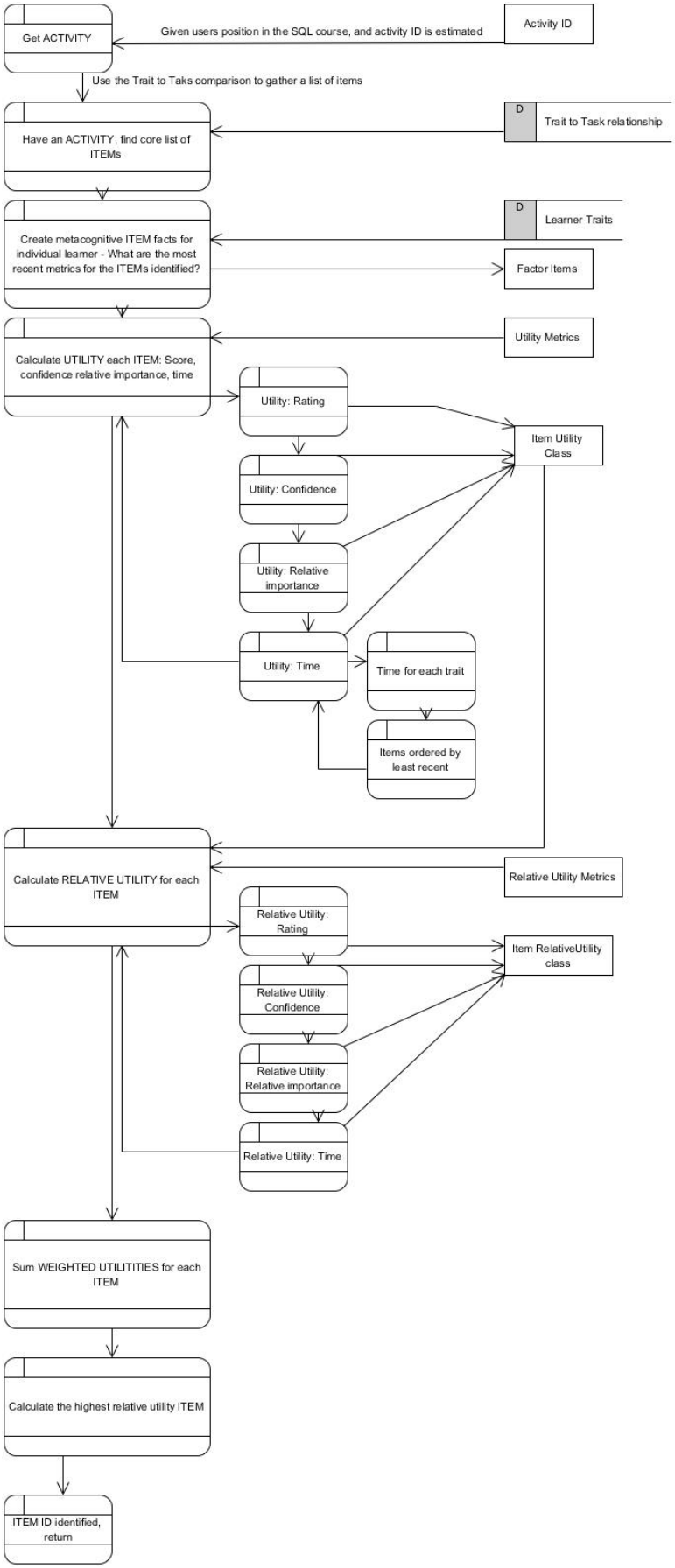

        </comment>
    </question>
    <question>
```

```
        <trait id="trait_evl" name="Evaluation" confidence="1">
            <item name="eval_well" qu="If you were evaluated on this course material, would you know how well you did once you
finished the test?" rating="3.485148515"/>
            <item name="eval_easy" qu="After you finish a task do you ask yourself if there was an easier way to do things?"
rating="3.811881188"/>
            <item name="eval_sumr" qu="After you finish this page or section will you summarise what you have learned ?"
rating="3.198019802"/>
            <item name="eval_goal" qu="When you were finished reading the previous page did you ask yourself how well you are
accomplish your goals ?" rating="3.178217822"/>
            <item name="eval_optn" qu="After completing the last page, did you asked yourself if you have considered all options?"
rating="3.277227723"/>
            <item name="eval_lern" qu="Have you asked yourself if you learned as much as you could have?" rating="2.782178218"/>
        </trait>
        <comment>


            Analysis of performance and strategy effectiveness after a learning episode


        </comment>
    </question>
</dialog>
```

Appendix I Multi-Attribute Decision Making in Goby



Appendix J Goby Screens



Figure J 1 - Goby Home Page

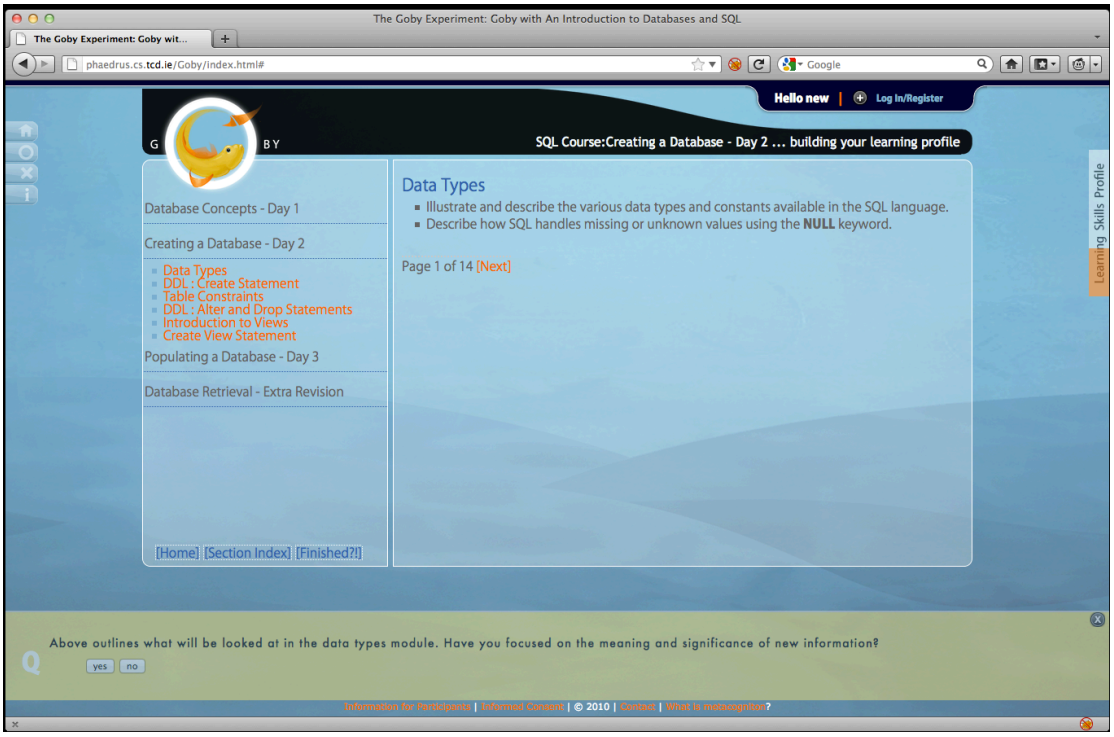


Figure J 2 - The SQL Course and links take up the main area, whereas the metacognitive popup has appeared from the bottom of the page. Here, a question is shown.

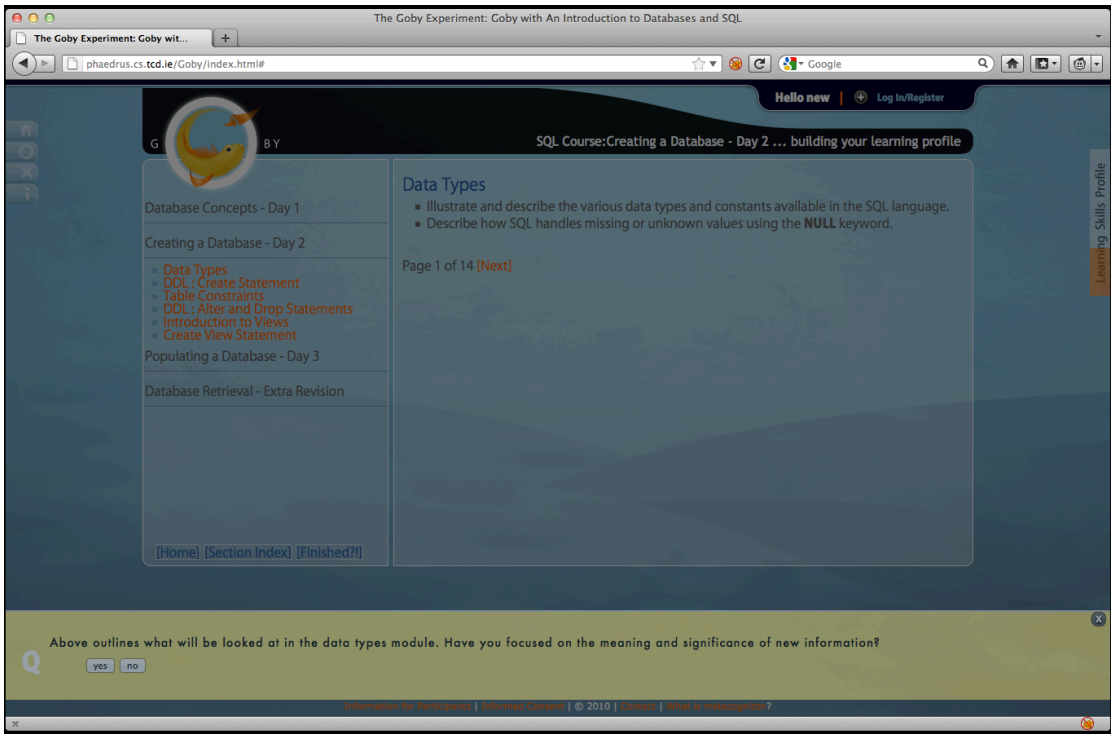


Figure J 3 - When the learner hovers over the metacognitive popup, the domain content is faded out in order to focus on the question shown



Figure J 4 - After responding to the dialog, the popup window closes at the bottom. The learner can also chose to close the popup menu if the wish.



Figure J 5 – Here, a prompt is shown in the metacognitive popup.

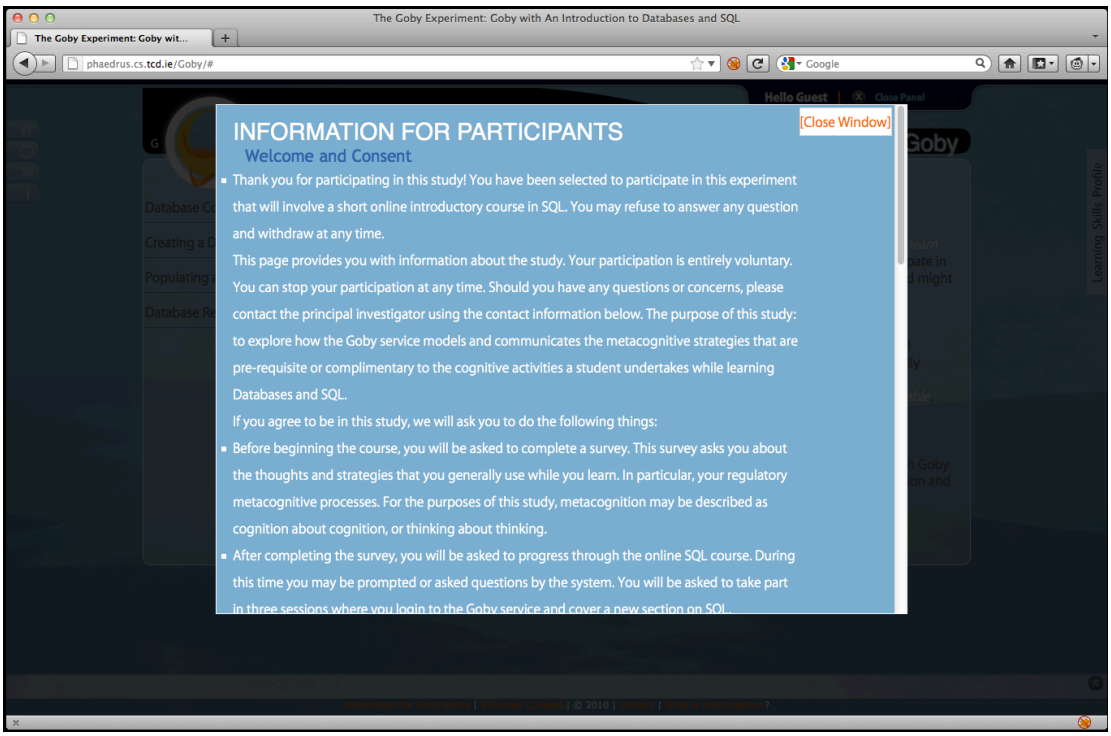


Figure J 6 - Extra information and resources are presented in a lightbox dialog.

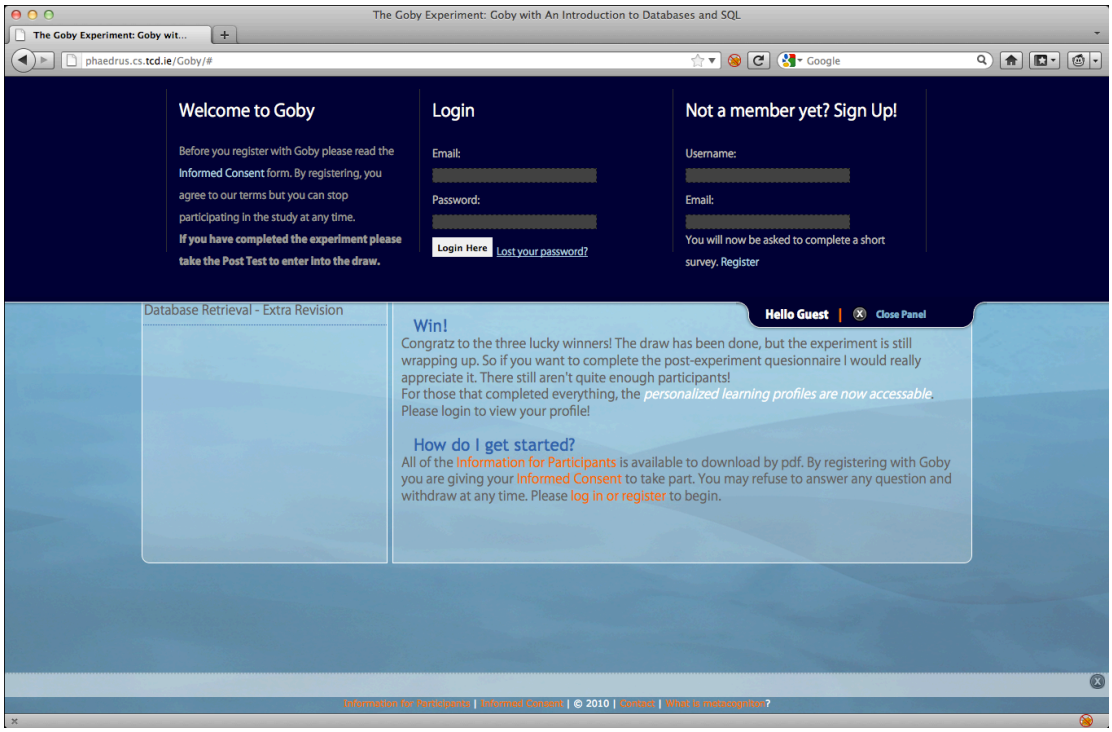


Figure J 7 - A slide down menu provides access to other course features and information.

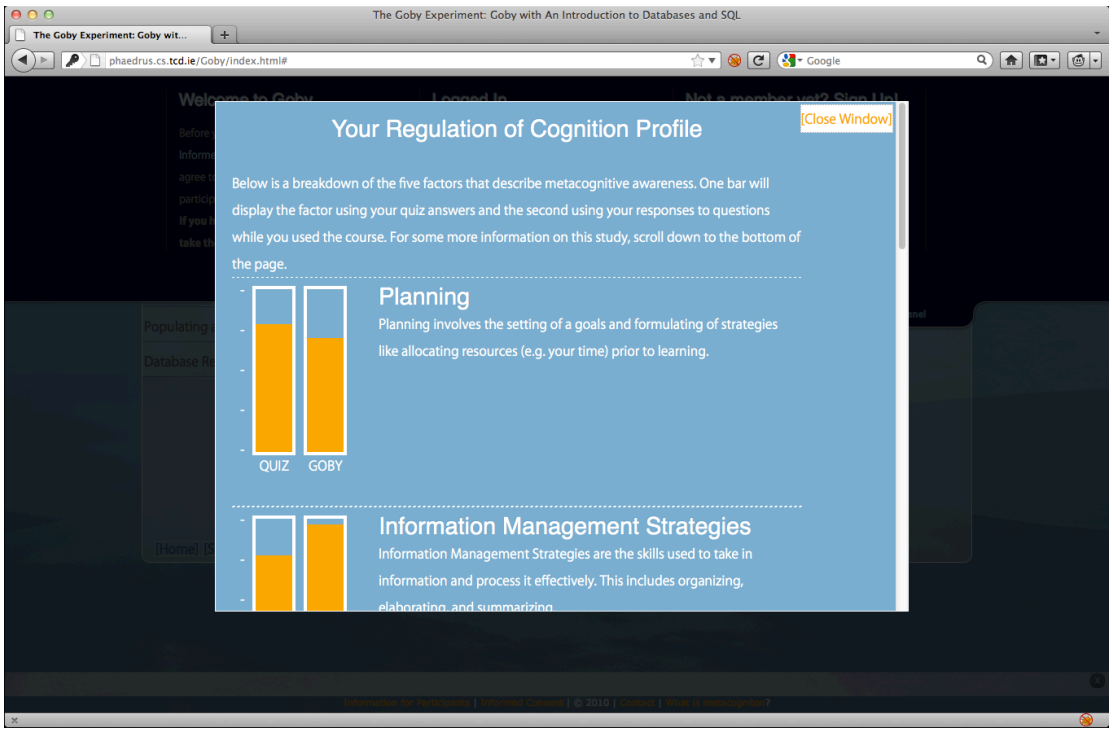


Figure J 8 - The OLM displays a visual representation of the learner's metacognitive scores - both the system model and the learner's post-test MAI overview are displayed.

Appendix K Parametric to Non-Parametric alternative

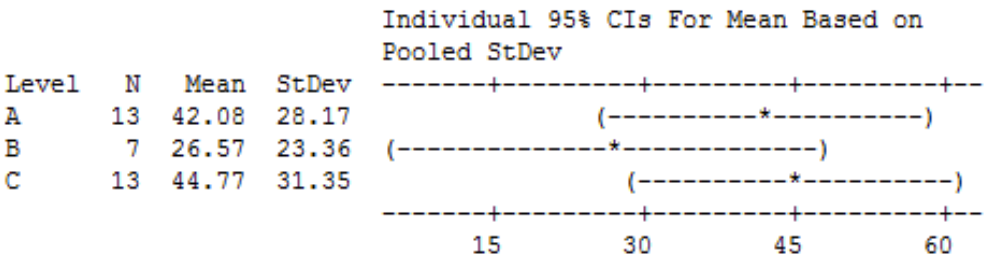
K.1. Knowledge Gain

An evaluation of the learning gains for participants who used the Goby service – analysing the state of the learner's database knowledge prior to using the Goby service.

One-way ANOVA: pre versus Group

```
Source  DF     SS   MS     F      P
Group    2   1613  807  0.98  0.386
Error   30  24593  820
Total   32  26206

S = 28.63   R-Sq = 6.16%   R-Sq(adj) = 0.00%
```




```
Pooled StDev = 28.63
```

Since the pre-Scores not normal distribution a Kruskal-Wallis was also carried out with similar results.

Kruskal-Wallis Test: pre versus Group

```
Kruskal-Wallis Test on pre

Group     N  Median  Ave Rank      Z
A        13   58.00      17.1   0.04
B         7   20.00      13.2  -1.17
C        13   57.00      19.0   0.94
Overall  33              17.0

H = 1.61  DF = 2  P = 0.447
H = 1.61  DF = 2  P = 0.447  (adjusted for ties)
```

K.2. Metacognitive Gain Assessment

An overview of the evaluation of the metacognitive gains for participants in Group B and Group C since there was some skewing in the data towards the tail.

Group B - The data were not normal - pre and post values skew towards tails.
Planning:

Paired T-Test and CI: B_pre_P, B_post_P

```
Paired T for B_pre_P - B_post_P

             N    Mean  StDev  SE Mean
B_pre_P     16   3.304  0.594    0.149
B_post_P    16   3.375  1.009    0.252
Difference  16  -0.071  0.948    0.237


95% CI for mean difference: (-0.576, 0.434)
T-Test of mean difference = 0 (vs not = 0): T-Value = -0.30  P-Value = 0.767
```

Mann-Whitney Test and CI: B_pre_P, B_post_P

```
           N  Median
B_pre_P   16   3.429
B_post_P  16   3.571


Point estimate for ETA1-ETA2 is -0.214
95.2 Percent CI for ETA1-ETA2 is (-0.714,0.429)
W = 246.0
Test of ETA1 = ETA2 vs ETA1 not = ETA2 is significant at 0.5095
The test is significant at 0.5083 (adjusted for ties)
```

Comprehension:

Paired T-Test and CI: B_pre_C, B_post_C

```
Paired T for B_pre_C - B_post_C

             N    Mean  StDev  SE Mean
B_pre_C     16   3.045  0.735    0.184
B_post_C    16   3.411  0.917    0.229
Difference  16  -0.366  0.920    0.230


95% CI for mean difference: (-0.856, 0.124)
T-Test of mean difference = 0 (vs not = 0): T-Value = -1.59  P-Value = 0.132
```

Mann-Whitney Test and CI: B_pre_C, B_post_C

```
           N  Median
B_pre_C   16   2.929
B_post_C  16   3.714


Point estimate for ETA1-ETA2 is -0.429
95.2 Percent CI for ETA1-ETA2 is (-1.143,0.143)
W = 221.0
Test of ETA1 = ETA2 vs ETA1 not = ETA2 is significant at 0.1092
The test is significant at 0.1080 (adjusted for ties)
```

Information Management Strategies:

Paired T-Test and CI: B_pre_I, B_post_I

```
Paired T for B_pre_I - B_post_I

             N    Mean  StDev  SE Mean
B_pre_I     16   3.281  0.615    0.154
B_post_I    16   3.637  0.799    0.200
Difference  16  -0.356  0.792    0.198


95% CI for mean difference: (-0.779, 0.066)
T-Test of mean difference = 0 (vs not = 0): T-Value = -1.80  P-Value = 0.092
```

Mann-Whitney Test and CI: B_pre_I, B_post_I

```
           N  Median
B_pre_I   16  3.3000
B_post_I  16  3.5500


Point estimate for ETA1-ETA2 is -0.4000
95.2 Percent CI for ETA1-ETA2 is (-0.9003,0.2001)
W = 225.5
Test of ETA1 = ETA2 vs ETA1 not = ETA2 is significant at 0.1521
The test is significant at 0.1513 (adjusted for ties)
```

Debugging:

Paired T-Test and CI: B_pre_D, B_post_D

```
Paired T for B_pre_D - B_post_D

             N    Mean  StDev  SE Mean
B_pre_D     16   3.575  0.915    0.229
B_post_D    16   3.900  0.803    0.201
Difference  16  -0.325  0.926    0.232


95% CI for mean difference: (-0.819, 0.169)
T-Test of mean difference = 0 (vs not = 0): T-Value = -1.40  P-Value = 0.181
```

Mann-Whitney Test and CI: B_pre_D, B_post_D

```
           N  Median
B_pre_D   16   3.800
B_post_D  16   4.200


Point estimate for ETA1-ETA2 is -0.200
95.2 Percent CI for ETA1-ETA2 is (-0.600,0.200)
W = 231.5
Test of ETA1 = ETA2 vs ETA1 not = ETA2 is significant at 0.2278
The test is significant at 0.2234 (adjusted for ties)
```

Evaluation:

Paired T-Test and CI: B_pre_E, B_post_E

```
Paired T for B_pre_E - B_post_E

             N    Mean  StDev  SE Mean
B_pre_E     16   3.167  0.748    0.187
B_post_E    16   3.583  0.905    0.226
Difference  16  -0.417  0.878    0.219


95% CI for mean difference: (-0.884, 0.051)
T-Test of mean difference = 0 (vs not = 0): T-Value = -1.90  P-Value = 0.077
```

Mann-Whitney Test and CI: B_pre_E, B_post_E

```
           N  Median
B_pre_E   16   3.083
B_post_E  16   3.750


Point estimate for ETA1-ETA2 is -0.500
95.2 Percent CI for ETA1-ETA2 is (-1.167,0.167)
W = 222.0
Test of ETA1 = ETA2 vs ETA1 not = ETA2 is significant at 0.1178
The test is significant at 0.1167 (adjusted for ties)
```

Group C

The MAI values in the post-test survey were slightly skewed towards tails however it looked almost normal.

Planning:

Paired T-Test and CI: C_pre_P, C_post_P

```
Paired T for C_pre_P - C_post_P

             N    Mean  StDev  SE Mean
C_pre_P     18   3.333  0.523    0.123
C_post_P    18   3.389  0.530    0.125
Difference  18  -0.056  0.433    0.102


95% CI for mean difference: (-0.271, 0.160)
T-Test of mean difference = 0 (vs not = 0): T-Value = -0.54  P-Value = 0.593
```

Mann-Whitney Test and CI: C_pre_P, C_post_P

```
           N  Median
C_pre_P   18  3.3571
C_post_P  18  3.4286


Point estimate for ETA1-ETA2 is -0.1428
95.2 Percent CI for ETA1-ETA2 is (-0.4287,0.2856)
W = 319.5
Test of ETA1 = ETA2 vs ETA1 not = ETA2 is significant at 0.6809
The test is significant at 0.6796 (adjusted for ties)
```

Information Management Strategies:

Paired T-Test and CI: C_pre_I, C_post_I

```
Paired T for C_pre_I - C_post_I

             N   Mean  StDev  SE Mean
C_pre_I     18  3.700  0.445    0.105
C_post_I    18  3.589  0.689    0.162
Difference  18  0.111  0.548    0.129


95% CI for mean difference: (-0.161, 0.383)
T-Test of mean difference = 0 (vs not = 0): T-Value = 0.86  P-Value = 0.401
```

Mann-Whitney Test and CI: C_pre_I, C_post_I

```
           N  Median
C_pre_I   18  3.7000
C_post_I  18  3.6500


Point estimate for ETA1-ETA2 is 0.1000
95.2 Percent CI for ETA1-ETA2 is (-0.2999,0.4997)
W = 346.0
Test of ETA1 = ETA2 vs ETA1 not = ETA2 is significant at 0.6925
The test is significant at 0.6912 (adjusted for ties)
```

Comprehension:

Paired T-Test and CI: C_pre_C, C_post_C

```
Paired T for C_pre_C - C_post_C

             N    Mean  StDev  SE Mean
C_pre_C     18   3.302  0.492    0.116
C_post_C    18   3.373  0.695    0.164
Difference  18  -0.071  0.732    0.173


95% CI for mean difference: (-0.436, 0.293)
T-Test of mean difference = 0 (vs not = 0): T-Value = -0.41  P-Value = 0.684
```

Mann-Whitney Test and CI: C_pre_C, C_post_C

```
           N  Median
C_pre_C   18  3.2857
C_post_C  18  3.3571


Point estimate for ETA1-ETA2 is -0.0714
95.2 Percent CI for ETA1-ETA2 is (-0.4289,0.2859)
W = 323.0
Test of ETA1 = ETA2 vs ETA1 not = ETA2 is significant at 0.7637
The test is significant at 0.7629 (adjusted for ties)
```

Debugging:

Paired T-Test and CI: C_pre_D, C_post_D

```
Paired T for C_pre_D - C_post_D

             N   Mean  StDev  SE Mean
C_pre_D     18  3.933  0.578    0.136
C_post_D    18  3.800  0.636    0.150
Difference  18  0.133  0.669    0.158


95% CI for mean difference: (-0.199, 0.466)
T-Test of mean difference = 0 (vs not = 0): T-Value = 0.85  P-Value = 0.409
```

Mann-Whitney Test and CI: C_pre_D, C_post_D

```
           N  Median
C_pre_D   18  4.0000
C_post_D  18  4.0000


Point estimate for ETA1-ETA2 is -0.0000
95.2 Percent CI for ETA1-ETA2 is (-0.2003,0.4001)
W = 344.5
Test of ETA1 = ETA2 vs ETA1 not = ETA2 is significant at 0.7278
The test is significant at 0.7224 (adjusted for ties)
```

Evaluation:

Paired T-Test and CI: C_pre_E, C_post_E

```
Paired T for C_pre_E - C_post_E

             N    Mean  StDev  SE Mean
C_pre_E     18   3.426  0.694    0.163
C_post_E    18   3.537  0.643    0.152
Difference  18  -0.111  0.911    0.215


95% CI for mean difference: (-0.564, 0.342)
T-Test of mean difference = 0 (vs not = 0): T-Value = -0.52  P-Value = 0.612
```

Mann-Whitney Test and CI: C_pre_E, C_post_E

```
           N  Median
C_pre_E   18  3.5000
C_post_E  18  3.6667


Point estimate for ETA1-ETA2 is -0.1667
95.2 Percent CI for ETA1-ETA2 is (-0.6667,0.3333)
W = 314.5
Test of ETA1 = ETA2 vs ETA1 not = ETA2 is significant at 0.5690
The test is significant at 0.5668 (adjusted for ties)
```

K.3. Goby Accuracy at Modelling Metacognitive Factors

An evaluation to compare the post MAI survey scores for experimentation groups with the Goby scores for each of: Comprehension, Debugging, Evaluation, Information Management, and Planning

Group B:

Planning *(Data from Goby not normal, survey data is normal)*

Two-Sample T-Test and CI: BsurveyP, BgobyP

```
Two-sample T for BsurveyP vs BgobyP

           N   Mean  StDev  SE Mean
BsurveyP  16   3.38   1.01     0.25
BgobyP    16  3.747  0.278    0.069


Difference = mu (BsurveyP) - mu (BgobyP)
Estimate for difference:  -0.372
95% CI for difference:  (-0.923, 0.180)
T-Test of difference = 0 (vs not =): T-Value = -1.42  P-Value = 0.173  DF = 17
```

Mann-Whitney Test and CI: BsurveyP, BgobyP

```
           N  Median
BsurveyP  16   3.571
BgobyP    16   3.843


Point estimate for ETA1-ETA2 is -0.236
95.2 Percent CI for ETA1-ETA2 is (-0.807,0.300)
W = 246.0
Test of ETA1 = ETA2 vs ETA1 not = ETA2 is significant at 0.5095
The test is significant at 0.5093 (adjusted for ties)
```

Information Management Strategies *(Data from Goby not normal)*

Two-Sample T-Test and CI: BsurveyI, BgobyI

```
Two-sample T for BsurveyI vs BgobyI

           N   Mean  StDev  SE Mean
BsurveyI  16  3.637  0.799     0.20
BgobyI    16  4.679  0.387    0.097


Difference = mu (BsurveyI) - mu (BgobyI)
Estimate for difference:  -1.041
95% CI for difference:  (-1.503, -0.580)
T-Test of difference = 0 (vs not =): T-Value = -4.69  P-Value = 0.000  DF = 21
```

Mann-Whitney Test and CI: BsurveyI, BgobyI

```
           N  Median
BsurveyI  16  3.5500
BgobyI    16  4.8703


Point estimate for ETA1-ETA2 is -0.9297
95.2 Percent CI for ETA1-ETA2 is (-1.4612,-0.5063)
W = 161.0
Test of ETA1 = ETA2 vs ETA1 not = ETA2 is significant at 0.0001
The test is significant at 0.0001 (adjusted for ties)
```

Evaluation *(Data from Goby not normal)*

Two-Sample T-Test and CI: BsurveyE, BgobyE

```
Two-sample T for BsurveyE vs BgobyE

           N   Mean  StDev  SE Mean
BsurveyE  16  3.583  0.905     0.23
BgobyE    16  3.771  0.201    0.050


Difference = mu (BsurveyE) - mu (BgobyE)
Estimate for difference:  -0.187
95% CI for difference:  (-0.678, 0.304)
T-Test of difference = 0 (vs not =): T-Value = -0.81  P-Value = 0.431  DF = 16
```

Mann-Whitney Test and CI: BsurveyE, BgobyE

```
           N  Median
BsurveyE  16  3.7500
BgobyE    16  3.8617


Point estimate for ETA1-ETA2 is -0.0700
95.2 Percent CI for ETA1-ETA2 is (-0.5594,0.3988)
W = 260.0
Test of ETA1 = ETA2 vs ETA1 not = ETA2 is significant at 0.8951
The test is significant at 0.8949 (adjusted for ties)
```

Debugging *(Data from Goby not normal)*

Two-Sample T-Test and CI: BsurveyD, BgobyD

```
Two-sample T for BsurveyD vs BgobyD

           N   Mean  StDev  SE Mean
BsurveyD  15  4.040  0.596     0.15
BgobyD    16  4.507  0.266    0.066


Difference = mu (BsurveyD) - mu (BgobyD)
Estimate for difference:  -0.467
95% CI for difference:  (-0.818, -0.116)
T-Test of difference = 0 (vs not =): T-Value = -2.79  P-Value = 0.012  DF = 19
```

Mann-Whitney Test and CI: BsurveyD, BgobyD

```
           N  Median
BsurveyD  15  4.2000
BgobyD    16  4.6146


Point estimate for ETA1-ETA2 is -0.3431
95.4 Percent CI for ETA1-ETA2 is (-0.7356,-0.1364)
W = 181.0
Test of ETA1 = ETA2 vs ETA1 not = ETA2 is significant at 0.0208
The test is significant at 0.0205 (adjusted for ties)
```

Comprehension

(Data from Goby not normal, normal survey)

Two-Sample T-Test and CI: BsurveyC, BgobyC

```
Two-sample T for BsurveyC vs BgobyC

           N   Mean  StDev  SE Mean
BsurveyC  15  3.571  0.677     0.17
BgobyC    16  3.801  0.217    0.054


Difference = mu (BsurveyC) - mu (BgobyC)
Estimate for difference:  -0.230
95% CI for difference:  (-0.618, 0.158)
T-Test of difference = 0 (vs not =): T-Value = -1.26  P-Value = 0.227  DF = 16
```

Mann-Whitney Test and CI: BsurveyC, BgobyC

```
           N  Median
BsurveyC  15  3.7143
BgobyC    16  3.9007


Point estimate for ETA1-ETA2 is -0.1239
95.4 Percent CI for ETA1-ETA2 is (-0.4278,0.1795)
W = 234.0
Test of ETA1 = ETA2 vs ETA1 not = ETA2 is significant at 0.8279
The test is significant at 0.8277 (adjusted for ties)
```

Appendix L Goby Experiment Information



TRINITY COLLEGE DUBLIN
INFORMATION SHEET FOR PARTICIPANTS

Welcome and Consent

- Thank you for participating in this study! You have been selected to participate in this experiment that will involve a short online introductory course in SQL. You may refuse to answer any question and withdraw at any time.

This page provides you with information about the study. Your participation is entirely voluntary. You can stop your participation at any time. Should you have any questions or concerns, please contact the principal investigator using the contact information below. *The purpose of this study: to explore how the Goby service models and communicates the metacognitive strategies that are pre-requisite or complementary to the cognitive activities a student undertakes while learning Databases and SQL.*

If you agree to be in this study, we will ask you to do the following things:

- Before beginning the course, you will be asked to complete a survey. This survey asks you about the thoughts and strategies that you generally use while you learn. In particular, your regulatory metacognitive processes. For the purposes of this study, metacognition may be described as cognition about cognition, or thinking about thinking.
- After completing the survey, you will be asked to progress through the online SQL course. During this time you may be prompted or asked questions by the system. You will be asked to take part in three sessions over three weeks where you login to the Goby service and cover a new section on SQL
- On completing the course, you will be asked to complete a further survey. The time required to complete this online course is estimated to average 1.5 hours over three weeks, including the time to review instructions, and complete and review the information collection.

Health and Safety:

- If you have a history of Photosensitive Epilepsy or any other condition that may cause you to experience difficulty with this experiment you are proceeding at your own risk. You may withdraw from the study now or at any time.

Legal Notes:

- All data collected will be private, and no one other than the investigator (and research assistants/research lecturers) will have access to your responses. All information collected for this study will be recorded anonymously and processed only for research purposes and, notwithstanding the fifth data protection principle, may be kept indefinitely. The data resulting from your participation may be made available to other researchers in the future for research purposes not detailed within this consent form. In these cases, the data will contain no identifying information that could associate you with it, or with your participation in any study. The records of this study will be stored securely and kept confidential. All publications will exclude any information that will make it possible to identify you as a subject.
- Responses to this data collection will be used only for experimental purposes. The reports prepared for this study will summarize findings across the sample and will not associate responses with a specific individual. We will not provide information that identifies you.
- Participation in this study is voluntary; you may withdraw from the study at any time for any reason and omit questions you do not wish to answer without penalty.
- In the extremely unlikely event that illicit activity is reported to me during the study I will be obliged to report it to appropriate authorities.

Consent:

I have read the above information and have sufficient information to make a decision about participating in this study. By registering with the Goby system, I am giving my consent to participate in the study.

If you have comments or concerns regarding the status of your individual participation in this study, contact the principal researcher below:

Name: Victoria Macarthur **Email:** macarthv@cs.tcd.ie **Tel:** 01 896 6431
Address: KDEG, Room F35, The O'Reilly Institute, Trinity College, Dublin 2

TRINITY COLLEGE DUBLIN
INFORMED CONSENT FORM

LEAD RESEARCHERS: Victoria Macarthur.

BACKGROUND OF RESEARCH:. The purpose of this research study is to determine whether the Goby service is able to model and support a learner's cognition. In particular, the Goby service models the learners' metacognitive awareness, according to the Metacognitive Awareness Inventory (MAI). This includes five factors including, planning, information management strategies, comprehension, monitoring, debugging strategies and evaluation. You may refuse to answer any question and withdraw at any time.

PROCEDURES OF THIS STUDY:

- You will be asked to fill in questionnaires before and after the experiment
- You will be asked to register and login to the Goby service.
- You will then be required to use the Goby service to learn about 'Databases and SQL'. You be asked to interact with prompts from the service while you are reading the content on screen.
- You will be asked to take part in three sessions over three weeks where you login to the Goby service and cover a new section on 'Databases and SQL'. The duration of each session of the study should be approximately 60 minutes.

PUBLICATION: It is intended that results of this study will be published in Victoria Macarthur's Ph.D. thesis and a relevant scientific journal. Individual results will be aggregated anonymously and research reported on aggregate results.

DECLARATION:

- I am 18 years or older and am competent to provide consent.
- I have read, or had read to me, this consent form. I have had the opportunity to ask questions and all my questions have been answered to my satisfaction and understand the description of the research that is being provided to me.
- I agree that my data is used for scientific purposes and I have no objection that my data is published in scientific publications in a way that does not reveal my identity.
- I freely and voluntarily agree to be part of this research study, though without prejudice to my legal and ethical rights.
- I understand that I may refuse to answer any question and that I may withdraw at any time.
- I understand that my participation is fully anonymous and that no personal details about me will be recorded.
- I understand that if I or anyone in my family has a history of epilepsy then I am proceeding at my own risk.
- I have received a copy of this agreement.
- By registering with the system I consent to take part.

Statement of investigator's responsibility: I have explained the nature and purpose of this research study, the procedures to be undertaken and any risks that may be involved. I have offered to answer any questions and fully answered such questions. I believe that the participant understands my explanation and has freely given informed consent.

RESEARCHERS CONTACT DETAILS:
Name: Victoria Macarthur **Email:** macarthv@cs.tcd.ie **Tel:** 01 896 6431
Address: KDEG, Room F35, The O'Reilly Institute, Trinity College Dublin, Dublin 2

INVESTIGATOR'S SIGNATURE:___Victoria Macarthur__ Date: _01/09/10____

TRINITY COLLEGE DUBLIN

Pre-Test Survey

Demographic Information

1. **Please enter your email address.**
   Comment:
   _____
   _____

2. **Are you male or female?**
   - Male
   - Female

3. **What is your age?**
   - 18-21
   - 22-25
   - 26-30
   - 31-40
   - 41-50
   - 51-60
   - 61+

4. **What is your nationality?**
   Comment:
   _____
   _____

5. **What is your position?**
   - Student
   - Employed
   - Self-employed
   - Unemployed
   - Retired
   - Home duties
   - Other _____

   Comment (Please include a brief elaboration e.g. job title or year and degree):
   _____
   _____

6. **What is the highest level of education you have attained?**
   - Secondary school education
   - Post-Leaving Cert course (PLC)
   - Higher Certificate
   - Ordinary Bachelor Degree
   - Honors Bachelor Degree
   - Higher diploma or postgraduate diploma
   - Master's degree
   - Doctoral degree

   Comment (Please include a brief elaboration):

   _____

   _____

Previous Experience

Please rate the following:

7. **I am comfortable using computers for work and/or personal use**
   - Strongly agree
   - Agree
   - Neither agree nor disagree
   - Disagree
   - Strongly disagree

8. **I can use the Internet to surf and check my e-mails**
   - Strongly agree
   - Agree
   - Neither agree nor disagree
   - Disagree
   - Strongly disagree

9. **I have taken part in an eLearning course**
   - Strongly agree
   - Agree
   - Neither agree nor disagree
   - Disagree
   - Strongly disagree

   Comment (Please include a brief elaboration):

   _____

   _____

10. **I have taken part in a blended learning course**
    - Strongly agree
    - Agree
    - Neither agree nor disagree
    - Disagree
    - Strongly disagree

    Comment (Please include a brief elaboration):

    _____

    _____

Database Systems

The following section includes some questions about databases. These are simply to evaluate your prior knowledge about the domain.

11. **Do you have experience of database systems?**
    - Expert
    - A lot
    - Some
    - None

    Comment (Please include a brief elaboration):

    _____

    _____

12. **Do you have experience of any of the following (please tick all that apply):**
    - Database Management Systems,
    - Creating Databases using SQL
    - Populating Databases
    - Retrieving data from Databases
    - Creating applications using Databases
    - Other related topics _____

    Comment (Please include a brief elaboration where necessary):

    _____

    _____

13. **Database Management Systems: Define what is meant by:**

    Database:

    _____

    _____

    Database Management System:

    _____

    _____

    The Relational Model:

    _____

    _____

    A row:

    _____

    _____

    A view:

    _____

    _____

    3 schema architecture:

    _____

    _____

    SQL:

    _____

    _____

14. Creating a Database: Describe

Data types:

_____

_____

Using the *create* statement:

_____

_____

The primary key:

_____

_____

A foreign key:

_____

_____

The *drop* statement:

_____

_____

Why you would use the *alter* statement:

_____

_____

A view:

_____

_____

15. Populating a Database: Describe

DML:

_____

_____

Relational closure:

_____

_____

Using the *insert* statement:

_____

_____

NULL keyword:

_____

_____

Using the *update* statement:

_____

_____

The outcome of: **UPDATE** *test* **SET** *x* = 5 **WHERE** *y* = 'test x'**;**

_____

_____

Using the *delete* statement:

_____

_____

16. Retrieving data from the Database: Describe

Using the *select* statement:

_____

_____

The use of the asterix (*) in SQL statements:

_____

_____

Using the *order by* statement:

_____

_____

Using arithmetic operators:

_____

_____

Using the *where* clause:

_____

_____

Joins

_____

_____

Metacognitive Awareness

17. Please rate the following:

Where 1 to 5 are:
1. Strongly disagree 2. Disagree 3. Neither agree nor disagree 4. Agree 5. Strongly agree

	1	2	3	4	5
1. I ask myself periodically if I am meeting my goals.					
2. I consider several alternatives to a problem before I answer.					
3. I try to use strategies that have worked in the past.					
4. I pace myself while learning in order to have enough time.					
5. I understand my intellectual strengths and weaknesses.					
6. I think about what I really need to learn before I begin a task					
7. I know how well I did once I finish a test.					
8. I set specific goals before I begin a task.					
9. I slow down when I encounter important information.					
10. I know what kind of information is most important to learn.					
11. I ask myself if I have considered all options when solving a problem.					
12. I am good at organising information.					
13. I consciously focus my attention on important information.					
14. I have a specific purpose for each strategy I use.					
15. I learn best when I know something about the topic.					
16. I know what the teacher expects me to learn.					
17. I am good at remembering information.					
18. I use different learning strategies depending on the situation.					
19. I ask myself if there was an easier way to do things after I finish a task.					
20. I have control over how well I learn.					
21. I periodically review to help me understand important relationships.					
22. I ask myself questions about the material before I begin.					
23. I think of several ways to solve a problem and choose the best one.					
24. I summarize what I've learned after I finish.					
25. I ask others for help when I don't understand something.					
26. I can motivate myself to learn when I need to					
27. I am aware of what strategies I use when I study.					
28. I find myself analyzing the usefulness of strategies while I study.					

29. I use my intellectual strengths to compensate for my weaknesses.					
30. I focus on the meaning and significance of new information.					
31. I create my own examples to make information more meaningful.					
32. I am a good judge of how well I understand something.					
33. I find myself using helpful learning strategies automatically.					
34. I find myself pausing regularly to check my comprehension.					
35. I know when each strategy I use will be most effective.					
36. I ask myself how well I accomplish my goals once I'm finished.					
37. I draw pictures or diagrams to help me understand while learning.					
38. I ask myself if I have considered all options after I solve a problem.					
39. I try to translate new information into my own words.					
40. I change strategies when I fail to understand.					
41. I use the organisational structure of the text to help me learn.					
42. I read instructions carefully before I begin a task.					
43. I ask myself if what I'm reading is related to what I already know.					
44. I reevaluate my assumptions when I get confused.					
45. I organise my time to best accomplish my goals.					
46. I learn more when I am interested in the topic.					
47. I try to break studying down into smaller steps.					
48. I focus on overall meaning rather than specifics.					
49. I ask myself questions about how well I am doing while I am learning something new.					
50. I ask myself if I learned as much as I could have once I finish a task.					
51. I stop and go back over new information that is not clear.					
52. I stop and reread when I get confused.					

TRINITY COLLEGE DUBLIN
Post-Test Survey

The Goby Service: Learning Environment Content

1. **Did the overall design of the learning environment facilitate reading?**
   - Strongly agree
   - Agree
   - Neither agree nor disagree
   - Disagree
   - Strongly disagree

   Comment (Please include a brief elaboration):
   _____
   _____

2. **Was it easy to find information in the learning environment?**
   - Strongly agree
   - Agree
   - Neither agree nor disagree
   - Disagree
   - Strongly disagree

   Comment (Please include a brief elaboration):
   _____
   _____

3. **Were the links provided organised?**
   - Strongly agree
   - Agree
   - Neither agree nor disagree
   - Disagree
   - Strongly disagree

   Comment (Please include a brief elaboration):
   _____
   _____

4. **Describe your impressions of the learning system:**

   Comment (Please include a brief elaboration):
   _____
   _____
   _____
   _____

The Goby Service: Popup Dialog Content

5. **Were the aims of the Goby service clear?**
   - Strongly agree
   - Agree
   - Neither agree nor disagree
   - Disagree
   - Strongly disagree

   Comment (Please include a brief elaboration):

   _____
   _____

6. **Did the popup content match the aims?**
   - Strongly agree
   - Agree
   - Neither agree nor disagree
   - Disagree
   - Strongly disagree

   Comment (Please include a brief elaboration):

   _____
   _____

7. **Considering the audience, is the popup dialog suitable?**
   - Strongly agree
   - Agree
   - Neither agree nor disagree
   - Disagree
   - Strongly disagree

   Comment (Please include a brief elaboration):

   _____
   _____

8. **Was the popup text concise and easy to understand?**
   - Strongly agree
   - Agree
   - Neither agree nor disagree
   - Disagree
   - Strongly disagree

   Comment (Please include a brief elaboration):

   _____
   _____

9. **Was the popup content sufficient?**
    - Strongly agree
    - Agree
    - Neither agree nor disagree
    - Disagree
    - Strongly disagree

    Comment:

    _____
    _____

10. **Were you motivated by the popup content?**
    - Strongly agree
    - Agree
    - Neither agree nor disagree
    - Disagree
    - Strongly disagree

    Comment:

    _____
    _____

11. **Did you feel that the Goby prompts added to the workload?**
    - Strongly agree
    - Agree
    - Neither agree nor disagree
    - Disagree
    - Strongly disagree

    Comment (Please include a brief elaboration):

    _____
    _____

12. **Did you feel that the Goby questions added to the workload?**
    - Strongly agree
    - Agree
    - Neither agree nor disagree
    - Disagree
    - Strongly disagree

    Comment:

    _____
    _____

13. **Did you feel that the Goby prompts interrupted the flow of the work?**
    - Strongly agree
    - Agree
    - Neither agree nor disagree
    - Disagree
    - Strongly disagree

    Comment:

    _____
    _____

14. **Did you feel that the Goby questions interrupted the flow of the work?**
    - Strongly agree
    - Agree
    - Neither agree nor disagree
    - Disagree
    - Strongly disagree

    Comment:

    _____
    _____

15. **Did interactions with the Goby popup box add much time to the learning task?**
    - Strongly agree
    - Agree
    - Neither agree nor disagree
    - Disagree
    - Strongly disagree

    Comment:

    _____
    _____

16. **Where the prompts and questions relevant to learning SQL?**
    - Strongly agree
    - Agree
    - Neither agree nor disagree
    - Disagree
    - Strongly disagree

    Comment:

    _____
    _____

17. **Where the prompts and questions relevant to learning Computer Science?**
    - Strongly agree
    - Agree
    - Neither agree nor disagree
    - Disagree
    - Strongly disagree

    Comment:

    _____
    _____

18. **Were the prompts and questions relevant to the right sections?**
    - Strongly agree
    - Agree
    - Neither agree nor disagree
    - Disagree
    - Strongly disagree

    Comment:

    _____
    _____

19. **Were there many times where the prompt/questions was not relevant?**
    - Strongly agree
    - Agree
    - Neither agree nor disagree
    - Disagree
    - Strongly disagree

    Comment:

    _____
    _____

20. **Did you feel as though the Goby interactions were more relevant over time?**
    - Strongly agree
    - Agree
    - Neither agree nor disagree
    - Disagree
    - Strongly disagree

    Comment:

    _____
    _____

21. Did you feel as though you thought about the prompts and questions?

- Strongly agree
- Agree
- Neither agree nor disagree
- Disagree
- Strongly disagree

Comment:

_____

_____

22. Did you feel as though you used the prompts and questions to help you organise your time?

- Strongly agree
- Agree
- Neither agree nor disagree
- Disagree
- Strongly disagree

Comment:

_____

_____

23. Did the Goby prompts and questions help you while learning?

- Strongly agree
- Agree
- Neither agree nor disagree
- Disagree
- Strongly disagree

Comment:

_____

_____

24. Did you feel frustrated with the Goby service?

- Strongly agree
- Agree
- Neither agree nor disagree
- Disagree
- Strongly disagree

Comment:

_____

_____

25. Did you feel angry at the Goby service?

- Strongly agree
- Agree
- Neither agree nor disagree
- Disagree
- Strongly disagree

Comment:

_____
_____

26. Would Goby be useful while learning other computer science modules?

- Strongly agree
- Agree
- Neither agree nor disagree
- Disagree
- Strongly disagree

Comment:

_____
_____

27. Would Goby be useful for other domains?

- Strongly agree
- Agree
- Neither agree nor disagree
- Disagree
- Strongly disagree

Comment (Please include a brief elaboration):

_____
_____

28. Would you like to have more features to support your cognition?

- Strongly agree
- Agree
- Neither agree nor disagree
- Disagree
- Strongly disagree

Comment (Please include a brief elaboration):

_____
_____
_____
_____

29. **Describe your impressions of the Goby service**
    Comment (Please include a brief elaboration):
    _____
    _____
    _____
    _____
    _____
    _____

30. **Would you be willing to be contacted about a further study on this system?**
    If yes, please supply contact info:
    _____
    _____

Database Systems Exam and Assessment of the MAI from the pre-test were also delivered as a post-test (Num. 11 – 17 in the pre-test above).

Appendix M Log Data Analysis

M.1 Introduction

This appendix comprises of the analyses and examinations of the Goby log data[79] and further comparisons between learners where they are arranged by percentile. Prior-ability was used to categorise these learners into their percentile. Learner percentile is described as high (H), medium (M), and low (L)[80]. In each of the analyses, the learner's prior ability was calculated using their pre-test SQL quiz. While the mid range results are initially plotted to see where they sat within the overall model, this sub-group does not form the basis of comparative analysis because there were so few learners within this medium range. Also, in one case their prior metacognitive ability was used to compare whether their metacognitive percentile affected learning gains. The probability chosen to define an exceptional outcome was significance level α=0.05. Also, the results from the experimental groups are combined in order to compare those who received metacognitive intervention (denoted by M) with the control group (denoted by C). The analysis of the differences between experimental groups (Group A and Group B both received metacognitive supports) is available in Section 6.3. A number of analyses have been possible, including examination of:

4. Overall learning time.
5. Number of pages visited.
6. Time on page.
7. Learning efficiency.
8. Response rate.
9. Reponses time.
10. Change in metacognitive ability – Low vs. high prior-domain ability.
11. Learning gain – Prior ability, intervention, and prior-metacognitive ability.
12. Analysis of the qualitative feedback when learners are categorised into low/high prior ability.

[79] The learner log data (.xml files) was parsed into a spread-sheet format in order for subsequent Minitab analysis to take place.

[80] A MiniTab script was used to categorise learners using indicator variables into the low (below 40th percentile), high (60th percentile and above) and mid (those between low and high) groups. For example, to create indicator variables for learners according to their prior domain ability, the following script can be used: *IF(('Prior Ability'<(PERCENTILE('Prior Ability',.4))),"L")*

M.2 Overall Learning Time

The first set of evaluations to be examined here is a comparison of the overall learning time taken (in seconds). Here, four sets of analysis were possible:

- An overall comparison of metacognitive supports (analysis of the variance between learner percentile and experimental group).
- Comparison of interventions in the intervention/ability model (M vs. C).
- Comparison of interventions with all learners (M vs. C).

M.2.1 Overall Learning Time – A comparison of metacognitive supports and percentile

The first analysis to be carried out is to examine whether learner percentile or intervention influences the overall learning time by comparing an analysis of variance of two factors – percentile and intervention.

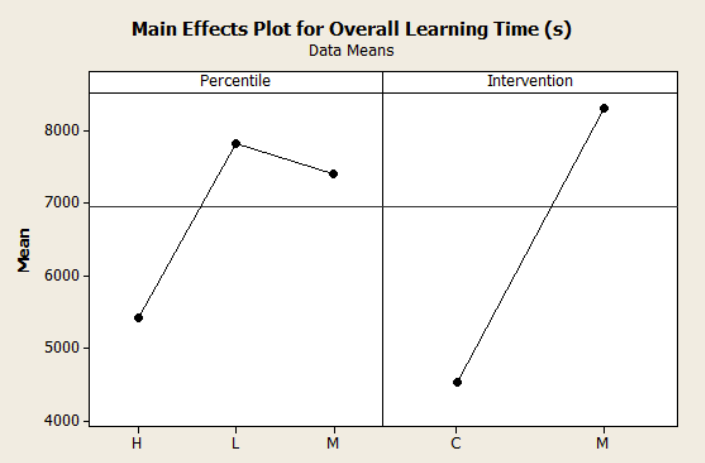


Figure M 1 - Overall Learning Time - Main Effects Plot

Here, if we examine the main effects plots illustrated in Figure M 1 above, we can see that it appears that learners with higher ability (in the percentile plot) and learners in the control (in the intervention plot) had lower overall learning times. This is to be expected, as the intervention conditions (M) added to the workload in the learning environment and learners with higher prior ability should be able to come to grips with the subject material quicker than their peers. In Figure M 2 below, there appears to be no strong suggestion of interaction between intervention and ability – in each case, those in the control took less time, however, it does appear that those in the lower ability cohort had a greater increase in time.

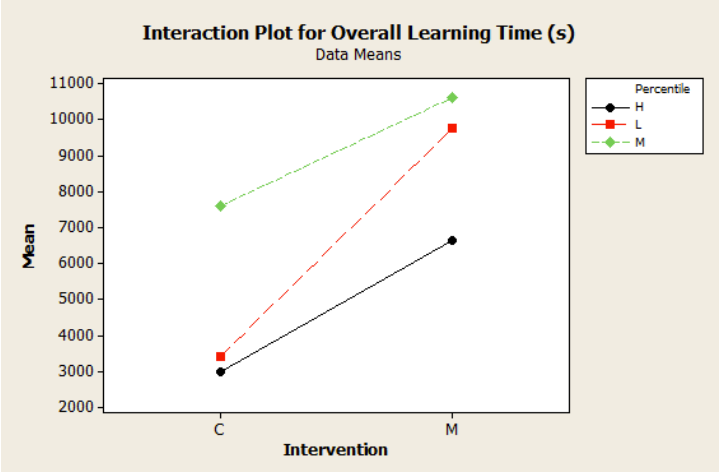


Figure M 2 - Overall Learning Time - Interaction Plot

Here a general linear model for analysis of variance for overall learning time was examined, to test for the factors and their interaction. Thus there are three hypotheses under evaluation:

1. Ho: There is no difference between the percentiles given that we have accounted for the intervention and their interaction.
2. Ho: There is no difference between the interventions given that we have accounted for the percentile and their interaction.
3. Ho: There is no interaction between percentile and intervention.

The general linear ANOVA was carried out to assess whether measures departed from these null hypotheses. There was a significant main effect for intervention, $F(1,21) = 7.04$, $p = 0.015$, but not for the percentile ($F(2,21) = 1.97$, $p = 0.165$) or their interaction ($F(2,21) = 0.46$, $p = 0.636$). Although percentile appeared to influence the overall learning time, the results here are not significant. Here, although this model explains some of the variation in the data (exemplified in the coefficient of determination) there is a large amount of variation in the data not explained by this model. Thus, there are other influential factors that affect overall learning time.

General Linear Model: Overall Learning versus Percentile, Intervention

Factor	Type	Levels	Values
Percentile	fixed	3	H, L, M
Intervention	fixed	2	C, M

Analysis of Variance for Overall Learning Time (s), using Adjusted SS for Tests

Source	DF	Seq SS	Adj SS	Adj MS	F	P
Percentile	2	46488945	55741984	27870992	1.97	0.165
Intervention	1	135949876	99854952	99854952	7.04	0.015
Percentile*Intervention	2	13128344	13128344	6564172	0.46	0.636
Error	21	297727906	297727906	14177519		
Total	26	493295070				

S = 3765.30 R-Sq = 39.65% R-Sq(adj) = 25.27%

Next, we will examine the extreme percentiles (H vs. L) – although results here show that there is no statistical significance for differences in percentiles, it is still interesting to examine these extremes and chart the plots which will let us visualise the differences between these categories of learner.

M.2.2 Overall Learning Time – Comparison of Low and High ability Learners

Here, the null hypothesis is that there is no difference between the low and high ability learners for overall learning time. The alternative hypothesis is that both sets of metacognitive factors have different means.

Ho: μ1 (H) = μ2 (L) = μ

H_1: μ1 ≠ μ2 ≠ μ

A two-sample *t*-test was carried out to compare overall learning time (in seconds) between these categories of learner. Here, as was expected from the above analysis, there was a significant difference between overall learning time for low and high ability learners; t=-1.3, *p*=0.207 M diff = -1980 (95% CI (-5145,1185)). Here, because of the range of variations seen within the groups (as seen in their SD) and small difference reported, the difference or indeed lack of significant difference here may be as a result of the limited sample size[81].

Two-Sample T-Test and CI: Overall Learning Time (s), Percentile

```
Two-sample T for Overall Learning Time (s)

Percentile   N  Mean  StDev  SE Mean
H           11  5828   3500     1055
L           13  7808   3954     1097


Difference = mu (H) - mu (L)
Estimate for difference:  -1980
95% CI for difference:  (-5145, 1185)
T-Test of difference = 0 (vs not =): T-Value = -1.30  P-Value = 0.207  DF = 21
```

[81] Here, in a post-hoc power analysis (for a two-sample t-test) - a sample size of 68 would be sufficient to assay differences of 1800s or 30 minutes (target power .8) with SD of 3712 (the reported SD of the overall cohort) and 18 for 3600s (1 hour).

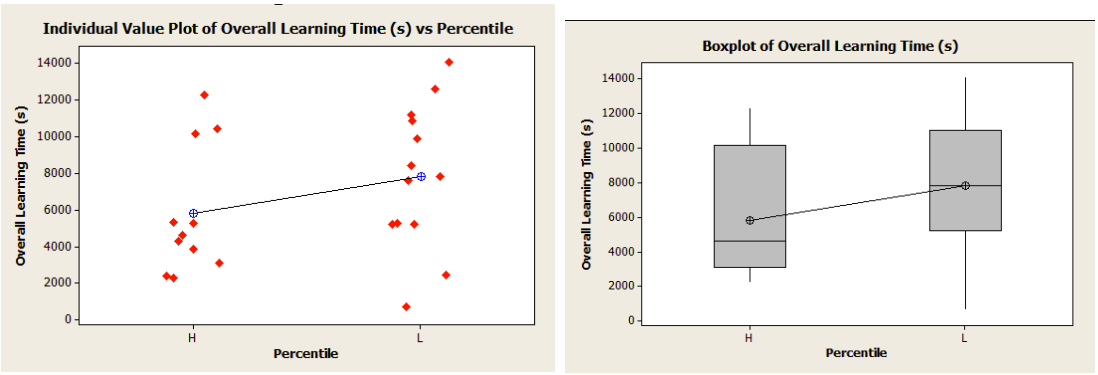


Figure M 3 - Overall Learning Time - Comparison of low and high percentile learners

What is interesting here is that when we examine the individual value plots of learning time, in Figure M 3 above, is that although there appear to be an increase in the mean time for lower ability learners, there is a wide range of learning time in both cases. This indicates that regardless of prior ability, learners will still take a varying amount of time to complete the learning task. Indeed, this may be as a result of confounding variables that may influence the amount of time taken (Internet connection speed, motivation, interest, ability to skim or use reading strategies, etc.).

M.2.3 Overall Learning Time – A comparison of intervention groups (M) with to the control (C) – Learners who completed Pre-Test

Next, we examine the overall learning time for intervention groups. The null hypothesis is that there is no difference between the intervention groups (M) and control (C) for overall learning time. The alternative hypothesis is that both sets of metacognitive factors have different means.

Ho: μ1 (M) = μ2 (C) = μ

H_1: μ1 ≠ μ2 ≠ μ

A two-sample *t*-test was carried out to compare overall learning time (in seconds). Here, in line with the above analysis, there was a significant difference reported between overall learning time; t=-3.94, *p*=0.001 M diff = -4338 (95% CI (-6610,-2067)).

Two-Sample T-Test and CI: Overall Learning Time (s), Intervention

```
Two-sample T for Overall Learning Time (s)

Intervention   N  Mean  StDev  SE Mean
C             11  4408   2521      760
M             16  8746   3183      796


Difference = mu (C) - mu (M)
Estimate for difference:  -4338
95% CI for difference:  (-6610, -2067)
T-Test of difference = 0 (vs not =): T-Value = -3.94  P-Value = 0.001  DF = 24
```

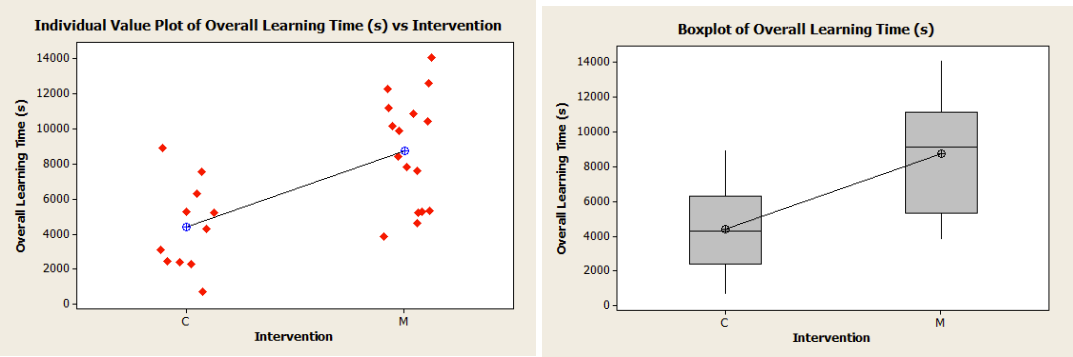


Figure M 4 - Overall Learning Time - Comparison of experimental (M) and control (C) group (learners who completed the SQL pre-test and are part of the above model)

On examination of the plots in Figure M 4 above, which compare the intervention groups (M) to the control groups (C), there is still a range of times reported, however these ranges tend to cluster towards the lower time range (in the case of the control) and the higher time range (in the case of the intervention groups). Indeed, this is to be expected if the learners were indeed interacting with the metacognitive dialogs as they reported in their qualitative feedback. However, in creating this model, a number of measurements for intervention were not included as not all participants completed the pre-test SQL examination. Thus, we will also re-examine the intervention and include this extra data.

M.2.4 Overall Learning Time – A comparison of the intervention groups (M) with to the control (C) – All results

A subsequent two-sample *t*-test was carried out to compare overall learning time (in seconds) for all participants, including those who did not complete the pre-test SQL exam and thus were not included in the initial learning time model (Ho: μ1 (Ma) = μ2 (Ca) = μ)[82]. Here, in line with the above analysis, there was a significant difference reported between overall learning time; t=-2.93, *p*=0.006 M diff = -3672 (95% CI (-6218,-1126)).

[82] A subsequent post-hoc power analysis was also carried out the strength of the tests – here a sample size of 118 would be required to assay differences of 1800s (30 minutes) (target power .8) with SD of 4913 (the reported SD of the overall cohort) or 31 for 3600s (1 hour). While this suggests that the test is somewhat underpowered (due to the size of the control) to assess the lesser differences in time, through examination of the individual value plots and interaction plots there are differences to be seen between control and intervention group.

Two-Sample T-Test and CI: Overall Learning Time (s), Intervention

```
Two-sample T for Overall Learning Time (s)

Intervention   N  Mean  StDev  SE Mean
C             12  4521   2749       794
M             29  8193   5237       972


Difference = mu (C) - mu (M)
Estimate for difference:  -3672
95% CI for difference:  (-6218, -1126)
T-Test of difference = 0 (vs not =): T-Value = -2.93  P-Value = 0.006  DF = 36
```

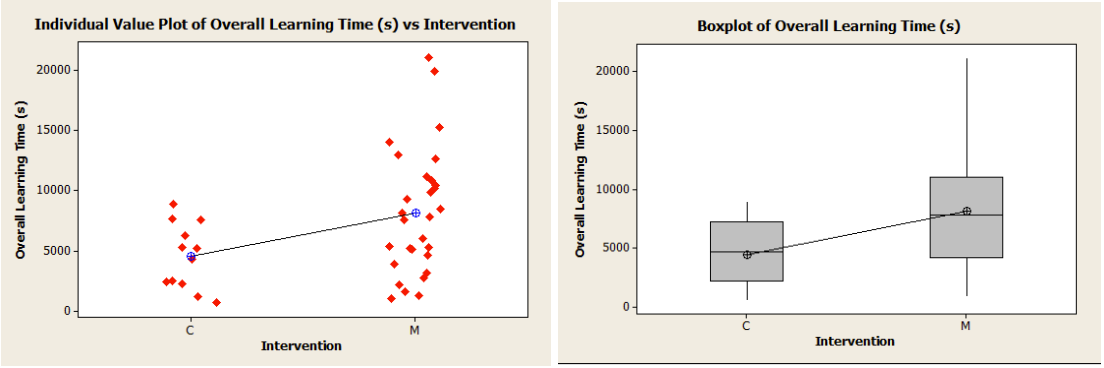


Figure M 5 - Overall Learning Time - Comparison of experimental (M) and control (C) group (all learners)

Again, on analysis of the plots, as illustrated in Figure M 5 above, there is a range of responses with the control group (C) clustering towards the lower end of the learning time. Interestingly, the intervention group (M) is wide-ranging (as seen in the SD) and some learners took similar time to complete as their control group peers. This is probably because some learners initially paid attention to the metacognitive dialog prompts and subsequently learner to attend to them quickly/ignore them (as discussed in the qualitative feedback section below).

M.3 Number of Pages Visited

The section presents an analysis of the number of pages. Here, four sets of analysis are carried out:

- An overall comparison of metacognitive supports (analysis of the variance between learner percentile and experimental group).
- Comparison of low vs. high ability learners (L vs. H).
- Comparison of interventions in the intervention/ability model (M vs. C).
- Comparison of interventions with all learners (M vs. C).

M.3.1 Number of Pages Visited – A comparison of Groups A, B and C (Low and High Percentile Learners)

The first analysis to be carried out is to examine whether learner percentile or intervention influences the number of pages[83] visited through the use of a general linear analysis of variance.

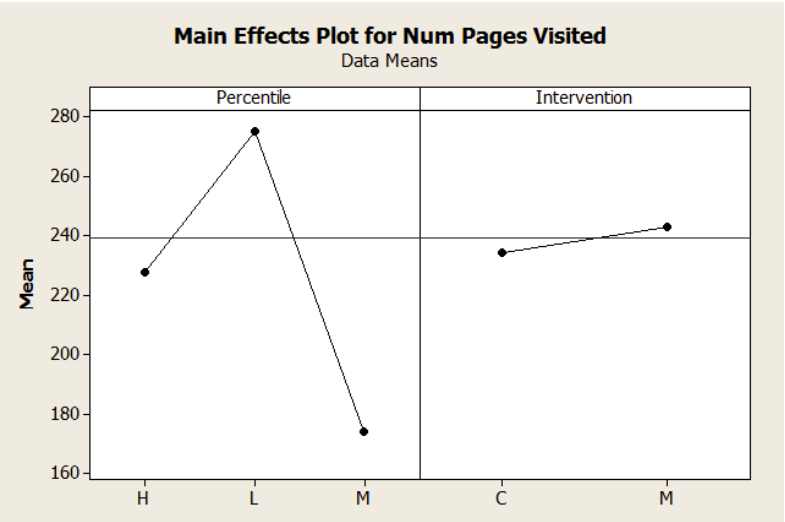


Figure M 6 - Number of Pages Visited - Main Effects Plot

The main effects plots illustrated in Figure M 6 above, we can see that it appears that learners with lower ability (in the percentile plot) visited more pages. It also appears as though learners in the intervention (metacognition) group (in the intervention plot) also had visited a higher number of pages, however this is very slight so is more likely to be through random figures in the data. Given that learners with prior ability may be able to skip ahead in introductory sections, it is possible that they could report lower pages visited overall. However, the nature of the learning environment (step-by-step pages) means that they would be more likely to skip through pages more quickly (as shown in the analysis of overall learning time in M.2.2 above). In Figure M 7 below, there appears to be no interaction between intervention and ability for learners in the intervention and control conditions – in these case, those in the higher ability learners views less pages than their low ability peers. However, here it does appear as though there is an interaction for the middle range learners, however this may be due to random variability as this sub-group contains a small number of participants.

[83] There were 258 pages in the total course. In the three sections (for their three days of study) that the learners were requested to complete, there was a total of 133 pages. The fourth section was optional, and contained 125 pages.

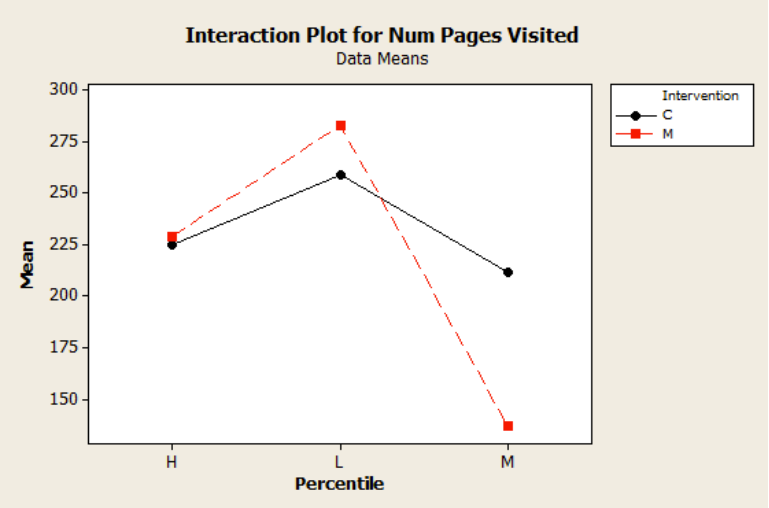


Figure M 7 - Number of Pages Visited - Interaction Plot

A subsequent a general linear model for analysis of variance for number of pages visited was examined, to test for the factors and their interaction. Thus, there are three hypotheses under evaluation:

1. Ho: There is no difference between the percentiles given that we have accounted for the intervention and their interaction.
2. Ho: There is no difference between the interventions given that we have accounted for the percentile and their interaction.
3. Ho: There is no interaction between percentile and intervention.

The general linear ANOVA was carried out to assess whether measures departed from these null hypotheses. Here, no significant effects were reported for percentile ($F(2,24) = 1.57$, $p = 0.229$), intervention ($F(1,24) = 0.14$, $p = 0.713$), or their interaction ($F(2,24) = 0.38$, $p = 0.687$). This model does not explain the variation in the data, as seen in the coefficient of determination. Although percentile appeared to influence the number of pages visited, the results here show that there was not a significant difference between them.

General Linear Model: Num Pages Visited versus Percentile, Intervention

```
Factor        Type   Levels  Values
Percentile    fixed       3  H, L, M
Intervention  fixed       2  C, M


Analysis of Variance for Num Pages Visited, using Adjusted SS for Tests

Source                  DF  Seq SS  Adj SS  Adj MS     F      P
Percentile               2   34193   29393   14697  1.57  0.229
Intervention             1       1    1300    1300  0.14  0.713
Percentile*Intervention  2    7139    7139    3569  0.38  0.687
Error                   24  224668  224668    9361
Total                   29  266001


S = 96.7532   R-Sq = 15.54%   R-Sq(adj) = 0.00%
```

This model did not explain the learning results (R-Sq adj = 0%). Although results here show that there is no statistical significance for differences in percentiles, it is still interesting to examine these extremes (H vs. L) and chart the plots, which will let us visualise the differences between these categories of learner. While the lower ability group did appear to visit more pages than their higher ability cohort, this test was not significant.

M.3.2 Number of Pages Visited – Comparison of low ability and high ability learners

Here, the null hypothesis is that there is no difference between the low and high ability learners for number of pages visited.

Ho: μ1 (H) = μ2 (L) = μ

H_1: μ1 ≠ μ2 ≠ μ

A two-sample *t*-test was carried out to compare overall learning time (in seconds) between these categories of learner. In line with the above results, although low ability students appear to have visited more pages, both high and low ability learners can be considered on par for the number of pages visited; t=-1.73, *p*=0.098 M diff = -69.8 (95% CI (-153.5,13.9)).

Two-Sample T-Test and CI: Num Pages Visited, Percentile

```
Two-sample T for Num Pages Visited

                                SE
Percentile   N   Mean  StDev  Mean
H           14  227.4   91.3    24
L           13    297    116    32


Difference = mu (H) - mu (L)
Estimate for difference:  -69.8
95% CI for difference:  (-153.5, 13.9)
T-Test of difference = 0 (vs not =): T-Value = -1.73  P-Value = 0.098  DF = 22
```

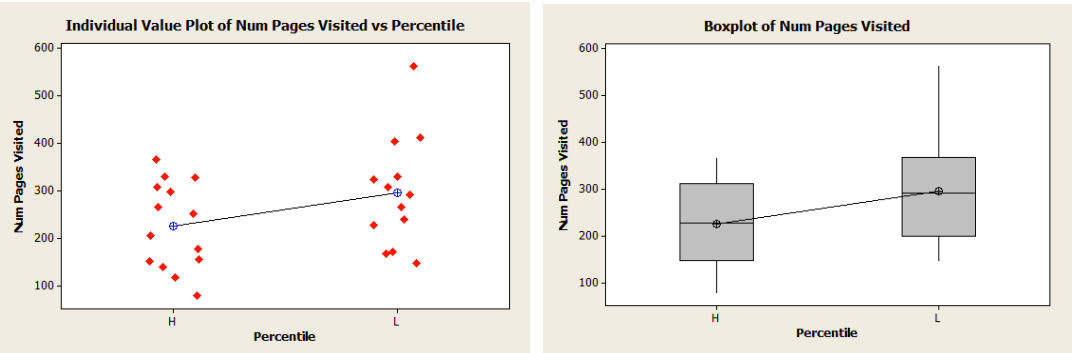


Figure M 8 - Number of Pages Visited - Comparison of low and high percentile learners

In the individual value plots shown in Figure M 8 above, both high (H) and low (L) ability learners are clustered in similar locations. While there is a small increase in

number of pages visited reported by the lower ability group, overall, indicates that no difference can be conclusively found between the two[84]. While the test is somewhat underpowered, the reported number of pages here is visually similar regardless of the two groups. A number of learners[85] accessed over the total number of pages suggesting that they reviewed previous work already complete before completing the final quiz. This indicates that regardless of prior ability, learners accessed a range of pages, and that there was a large variance in the total number of pages visited. Indeed, the lack of differences found here might be as a result of the relatively small sample size, however it can be postulated that there were other confounding variables (e.g. study style, or motivation before completing the final SQL quiz).

M.3.3 Number of Pages Visited - A comparison of the intervention groups (M) to the control (C) – Those who completed pre-test

Next, we examine the number of pages visited for intervention groups. The null hypothesis is that there is no difference between the intervention groups (M) and control (C) for overall learning time (Ho: μ1 (M) = μ2 (C) = μ). Again, it is expected that these results are on par because of the initial analysis, but we will examine the individual value plots to assess whether there are any trends in the data. The two-sample *t*-test was carried out to the number of pages visited and the groups can be considered to be on par; t=-0.45, *p*=0.656 M diff = -17.4 (95% CI (-98.2, 63.4)).

Two-Sample T-Test and CI: Num Pages Visited, Intervention

```
Two-sample T for Num Pages Visited

                                SE
Intervention   N   Mean  StDev  Mean
C             10  238.7   98.9    31
M             16  256.1   88.4    22


Difference = mu (C) - mu (M)
Estimate for difference:  -17.4
95% CI for difference:  (-98.2, 63.4)
T-Test of difference = 0 (vs not =): T-Value = -0.45  P-Value = 0.656  DF = 17
```

[84] In a post-hoc power analysis suggested that this test is somewhat underpowered– here a sample size of 15 would be sufficient to assay differences of 100 pages (target power .8) with SD of 91 (the reported SD of this subgroup) and 28 for 70 pages (half of the required course).

[85] 13 in total.

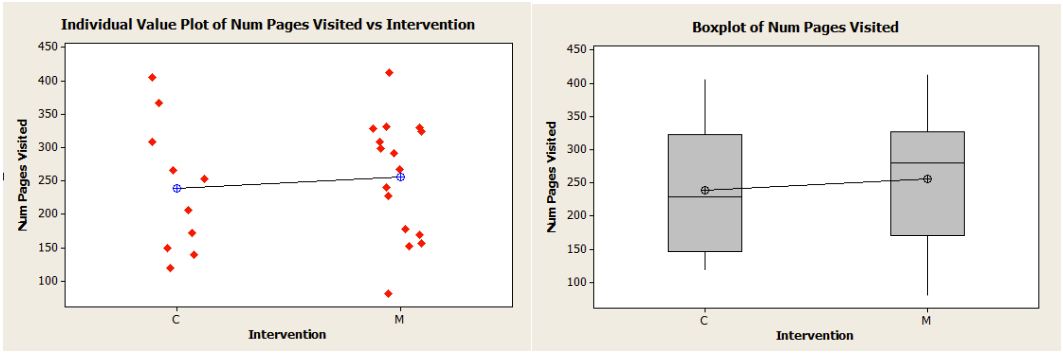


Figure M 9 - Number of Pages Visited - Comparison of experimental (M) and control (C) group (learners who completed the SQL pre-test and are part of the above model in M.3.1)

On examination of the plots in Figure M 9 above, both groups appear to be evenly clustered – within each there is a range of number of pages visited regardless of prior ability. Again, however, if differences did exist, this may be difficult to find with the small sample size. As this group does not contain all of the learner information, we next examine all of the learners (to now include those that did not complete the pre-test SQL quiz) in order to add power to this test.

M.3.4 Number of Pages Visited - A comparison of the intervention groups (M) with to the control (C) – All results

Here we examine the same null hypothesis, that the number of pages visited for intervention groups is the same (Ho: μ1 (Ma) = μ2 (Ca) = μ). Here, in line with the prior analysis, there was no difference reported between overall learning time; t=-0.21, *p*=0.834 M diff = -6.7 (95% CI (-72.4,58.9)).

Two-Sample T-Test and CI: Num Pages Visited, Intervention

```
Two-sample T for Num Pages Visited

                                 SE
Intervention   N   Mean  StDev  Mean
C             14    227    101    27
M             31  234.1   93.0    17


Difference = mu (C) - mu (M)
Estimate for difference:  -6.7
95% CI for difference:  (-72.4, 58.9)
T-Test of difference = 0 (vs not =): T-Value = -0.21  P-Value = 0.834  DF = 23
```

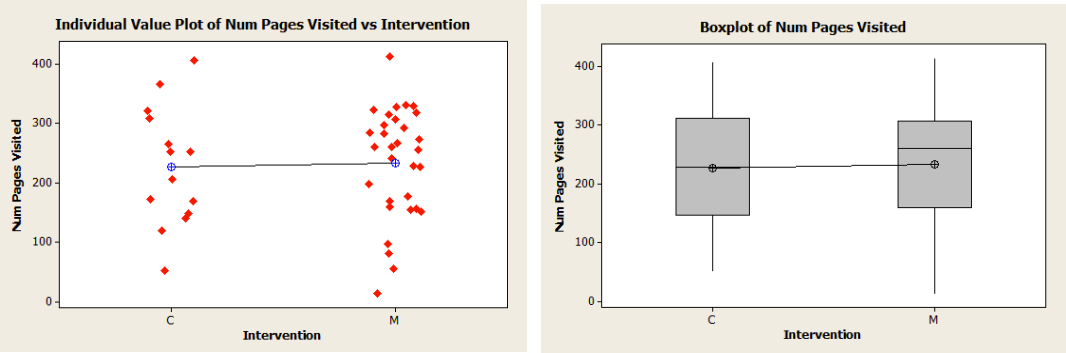


Figure M 10 - Number of Pages Visited - Comparison of experimental (M) and control (C) group (all learners)

In the individual value plot in above, there are clear trends for clusters regardless of the intervention[86]. This test can be considered to be of a relatively strong power for assessing a large difference between groups, indicating that there the intervention group did not effect the number of pages visited. This is a valuable result, because the added workload created by the addition of the metacognitive dialog did not have negative effects in terms of the number of pages visited. These additions did not result in learners stopping their learning experience early due to the additional time and cognitive resources required of them.

M.4 Time on Page

The section presents an analysis of the amount of time typically spent per page (in seconds). Again, four sets of analysis are carried out:

- An overall comparison of metacognitive supports (analysis of the variance between learner percentile and experimental group).
- Comparison of low vs. high ability learners (L vs. H).
- Comparison of interventions in the intervention/ability model (M vs. C)
- Comparison of interventions with all learners (M vs. C).

M.4.1 Time on Page – A comparison of Groups A, B and C (Low and High Percentile Learners)

The first analysis to be carried out is to examine whether learner percentile or intervention influences the time spent on page.

86 86 In a post-hoc power analysis suggested that this test is somewhat underpowered– here a sample size of 15 would be sufficient to assay differences of 100 pages (target power .8) with SD of 94 (the reported SD of the overall cohort) and 30 for 70 pages (half of the required course).

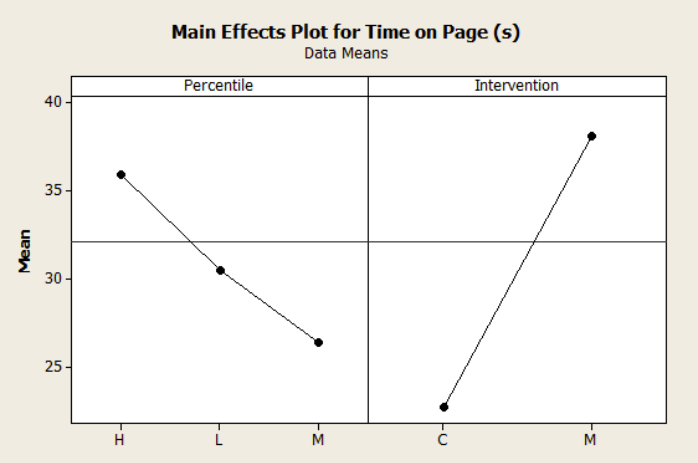


Figure M 11 - Time on Page - Main Effects Plot

Here, if we examine the main effects plots illustrated in Figure M 11 above, we can see that it appears that learners with higher ability (in the percentile plot) and learners in the control (in the intervention plot) took less time per page. This is in line with the results reported in the overall learning time and is to be expected, as the intervention conditions (M) added to their workload. Interestingly, the medium group (M) in the percentile plot appear to have taken less time than their lower ability peers, however this was a small sub-group (n=6) and there may be no real significant difference between groups. In Figure M 12 below, there appears to be no strong suggestion of interaction between intervention and ability for high (H) and low (L) ability learners – in both cases, those in the control took less time. Interestingly, the mid range learners appear to have reported a different effect – whereby those in the control took more time than mid range learners in the intervention group. However, this is most likely due to the fact that there were very few learners in this mid-range group.

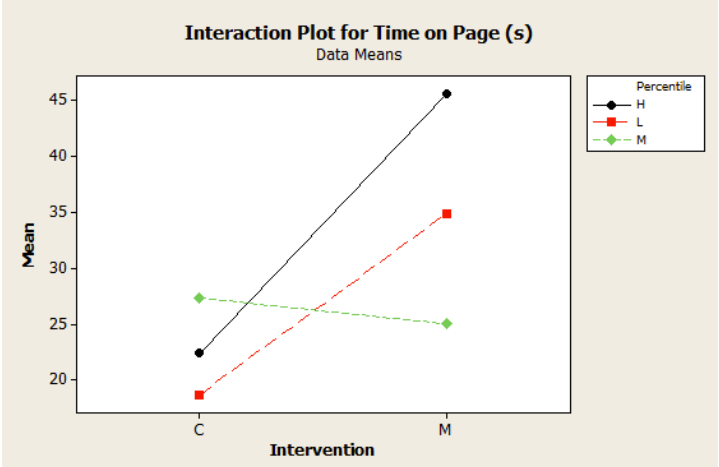


Figure M 12 - Time on Page - Interaction Plot

To assess these trends and examine whether an interaction is at play here, a general linear model for analysis of variance for time on page was examined, to test for the factors and their interaction. Again, three hypotheses under evaluation:

1. Ho: There is no difference between the percentiles given that we have accounted for the intervention and their interaction.
2. Ho: There is no difference between the interventions given that we have accounted for the percentile and their interaction.
3. Ho: There is no interaction between percentile and intervention.

In line with the results from the overall learning time analysis, there was a significant main effect for intervention, $F(1,22) = 5.19$, $p = 0.033$, but not for the percentile ($F(2,22) = 1.07$, $p = 0.360$) or their interaction ($F(2,22) = 1.71$, $p = 0.204$). Again, although percentile appeared to influence the time on page the results here are not significant. While intervention has probably gone towards explaining some of the variation in the data, there is most likely other variables at play here as well.

General Linear Model: Time on Page (s) versus Percentile, Intervention

```
Factor        Type   Levels  Values
Percentile    fixed       3  H, L, M
Intervention  fixed       2  C, M


Analysis of Variance for Time on Page (s), using Adjusted SS for Tests

Source                  DF  Seq SS  Adj SS  Adj MS     F      P
Percentile               2   367.0   346.9   173.4  1.07  0.360
Intervention             1  1592.4   839.7   839.7  5.19  0.033
Percentile*Intervention  2   553.4   553.4   276.7  1.71  0.204
Error                   22  3561.1  3561.1   161.9
Total                   27  6073.9


S = 12.7228   R-Sq = 41.37%   R-Sq(adj) = 28.04%
```

Next, we will examine the outer percentiles (H vs. L) and compare the intervention groups (M vs. C) to analyse the extremes and individual value plots to assay whether there are any visual trends in the data.

M.4.2 Time on Page – Comparison of Low and High Ability

Here, the null hypothesis is that there is no difference between the low and high ability learners for number of pages visited (Ho: μ1 (H) = μ2 (L) = μ). A two-sample *t*-test was carried out to compare time on page (in seconds) between low (L) and high (H) ability learners. In line with the overall learning time results, although low ability students appear to have spent more time on page, both high and low ability learners can be considered on par; t=1.27, p=0.220, M diff = 8.38 (95% CI (-5.43,22.19)).

Two-Sample T-Test and CI: Time on Page (s), Percentile

```
Two-sample T for Time on Page (s)

Percentile   N  Mean  StDev  SE Mean
H           12  35.9   18.6      5.4
L           13  27.5   14.0      3.9


Difference = mu (H) - mu (L)
Estimate for difference:  8.38
95% CI for difference:  (-5.43, 22.19)
T-Test of difference = 0 (vs not =): T-Value = 1.27  P-Value = 0.220  DF = 20
```

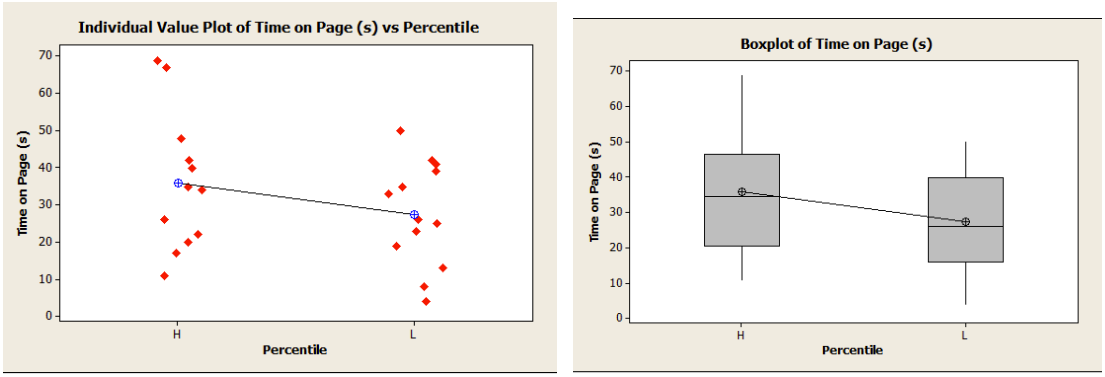


Figure M 13 - Time on Page - Comparison of low and high percentile learners

On examination of Figure M 13 the data revealed that there was a range of time spent on page, regardless of prior ability. While there were a sufficient number of results to assay a difference of 20s, learners' prior ability does not appear to influence the time on page[87]. As with overall learning time, this may be as a result of confounding factor, such as Internet connection speed, motivation, ability to skim or use reading strategies, etc.

M.4.3 Time on Page - A comparison of the intervention groups (M) compared to the control (C) – Those who completed pre-test

Next, we examine the overall learning time for intervention groups. The null hypothesis is that there is no difference between the intervention groups (M) and control (C) for overall learning time (Ho: μ1 (M) = μ2 (C) = μ). The two-sample *t*-test was carried out to compare time on page (in seconds). Here, in line with the above analysis, there was a significant difference reported between overall learning time; t=-3.16, *p*=0.004 M diff = -15.39 (95% CI (-25.44, -5.34)).

[87] Here, a power analysis suggested that a sample size of 10 would be required to assay differences of 20s (target power .8) with SD of 15 (the reported SD of the overall cohort) or 3 for 60s.

Two-Sample T-Test and CI: Time on Page (s), Intervention

```
Two-sample T for Time on Page (s)

Intervention   N  Mean  StDev  SE Mean
C             11  22.7   11.5      3.5
M             17  38.1   14.1      3.4


Difference = mu (C) - mu (M)
Estimate for difference:  -15.39
95% CI for difference:  (-25.44, -5.34)
T-Test of difference = 0 (vs not =): T-Value = -3.16  P-Value = 0.004  DF = 24
```

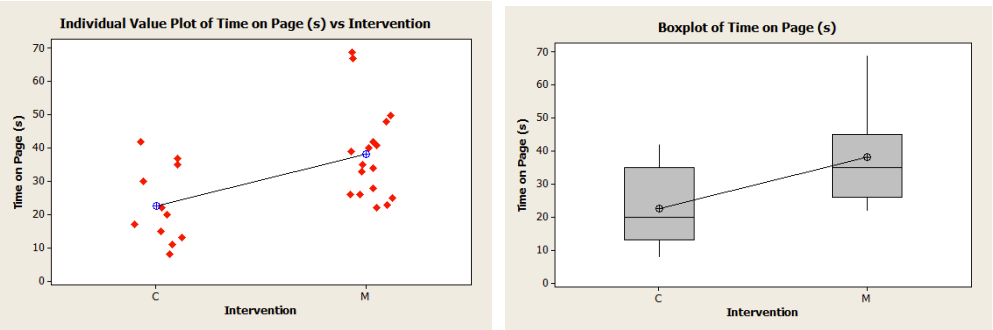


Figure M 14 - Time on Page - Comparison of experimental (M) and control (C) group (learners who completed the SQL pre-test and are part of the above model in M.4.1)

On examination of the plots in Figure M 14 above, which compare the intervention groups (M) to the control groups (C), they cluster around the lower and higher time ranges respectively. While this test already has a relatively strong power the extra data available will now be included to examine the overall cohort.

M.4.4 Time on Page - A comparison of the intervention groups (M) compared to the control (C) – All results

Again, a subsequent two-sample *t*-test was carried out to compare time on page (in seconds) for all participants (Ho: µ1 (Ma) = µ2 (Ca) = µ)[88]. Here, in line with the above analysis, there was a significant difference reported between overall learning time; t=--2.3, *p*=0.03 M diff = -8.38 (95% CI (-15.88, -0.87)).

Two-Sample T-Test and CI: Time on Page (s), Intervention

```
Two-sample T for Time on Page (s)

Intervention   N  Mean  StDev  SE Mean
C             13  22.8   10.5      2.9
M             27  31.1   11.3      2.2


Difference = mu (C) - mu (M)
Estimate for difference:  -8.38
95% CI for difference:  (-15.88, -0.87)
T-Test of difference = 0 (vs not =): T-Value = -2.30  P-Value = 0.030  DF = 25
```

[88] Same overall SD as the initial model.

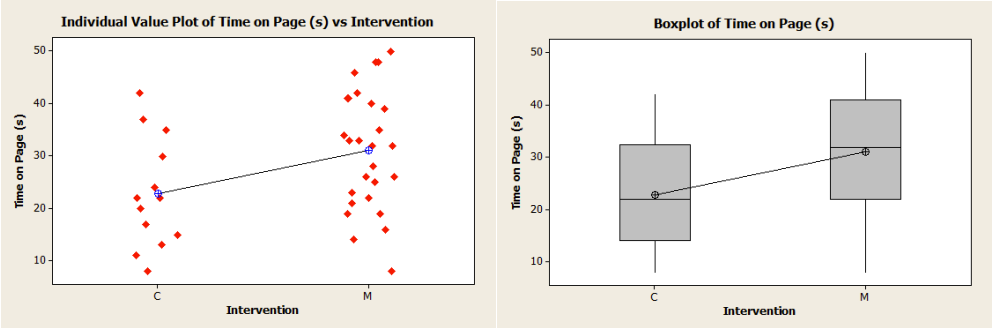


Figure M 15 - Time on Page - Comparison of experimental (M) and control (C) group (all learners)

Again, on analysis of the plots, as illustrated in Figure M 15 above, there is a range of responses with the control group (C) clustered at the lower end of the time scale. Interestingly, a number of learners in the intervention group (M) took similar time as their control group peers. A similar graph was presented in the analysis of overall learning time above (c.f. Figure M 5) and as discussed in the qualitative feedback, this is probably because they learned to ignore or quickly attend to the metacognitive dialog. Nonetheless, there is a clearly significant difference here between the intervention and control group.

M.5 Learning Efficiency

The section presents an analysis of learning efficiency. A *learning efficiency* score is calculated by dividing the raw post-test score by time on task[89] (c.f. Azevedo, Johnson, Burkett, et al., 10; Gaun, 09). Here, three sets of analysis were possible:

- An overall comparison of metacognitive supports (analysis of the variance between learner percentile and experimental group).
- Comparison of low vs. high ability learners (L vs. H).
- Comparison of interventions (M vs. C).

M.5.1 Learning Efficiency – A comparison of Groups A, B and C (Low and High Percentile Learners)

Here we examine whether learner percentile, intervention, or their interaction influences learning efficiency.

[89] LE = ((post SQL/LT in s)*100). Learning efficiency is multiplied by 100 to avoid comparing fractions (Gaun, 09). Learning efficiency is high when the score of post-test is high and learning time is short.

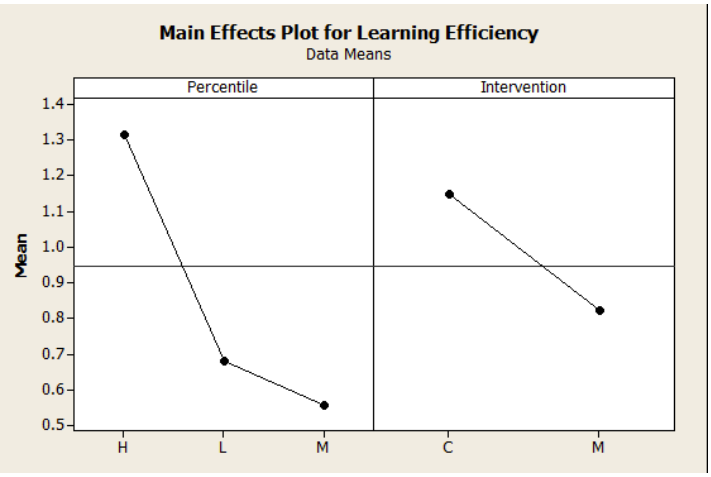


Figure M 16 - Learning Efficiency - Main Effects Plot

In Figure M 16 above, the main effects plot show that learners with higher ability (in the percentile plot) and learners in the control (in the intervention plot) had greater learning efficiency. In previous analysis, a lower learner time was similarly present for these cohorts, however intervention was not shown to be significantly different in subsequent examination of the data. In Figure M 17 below, there appears to be no interaction between intervention and ability – in each case, those in the control group had higher mean learning efficiency scores.

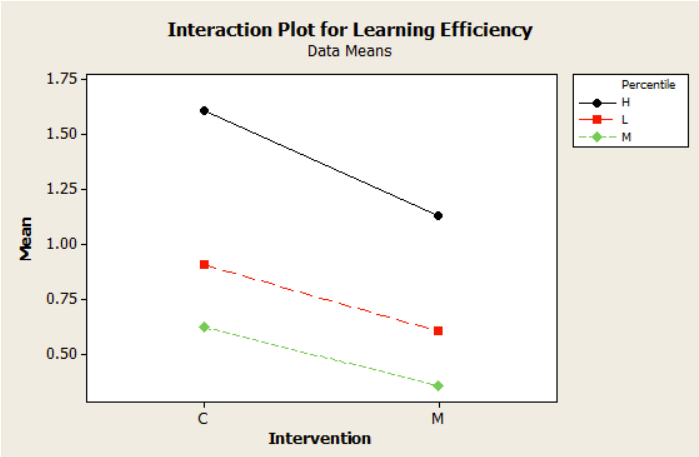


Figure M 17 - Learning Efficiency - Interaction Plot

Here a general linear model for analysis of variance for overall learning time was examined, to examine the effects of the factors and their interaction. Thus there are three hypotheses under evaluation:

Ho: There is no difference between the percentiles given that we have accounted for the intervention and their interaction.

Ho: There is no difference between the interventions given that we have accounted for the percentile and their interaction.

Ho: There is no interaction between percentile and intervention.

The general linear ANOVA was carried out to assess whether measures departed from these null hypotheses. There was a significant main effect for percentile, $F(2,23) = 4.2$, $p = 0.028$, but not for the intervention ($F(1,23) = 1.47$, $p = 0.237$) or their interaction ($F(2,23) = 0.07$, $p = 0.928$). Again, as seen in previous analysis, these metrics only explain a small amount of the variation in the data, which means that there are most likely other influencing factors that affect learning efficiency.

General Linear Model: Learning Efficie versus Percentile, Intervention

```
Factor        Type   Levels  Values
Percentile    fixed       3  H, L, M
Intervention  fixed       2  C, M


Analysis of Variance for Learning Efficiency, using Adjusted SS for Tests

Source                   DF   Seq SS  Adj SS  Adj MS     F      P
Percentile                2   3.2136  2.9644  1.4822  4.20  0.028
Intervention              1   0.9097  0.5202  0.5202  1.47  0.237
Percentile*Intervention   2   0.0526  0.0526  0.0263  0.07  0.928
Error                    23   8.1167  8.1167  0.3529
Total                    28  12.2925


S = 0.594054   R-Sq = 33.97%   R-Sq(adj) = 19.62%
```

Next, we will examine the learner percentiles and intervention groups (M vs. C). Although the intervention did not result in a statistical difference here, further analysis will make it possible to examine the individual values and the trends in the way that the results are distributed within the groups.

M.5.2 Learning Efficiency – Comparison of low ability and high ability learners

In the examination of learning efficiency, learner percentile was indicated as being influential on the learners' efficiency. As a result, it is first interesting to examine whether there is variance between the percentiles (L v M v H). This means that the null hypothesis is that there is no difference between the low, mid, and high percentile learners for learning efficiency. The alternative hypothesis is that both sets of metacognitive factors have different means.

Ho: μ1 (L) = μ2 (M) = μ3 (H) = μ

H_1: μ1 ≠ μ2 ≠ μ3 ≠ μ

A one-way AVOVA was used to test this hypothesis and a significant effect found for percentile, $F(2,26) = 4.60$, $p = 0.019$.

One-way ANOVA: Learning Efficiency versus Percentile

```
Source      DF      SS     MS     F      P
Percentile   2   3.214  1.607  4.60  0.019
Error       26   9.079  0.349
Total       28  12.292

S = 0.5909   R-Sq = 26.14%   R-Sq(adj) = 20.46%

                          Individual 95% CIs For Mean Based on
                          Pooled StDev
Level   N    Mean   StDev  -+---------+---------+---------+--------
H      13  1.3127  0.7958                      (-----*------)
L      12  0.6793  0.3596           (------*------)
M       4  0.5549  0.1384   (-----------*-----------)
                           -+---------+---------+---------+--------
                          0.00      0.50      1.00      1.50

Pooled StDev = 0.5909
```

On examination of the ANOVA results, and as illustrated in the main effects plot in Figure M 16 above, there was greater learning efficiency reported by the higher ability group, over their lower and medium ability peers. Here, the medium cohort is too small (n=4) to be included in this discussion[90] although it does appear that these learners reported an average range of responses when compared to their higher and lower ability peers. Subsequent to this ANOVA analysis, it is worthwhile to examine the extreme percentiles (H vs. L). Thus, the null hypothesis is that the high (H) and low (L) percentile learners have the same mean learning efficiency score (Ho: μ1 (L) = μ2 (H) = μ). The two-sample *t*-test was carried out to compare learning efficiency. Here, there was a significant difference reported between the low and high ability learners; t=2.60, *p*=0.019 M diff = 0.633 (95% CI (0.116, 1.150)).

Two-Sample T-Test and CI: Learning Efficiency, Percentile

```
Two-sample T for Learning Efficiency

Percentile   N   Mean  StDev  SE Mean
H           13  1.313  0.796     0.22
L           12  0.679  0.360     0.10


Difference = mu (H) - mu (L)
Estimate for difference:  0.633
95% CI for difference:  (0.116, 1.150)
T-Test of difference = 0 (vs not =): T-Value = 2.60  P-Value = 0.019  DF = 16
```

[90] Here, a power analysis reported that a sample size of 13 would be sufficient (in a two-sample t-test) to assay differences of 0.7 on the learning efficiency scale (target power .8) with a SD of 0.6.

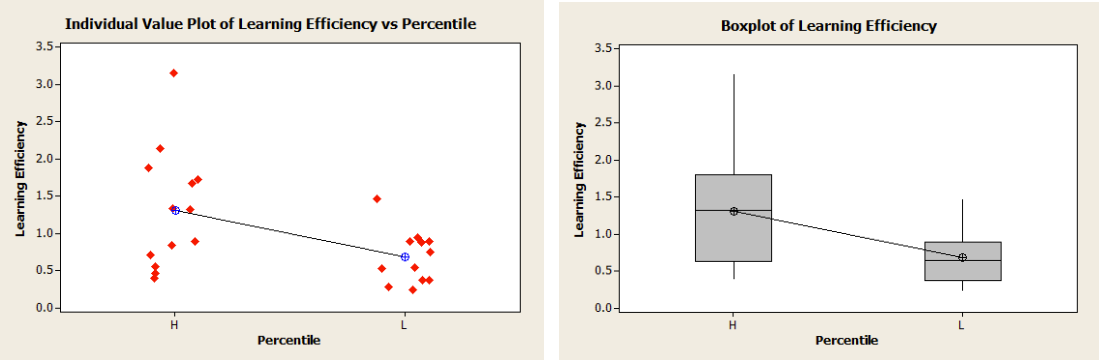


Figure M 18 - Learning Efficiency - Comparison of low and high percentile learners

On examination of the plots in Figure M 18 above, both high and low ability learners cluster towards the lower end of the learning efficiency scale with a number of learners within the higher ability cohort also evident in toward the higher end of the scale. Here, it appears that there is greater deviation in the higher ability learners rather (as also seen in the results above) rather than the group simply having a greater learning efficiency. While this test already has a relatively strong power, this indicates that prior ability may not be the only factor that affects learning efficiency. In the initial model – which incorporated prior ability, intervention group and their interaction, prior ability was the only factor to be highlighted as having an effect. However, this may be because of the overall sample size not being sufficient to deal with the range or deviation of learner results. Next, we examine the learning efficiency for intervention groups in order to examine the estimated differences and trends in the data that are visible in the learning plots.

M.5.3 Learning Efficiency - A comparison of the intervention groups (M) compared to the control (C)

The null hypothesis is that there is no difference between intervention groups (Ho: μ1 (M) = μ2 (C) = μ). The two-sample *t*-test was carried out to compare learning efficiency. Here, in line with the above analysis, the groups can be considered to be on par overall learning time; t=1.15, *p*=0.270 M diff = 0.324 (95% CI (-0.281, 0.929)).

Two-Sample T-Test and CI: Learning Efficiency, Intervention

```
Two-sample T for Learning Efficiency

Intervention   N   Mean  StDev  SE Mean
C             11  1.147  0.846     0.26
M             18  0.823  0.509     0.12


Difference = mu (C) - mu (M)
Estimate for difference:  0.324
95% CI for difference:  (-0.281, 0.929)
T-Test of difference = 0 (vs not =): T-Value = 1.15  P-Value = 0.270  DF = 14
```

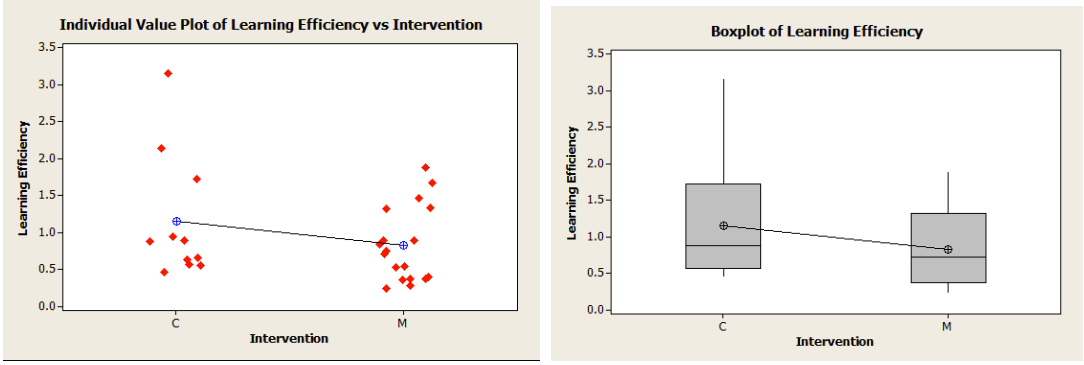


Figure M 19 - Learning Efficiency - Comparison of experimental (M) and control (C) group

In this case, the test was somewhat underpowered [91] and the estimated difference between the two groups was quite small. However, on analysis Figure M 19 above, it appears that both groups are more evenly distributed with the control group having a slightly better learning efficiency overall. Thus, despite the addition of the metacognitive dialog supports, learners were not overburdened to the extent that they reported a large decrease in learning efficiency.

M.6 Response Rate

The section presents an analysis of response rate. This means examining the learners who received metacognitive supports to examine amount of response gathered from learners. A *response rate* score was calculated *by dividing number of responses by the number of prompts/questions sent*[92]*.* Here, three sets of analysis were possible:

- Initial overall comparison of response rate (analysis of the variance between learner percentile and learner groups).
- Comparison of low vs. high ability learners (L vs. H).
- Comparison of learner group (A vs. B)[93].

[91] When comparing the learning efficiency it would have been preferable to have n=13 participants in each group (as illustrated in the power analysis above), however there were only 11 in the control. Indeed, this number would have to be even greater if we wanted to distinguish a greater difference between groups. Here, unlike prior analysis (e.g. overall learning time, number of pages, time on page) there are no other participants to be included. This is because this set of results specifically focuses on those learners that SQL quizzes.

[92] RR = ((Responded/Sent)*100)

[93] Further discussion of the group conditions for Group A and Group B are available in Section 6.2.4. In short, Group A, the *cold-start group* typically received more prompts than questions (on average 1:2 ration of questions to prompts), whereas Group B, the *stereotype group,* typically received more questions (2:1 ration of questions to prompts).

M.6.1 Response Rate– A comparison of Groups (A and B) and Percentile (Low and High)

This section looks at the overall response rate for learners according to their group and prior-ability percentile. Here, Groups A and Group B are examined separately, because there were no response rate figures to assess within the control Group C (as the control did not receive any metacognitive dialog support). Also, only the extreme percentiles are examined because these are the most interesting cohorts to assess and a small number of results were available for the mid-range.

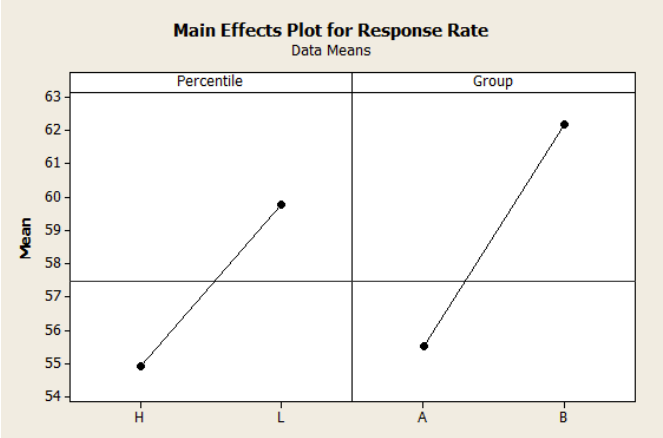


Figure M 20 - Response Rate - Main Effects Plot

In Figure M 20 above, it appears that learners with lower ability (in the percentile plot) and learners in Group B (in the group plot) had a higher response rate. Next, in Figure M 21 below, there also appears to be an indication that there is interaction between these factors – low ability learners had a greater response rate in Group B than in Group A, whereas, higher ability learners seemed to have a reduced response rate. However, these visual representations of the data may not be significant, instead representing small differences between cohort means.

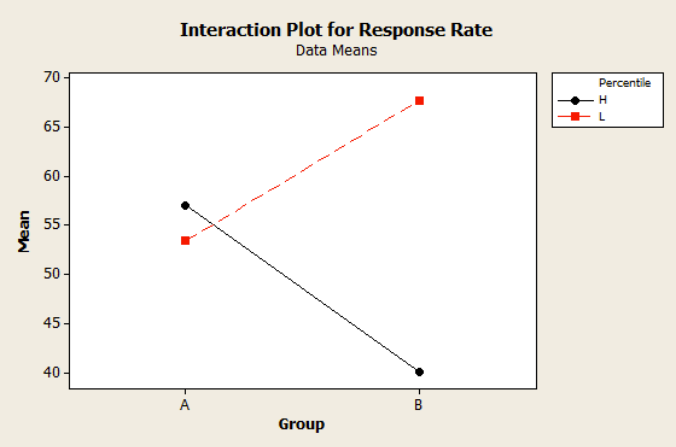


Figure M 21 - Response Rate - Interaction Plot

Thus, a general linear model for analysis of variance for response rate was examined, to test for the factors and their interaction. There are three hypotheses under evaluation:

1. Ho: There is no difference between the percentiles given that we have accounted for the intervention and their interaction.
2. Ho: There is no difference between the groups given that we have accounted for the percentile and their interaction.
3. Ho: There is no interaction between percentile and group.

There was no significant result found in each of the three analysis - percentile, $F(1,13) = 0.50$, $p = 0.491$, group $F(1,13) = 0.01$, $p = 0.937$ or their interaction ($F(1,13) = 0.85$, $p = 0.372$). Here, the variance in the data has not been explained this general linear model (as indicated by the R-Sq coefficient of determination).

General Linear Model: Response Rate versus Percentile, Group

```
Factor      Type   Levels  Values
Percentile  fixed       2  H, L
Group       fixed       2  A, B


Analysis of Variance for Response Rate, using Adjusted SS for Tests

Source            DF   Seq SS  Adj SS  Adj MS     F      P
Percentile         1     99.8   364.3   364.3  0.50  0.491
Group              1     92.5     4.7     4.7  0.01  0.937
Percentile*Group   1    618.2   618.2   618.2  0.85  0.372
Error             13   9417.5  9417.5   724.4
Total             16  10228.0


S = 26.9151   R-Sq = 7.92%   R-Sq(adj) = 0.00%
```

Although no significance is expected, we will next examine the extreme percentiles (H vs. L) and groups (A vs. B) in order to analyse the plots of the data and examine how the deviations between these groups and plot the variations in the data.

M.6.2 Response Rate – Comparison of low ability and high ability learners

Here, the null hypothesis is that there is no difference between the low and high ability learners for response rate (Ho: μ1 (H) = μ2 (L) = μ). A two-sample *t*-test was carried out to compare response rate. Here, as was expected from the above analysis, there was no significant difference between response rate for low and high ability learners; t=-1.3, p=0.207 M diff = -4.9 (95% CI (-33.4, 23.7)). Here, because of the range of variations seen within the groups and small difference reported, the

difference or indeed lack of significant difference here may be as a result of the very small sample size[94].

Two-Sample T-Test and CI: Response Rate, Percentile

```
Two-sample T for Response Rate

Percentile  N  Mean  StDev  SE Mean
H           8  54.9   31.5       11
L           9  59.8   20.0      6.7


Difference = mu (H) - mu (L)
Estimate for difference:  -4.9
95% CI for difference:  (-33.4, 23.7)
T-Test of difference = 0 (vs not =): T-Value = -0.37  P-Value = 0.715  DF = 11
```

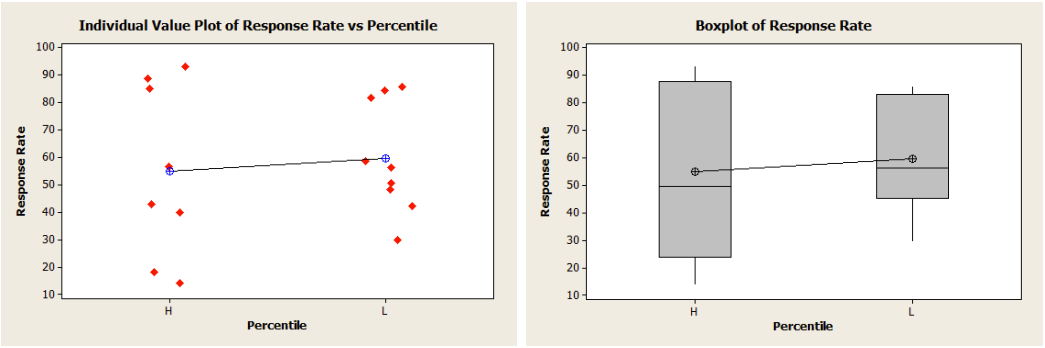


Figure M 22 - Response Rate - Comparison of low and high percentile learners

Here, from the visual description of the response rates, the difference between the two groups is so small it appears as though they are on par. As shown in Figure M 22 above, the large deviation within the groups can clearly be seen, whereas the comparison of means is almost horizontal. This indicates that regardless of prior ability, learners will respond at different rates to dialog prompts. In particular, this may be as a result of other factors, such as motivation, level of engagement with the main learning material, and perceptions about the usefulness of the dialog.

M.6.3 Response Rate – Comparison of Group A to Group B

In comparing the two experimental groups, the null hypothesis is that there is no difference between Group A and Group B response rate (Ho: μ1 (A) = μ2 (B) = μ). A two-sample *t*-test was carried out to compare response rate. Again, as was expected from the above analysis, there was a significant difference between response rate for learners in Group A or B; t=-0.67, *p*=0.508 M diff = -5.69 (95% CI (-23.04, 11.66)). Despite the greater amount of questions delivered to Group B, there is only a slight increase in mean response rate. However, this examination suffers from the same

[94] Here, in a post-hoc power analysis (for a two-sample t-test) - a sample size of 100 would be sufficient to assay differences of 10 (target power .8) with SD of 25 and 394 for 10.

issues – this is a very small sub sample to compare, with large deviations within the groups.

Two-Sample T-Test and CI: Response Rate, Group

```
Two-sample T for Response Rate

Group   N  Mean  StDev  SE Mean
A      17  58.5   26.1      6.3
B      16  64.2   22.7      5.7


Difference = mu (A) - mu (B)
Estimate for difference:  -5.69
95% CI for difference:  (-23.04, 11.66)
T-Test of difference = 0 (vs not =): T-Value = -0.67  P-Value = 0.508  DF = 30
```

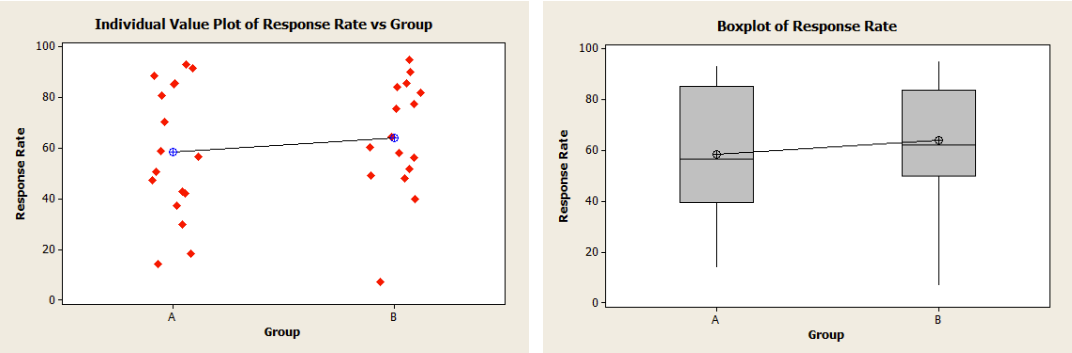


Figure M 23 - Response Rate - Comparison of Groups A and B

Again, when comparing groups, the learners appear to be on par, with a large range of deviations seen across the board. As shown in Figure M 23 above, the deviations within the groups can clearly be seen, whereas the comparison of means minimal. Again, regardless of group the learners in this experiment have responded at different rates to dialog prompts.

M.7 Response Time

The section presents an exploration of response time – the amount of time (in seconds s) taken by learners to respond to a metacognitive dialog prompt[95]. Here, three sets of analysis were possible:

- Initial overall comparison of response time (analysis of percentile, group and their interaction).
- Comparison of low vs. high ability learners (L vs. H).
- Comparison of learner group (A vs. B).

[95] Note: If learners did not respond to a prompt/question, there was no response time figure.

M.7.1 Response Time– A comparison of Groups A, B and C (Low and High Percentile Learners)

Here, we examine the average response time for learners according to their group and prior-ability percentile. Similar to the response rate analysis above, learner group (groups A and B), percentile (low prior-ability (L) and high prior-ability (H)) and their interaction (interaction between group and percentile).

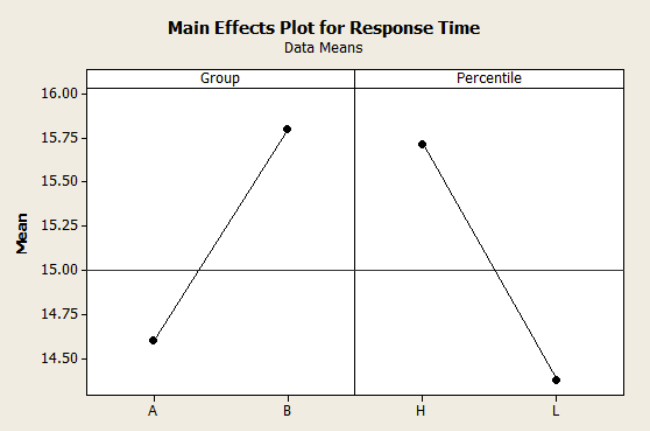


Figure M 24 - Response Time - Main Effects Plot

As illustrated in Figure M 24 above, it appears that learners with lower ability (in the percentile plot) and learners in Group A (in the group plot) had a higher greater response times, meaning that these learners typically took longer to respond to the metacognitive dialog. In the interactions plot in Figure M 25 below, there appears to be a strong interaction – high ability learners had greater respond time in Group A and lower responses if assigned to Group B, whereas lower-ability learners had greater response times in Group B and took longer in Group A. It is important to analyse these cohorts, as the visual representations of the data may not necessarily reflect significant differences or interactions.

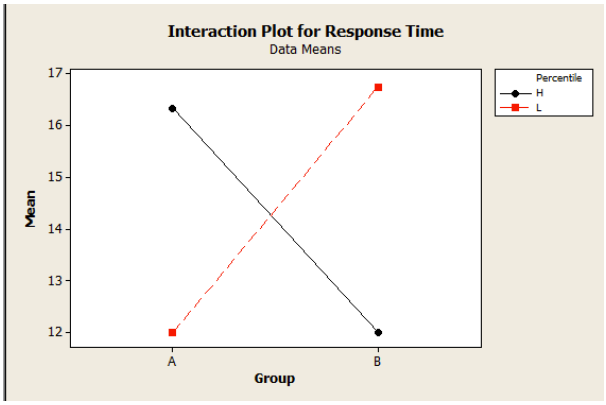


Figure M 25 - Response Time - Interaction Plot

Subsequently, a general linear model for analysis of variance for response time was carried out. Here, there are three hypotheses under evaluation:

1. Ho: There is no difference between the percentiles given that we have accounted for the intervention and their interaction.
2. Ho: There is no difference between the groups given that we have accounted for the percentile and their interaction.
3. Ho: There is no interaction between percentile and intervention.

The general linear ANOVA was carried out to assess whether measures departed from these null hypotheses. There was no significant main effect or interaction effect for each - percentile, F(1,11) = 0.00, p = 0.963, group F(1,11) = 0.00, p = 0.963 or their interaction (F(1,11) = 1.07, p = 0.323). Here, the R-Sq indicates that this model has not explained the variation in the data and when adjusted will not prove useful for prediction of response time.

General Linear Model: Response Time versus Percentile, Group

```
Factor      Type   Levels  Values
Percentile  fixed       2  H, L
Group       fixed       2  A, B


Analysis of Variance for Response Time, using Adjusted SS for Tests

Source            DF  Seq SS  Adj SS  Adj MS     F      P
Percentile         1    6.70    0.10    0.10  0.00  0.963
Group              1   11.72    0.10    0.10  0.00  0.963
Percentile*Group   1   49.50   49.50   49.50  1.07  0.323
Error             11  508.08  508.08   46.19
Total             14  576.00


S = 6.79628   R-Sq = 11.79%   R-Sq(adj) = 0.00%
```

Although no significance is expected, next we will analyse the extreme percentiles (H vs. L) and groups (A vs. B) in order to show the deviations and differences between these groups and examine the plots of the data.

M.7.2 Response Time – Comparison of low ability and high ability learners

The hypothesis under examination is that there is no difference between the low and high ability learners for response time (Ho: μ1 (H) = μ2 (L) = μ). A two-sample *t*-test was carried out to compare response time. As expected, there was no significant difference between response rate for low and high ability learners; t=0.94, p=0.367 M diff = 3.75 (95% CI (-4.96, 12.46)). However, this analysis carried out on a small

sample, insufficient to analyse trends distinguish accurately significant differences of only a few seconds[96].

Two-Sample T-Test and CI: Time to Respond (s), Percentile

```
Two-sample T for Time to Respond (s)

Percentile  N   Mean  StDev  SE Mean
H           8  18.13   9.20      3.3
L           8  14.38   6.57      2.3


Difference = mu (H) - mu (L)
Estimate for difference:  3.75
95% CI for difference:  (-4.96, 12.46)
T-Test of difference = 0 (vs not =): T-Value = 0.94  P-Value = 0.367  DF = 12
```

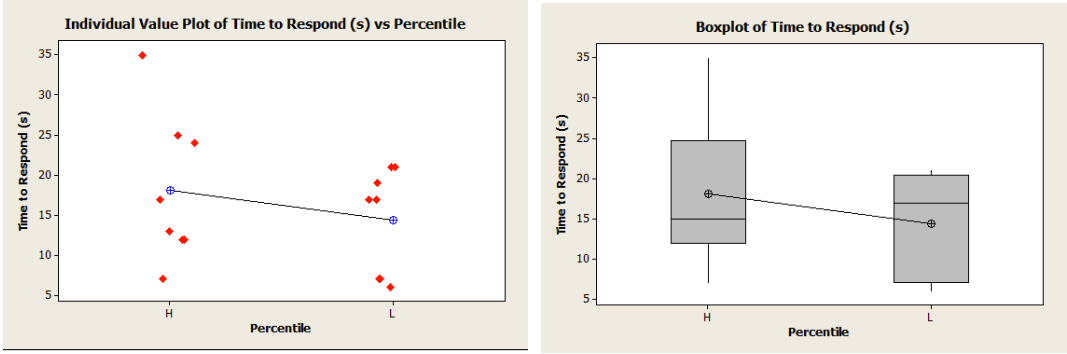


Figure M 26 - Response Time - Comparison of low and high percentile learners

On analysis of the value plots in Figure M 26 above, it appears that regardless of prior ability, learners reported a range of average response times to the metacognitive dialog. Although several higher ability learners had slightly higher response times, the difference in the means is so small, and overall sample size also so small, this is probably due to the variability within this cohort of learners. Here, it appears that prior ability does not have any influence on the amount of time taken to respond to metacognitive dialog prompts, however further analysis would be required with a sufficiently powered test to investigate this area further.

M.7.3 Response Time – Comparison of Group A to Group B

Here, the null hypothesis under examination is that there is no difference between the two experimental groups (Group A and Group B) for response time (Ho: μ1 (A) = μ2 (B) = μ). A two-sample *t*-test was carried out to compare response time. Again, as expected, there was no significant difference between response rate in these groups; t=0.71, *p*=0.482 M diff = 2.96 (95% CI (-5.52, 11.43)). However, this analysis also suffers from a very low power.

[96] Here, in a post-hoc power analysis (for a two-sample t-test) - a sample size of 10 would be sufficient to assay differences of 10s (target power .8) with SD of 6.5, however 75 would be needed for differences of 3s.

Two-Sample T-Test and CI: Time to Respond (s), Group

```
Two-sample T for Time to Respond (s)

Group   N  Mean  StDev  SE Mean
A      17  17.7   12.0      2.9
B      16  14.8   11.9      3.0


Difference = mu (A) - mu (B)
Estimate for difference:  2.96
95% CI for difference:  (-5.52, 11.43)
T-Test of difference = 0 (vs not =): T-Value = 0.71  P-Value = 0.482  DF = 30
```

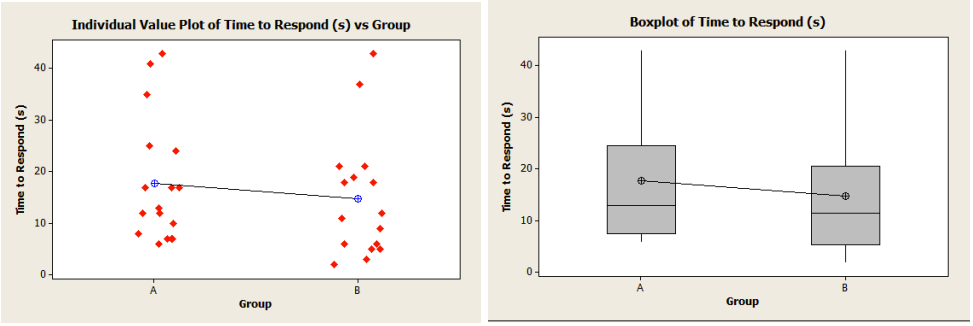


Figure M 27 - Response Time - Comparison of Groups A and B

On analysis of the value plots in Figure M 27 above, a range of responses have been measured within each groups, indicating that for this section of participants that the learner group did not influence the amount of time taken to respond.

M.8 Change in Metacognitive Ability

M.8.1 Metacognitive Ability Overview

This section examines the extreme percentiles – low (L) vs. high (H) prior ability and inspects whether this prior domain ability influenced the metacognitive results for learners. This means comparing the metacognitive gain[97] that was calculated for these two groups. The change in learners' metacognitive ability was calculated for the following five regulatory strategies; planning, information management, comprehension, debugging, and evaluation.

M.8.2 Change in Planning for Low vs. High Prior-Domain Ability Learners

The first null hypothesis is that there is no difference between the low and high ability learners for *planning ability change* (Ho: μ1 (Hp) = μ2 (Lp) = μ). A two-sample *t*-test was carried out to compare change in *planning* ability between these categories of learner, and no significant difference found for change in *planning ability* between

[97] For each metacognitive factor, the *gain* was calculated by comparing their post-test MAI scores to their pre-test MAI scores.

low and high ability learners; t=-0.23, *p*=0.823 M diff = -0.048 (95% CI (-0.490, 0.394)) [98].

Two-Sample T-Test and CI: Planning, Percentile

```
Two-sample T for Planning

Percentile   N   Mean  StDev  SE Mean
H           14  0.051  0.383     0.10
L           13  0.099  0.663     0.18


Difference = mu (H) - mu (L)
Estimate for difference:  -0.048
95% CI for difference:  (-0.490, 0.394)
T-Test of difference = 0 (vs not =): T-Value = -0.23  P-Value = 0.823  DF = 18
```

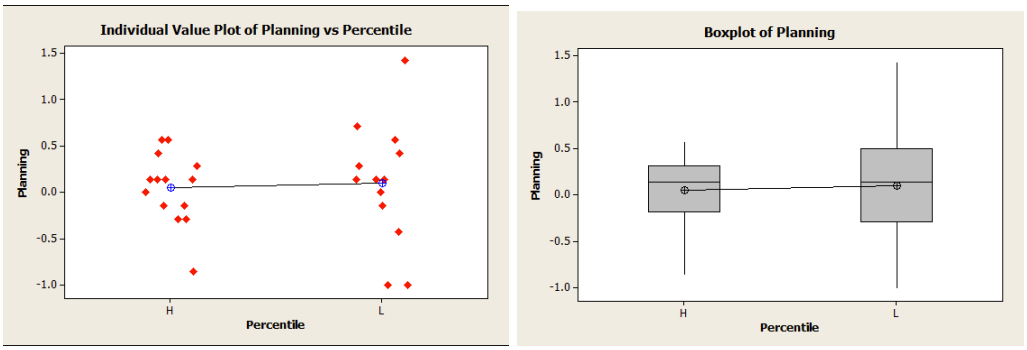


Figure M 28 - *Planning* Change - Comparison of low and high percentile learners

As illustrated in Figure M 28 above, the planning ability change appears to be consistent across both groups (of low (L) and high (H) ability learners, as is illustrated in the small estimate for mean difference between the two groups. While a range of differences is reported, this is similarly seen in both high and low ability learners. In this experiment, regardless of prior ability, learners were reported to have a range of changes in planning.

M.8.3 Change in Information Management Strategies Ability for Low vs. High Prior-Domain Ability Learners

The second null hypothesis is that there is no difference between the low and high ability learners for *information management strategies change* (Ho: μ1 (Hi) = μ2 (Li) = μ). A two-sample *t*-test was carried out to compare change in *information management* ability between these categories of learner, and no significant difference

[98] Here, in a post-hoc power analysis (for a two-sample t-test) –of planning a sample size of 15 (per group) would be sufficient to assay differences of 0.5 (target power .8) with SD of 0.46.

found for change in *information management ability* between low and high ability learners; t=0.17, *p*=0.869 M diff = 0.028 (95% CI (-0.316, 0.371)) [99].

Two-Sample T-Test and CI: Info Mgmt, Percentile

```
Two-sample T for Info Mgmt

Percentile   N   Mean  StDev  SE Mean
H           13  0.169  0.325    0.090
L           12  0.142  0.476     0.14


Difference = mu (H) - mu (L)
Estimate for difference:  0.028
95% CI for difference:  (-0.316, 0.371)
T-Test of difference = 0 (vs not =): T-Value = 0.17  P-Value = 0.869  DF = 19
```

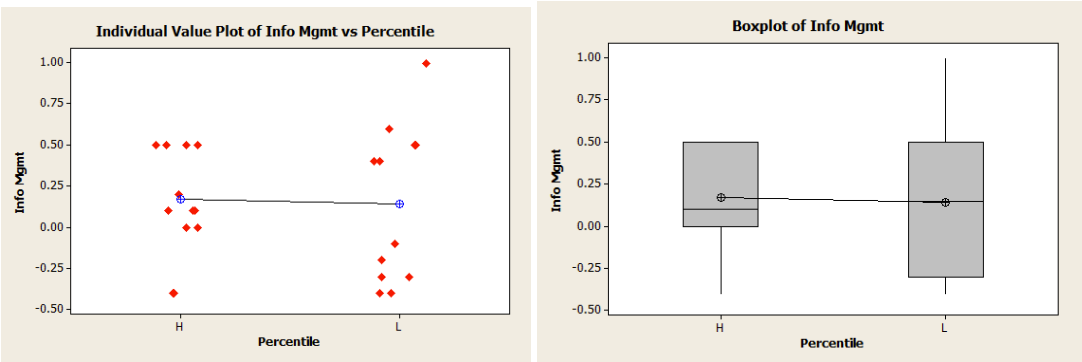


Figure M 29 - *Information Management* Change - Comparison of low v high percentile learners

As illustrated in Figure M 29 above, the information management ability change appears to be consistent across both groups (of low (L) and high (H) ability learners in line with the small mean difference calculated between the two groups. Again, regardless of prior ability, this group of learners reported a range of changes in their information management abilities.

M.8.4 Change in Comprehension Strategies Ability for Low vs. High Prior-Domain Ability Learners

Next, the third factor to be examined is *comprehension strategies.* Thus, the null hypothesis is that there is no difference between the low and high ability learners for change in *comprehension ability* (Ho: μ1 (Hc) = μ2 (Lc) = μ). A two-sample *t*-test was carried out to compare change in *comprehension* ability between these categories of learner, and no significant difference found for change in *comprehension ability*

[99] Here, in a post-hoc power analysis (for a two-sample t-test) of information management strategies- a sample size of 11 (per group) would be sufficient to assay differences of 0.5 (target power .8) with SD of 0.396.

between low and high ability learners; t=-1.12, *p*= 0.282 M diff = -0.288 (95% CI (-0.842, 0.265)) [100].

Two-Sample T-Test and CI: Comprehension, Percentile

```
Two-sample T for Comprehension

Percentile   N   Mean  StDev  SE Mean
H           12  0.107  0.287    0.083
L           13  0.396  0.881     0.24


Difference = mu (H) - mu (L)
Estimate for difference:  -0.288
95% CI for difference:  (-0.842, 0.265)
T-Test of difference = 0 (vs not =): T-Value = -1.12  P-Value = 0.282  DF = 14
```

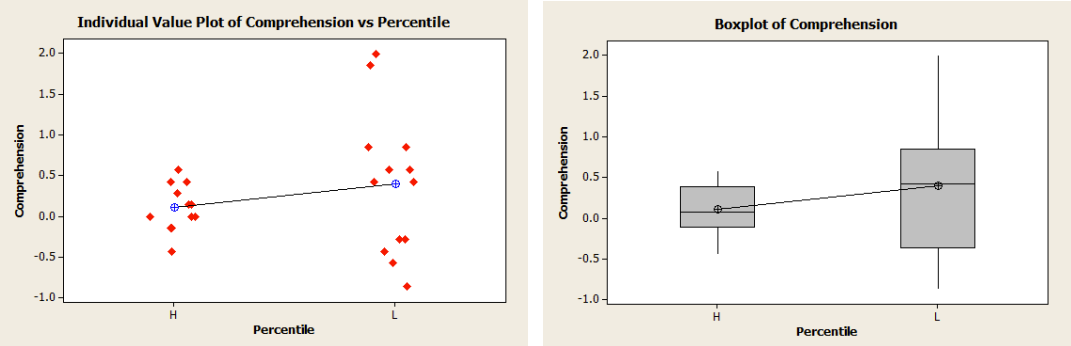


Figure M 30 - *Comprehension* Change - Comparison of low and high percentile learners

As illustrated in Figure M 30 above, the comprehension ability change appears to be consistent across both groups (of low (L) and high (H) ability learners. Here, while it appears that the lower ability learners reported a greater range of changes in comprehension ability, there was no significant change in this group compared to their higher ability peers.

M.8.5 Change in Debugging Strategies for Low vs. High Prior-Domain Ability Learners

The fourth factor to be examined is *debugging strategies.* Thus, the null hypothesis is that there is no difference between the low and high ability learners for change in *debugging ability* (Ho: μ1 (Hd) = μ2 (Ld) = μ). A two-sample *t*-test was carried out to compare change in *debugging* ability between these categories of learner, and no significant difference found for change in *debugging ability* between low and high ability learners; t= 0.31, *p*= 0.762 M diff = 0.062(95% CI (-0.362, 0.486)) [101].

[100] Here, in a post-hoc power analysis (for a two-sample t-test) of comprehension- a sample size of 15 (per group) would be sufficient to assay differences of 0.5 (target power .8) with SD of 0.471.
[101] Here, in a post-hoc power analysis (for a two-sample t-test) of debugging strategies - a sample size of 12 (per group) would be sufficient to assay differences of 0.5 (target power .8) with SD of 0.411.

Two-Sample T-Test and CI: Debugging, Percentile

```
Two-sample T for Debugging

Percentile   N    Mean  StDev  SE Mean
H           14  -0.071  0.691     0.18
L           12  -0.133  0.274    0.079


Difference = mu (H) - mu (L)
Estimate for difference:  0.062
95% CI for difference:  (-0.362, 0.486)
T-Test of difference = 0 (vs not =): T-Value = 0.31  P-Value = 0.762  DF = 17
```

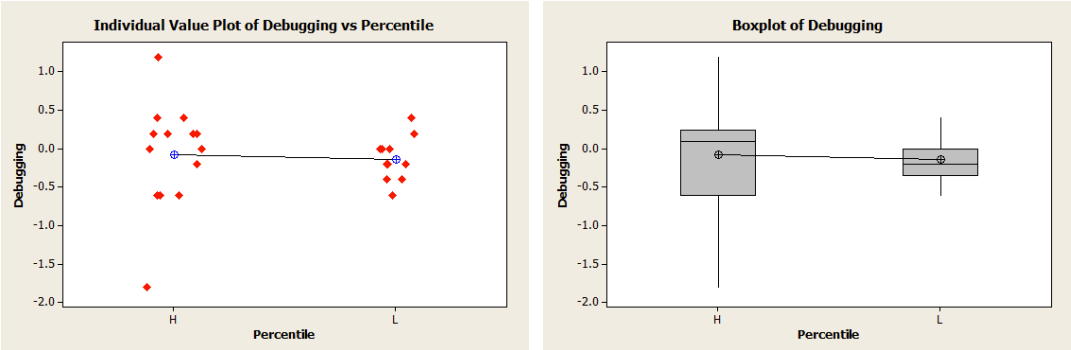


Figure M 31 - *Debugging* Change - Comparison of low and high percentile learners

As illustrated in Figure M 31 above, the *debugging ability change* appears to be consistent across both groups (low (L) and high (H) ability learners) is similarly exemplified in the small mean difference calculated between the two groups.

M.8.6 Change in Evaluation Strategies Ability for Low vs. High Prior-Domain Ability Learners

The final null hypothesis to be examined is that there is no difference between the low and high ability learners for change in *evaluation strategies ability* (Ho: μ1 (He) = μ2 (Le) = μ). A two-sample *t*-test was carried out to compare change in *evaluation* ability between these categories of learner, and no significant difference found for change in *evaluation ability* between low and high ability learners; t= -0.58, *p*= 0.571 M diff = -0.088 (95% CI (-0.405, 0.299)) [102].

[102] Here, in a post-hoc power analysis (for a two-sample t-test) of evaluation strategies - a sample size of 10 (per group) would be sufficient to assay differences of 0.5 (target power .8) with SD of 0.371.

Two-Sample T-Test and CI: Evaluation, Percentile

```
Two-sample T for Evaluation

Percentile   N   Mean  StDev  SE Mean
H           14  0.155  0.372     0.10
L           11  0.242  0.383     0.12


Difference = mu (H) - mu (L)
Estimate for difference:  -0.088
95% CI for difference:  (-0.405, 0.229)
T-Test of difference = 0 (vs not =): T-Value = -0.58  P-Value = 0.571  DF = 21
```

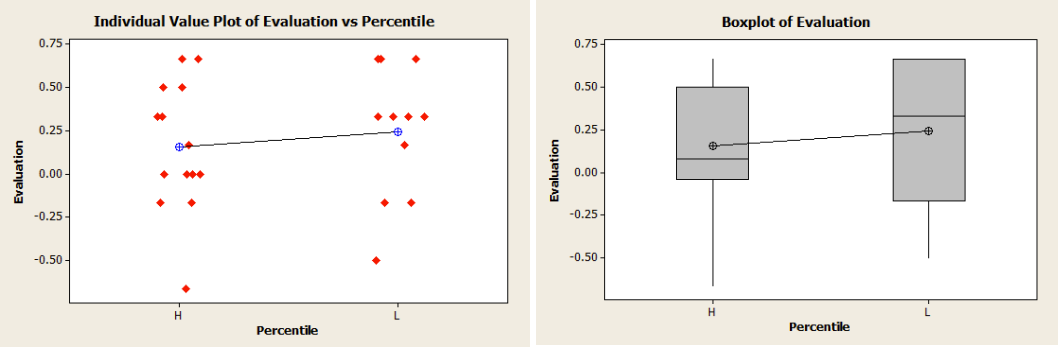


Figure M 32 - Evaluation Change - Comparison of low and high percentile learners

As illustrated in Figure M 32 above, the *evaluation ability change* appears to be consistent across both groups (of low (L) and high (H) ability learners), is in line with the small mean difference exemplified within the groups. Here, a range of changes was observed across both of these groups, regardless of their prior ability.

M.9 Learning Gain – Prior Metacognitive and Domain Ability and Intervention Group

While previous analysis looked at learners' prior domain ability, here we examine whether prior metacognitive ability influenced the learning outcomes of for the learners. In this section, learners are categorised according to metacognitive percentiles. Here, we are interested in the extreme metacognitive percentiles – low (L) vs. high (H) prior metacognitive ability. The learners' metacognitive prior-ability was calculated for the five regulatory strategies.

M.9.1 Learning Gain – Influences from Prior-Ability and Intervention

Learners' were categorised into their metacognitive percentile – high (H) and low (L)[103]. An overall analysis was first carried out to assess whether the metacognitive

[103] Using the same process that was carried out to categorise learners into low and high prior-domain ability. An automatic MiniTab script was used to categorise learners into the low (below 40th percentile), high (60th percentile and above) and medium (those between low and high). For example,

percentiles (in each factor), the prior-domain-ability (SQL percentile), the intervention (metacognitive support (M) vs. control (C)), and/or the interaction between intervention and prior-domain-ability influenced the outcome of the learning gain. Here, there was sufficient data to create eight hypotheses.[104] In each case the hypothesis is that Ho: "There is no difference between the percentiles (each of the metacognitive and the domain percentile) or interaction (between the prior-domain-ability and intervention) given that we have accounted for the other variables". On completion of the analysis, the significant effects were found for learners' prior domain-ability (SQL percentile, $F(2,9) = 43.00$, $p = 0.000$) the intervention (M vs. C, $F(1,9) = 31.31$, $p = 0.000$) and the interaction of the prior-domain-ability and the intervention ($F(2,9) = 6.23$, $p = 0.020$). There was no significant effects for each metacognitive variable: Planning (P), $F(2,9) = 0.04$, $p = 0.962$; Information Management Strategies (I) $F(2,9) = 2.12$, $p = 0.176$; Comprehension (C) $F(2,9) = 1.91$, $p = 0.204$; Debugging (D) $F(2,9) = 0.98$, $p = 0.411$; or Evaluation (E) $F(2,9) = 2.36$, $p = 0.150$.

General Linear Model: Learning Gai versus P Percentile, I Percentile, ...

Factor	Type	Levels	Values
P Percentile	fixed	3	H, L, M
I Percentile	fixed	3	H, L, M
C Percentile	fixed	3	H, L, M
D Percentile	fixed	3	H, L, M
E Percentile	fixed	3	H, L, M
SQL Percentile	fixed	3	H, L, M
Intervention	fixed	2	C, M

Analysis of Variance for Learning Gain, using Adjusted SS for Tests

Source	DF	Seq SS	Adj SS	Adj MS	F	P
P Percentile	2	636.01	1.26	0.63	0.04	0.962
I Percentile	2	217.59	68.93	34.46	2.12	0.176
C Percentile	2	320.25	62.13	31.07	1.91	0.204
D Percentile	2	343.40	31.98	15.99	0.98	0.411
E Percentile	2	96.18	76.90	38.45	2.36	0.150
SQL Percentile	2	1139.40	1399.96	699.98	43.00	0.000
Intervention	1	525.42	509.70	509.70	31.31	0.000
SQL Percentile*Intervention	2	202.98	202.98	101.49	6.23	0.020
Error	9	146.52	146.52	16.28		
Total	24	3627.76				

S = 4.03484 R-Sq = 95.96% R-Sq(adj) = 89.23%

Here, the R-Sq adj. suggests that this model explains a lot of the variation in the data, however there is still unexplained variation. The main problem with the general

---

to create indicator variables for learners according to their prior planning ability, the following script is used: *IF(('Planning Pre'<(PERCENTILE('Planning Pre',.4))),"L").*

[104] An analysis of the interaction between prior-domain and prior-metacognitive ability was not possible due to the overall limited data model.

linear model is model specification – while the variables above represent the best guess with the data available, there may be other cofounding variables or influences at play (e.g. motivation, interest). What we are interested in are the important few as distinct from the trivial many. Here, the interaction between the prior-domain ability and intervention has almost been indicated to be significant, however 0.02 is still difficult to accept as an indication of significance when considering that there were 8 tests carried out in total. With such a small data set (n = 25) to analyse such a range of conditions, there is most likely not enough power. Also, including explanatory variables that may be independent of the dependent variable can mask other results. On reanalysis, after removing the prior-metacognitive abilities, to reduce the number of hypothesis under analysis, the interaction p value was reduced.

General Linear Model: Learning Gain versus SQL Percentile, Intervention

```
Factor          Type   Levels  Values
SQL Percentile  fixed       3  H, L, M
Intervention    fixed       2  C, M


Analysis of Variance for Learning Gain, using Adjusted SS for Tests

Source                       DF   Seq SS   Adj SS   Adj MS      F      P
SQL Percentile                2  2042.22  2304.03  1152.02  59.52  0.000
Intervention                  1   960.94   941.52   941.52  48.64  0.000
SQL Percentile*Intervention   2   256.82   256.82   128.41   6.63  0.007
Error                        19   367.77   367.77    19.36
Total                        24  3627.76


S = 4.39960   R-Sq = 89.86%   R-Sq(adj) = 87.19%
```

In each case, prior-domain ability (F(2,19) = 59.92, p = 0.000), intervention (F(1,19) = 48.64, p = 0.000), and their interaction (F(2,19) = 6.63, p = 0.007) resulted in a significant effect. The influence of prior ability is to be expected, as those with lower prior ability would have more to learn and should benefit more from the learning intervention. Conversely, learners with higher prior knowledge have less to learn and can experience a ceiling effect. On subsequent analysis of this check, using a two-sample t-test[105] to compare the low to high prior-domain ability learners, there as a significant difference reported (t= -5.31, p= 0.000 M diff = -21.17 (95% CI (-29.58, -12.76)). Here, those learners who had lower initial learning ability displayed a greater learning gain.

[105] Here, there was sufficient data to compare low and high ability learners, but not the mid range group. Nonetheless these are the two most interesting groups to examine as they allow us to analyse any trends in the data, plots and examine how different these two sets are. In a post-hoc power analysis (for a two-sample t-test) of evaluation strategies - a sample size of 9 (per group) would be sufficient to assay differences of 20 (target power .8) with SD of 14.07. Note: The mid range group was n=6 - using an ANOVA for three samples would have required 11 learners per group.

```
Two-sample T for Learning Gain

SQL
Percentile   N  Mean  StDev  SE Mean
H           14  9.43   8.78      2.3
L           10  30.6   10.2      3.2


Difference = mu (H) - mu (L)
Estimate for difference:  -21.17
95% CI for difference:  (-29.58, -12.76)
T-Test of difference = 0 (vs not =): T-Value = -5.31  P-Value = 0.000  DF = 17
```

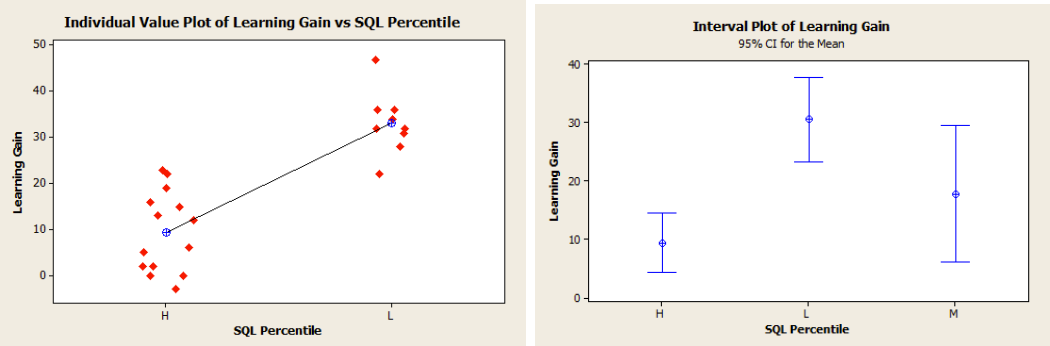


Figure M 33 - Learning Gain when Comparing Prior-Domain-Ability

As shown in Figure M 33 above, there is a clear trend for those in the low prior-domain-ability group to have a greater learning gain. Here, an interval plot (including the mid range group) shows how these three groups are distributed – the mid range participants reported a range of learning gain, the higher ability group reported smaller learning gain, and the lower ability group reported a greater learning gain. This is most likely because they have the most to learn, and are the group that could benefit the most from the learning experience. While those in the higher-ability group may be able to polish up on their knowledge, they do not have as much of a range within which to improve. This effect has been similarly shown in a number of studies, whereby lower ability learners, benefit the most (in terms of learning gain) whereas those with higher ability have less to learn and consequently report lower learning gains (For example, c.f. Koedel & Betts, 08; Sadler & Good, 06).

On analysis of the learning gain for learners in the metacognitive support cohort (M) versus those in the control (C), there as a significant difference reported (t= -3.36, *p*= 0.004 M diff = -14.16(95% CI (-23.84, -5.40)). Here, those learners who had lower initial learning ability displayed a greater learning gain.

Two-Sample T-Test and CI: Learning Gain, Intervention

```
Two-sample T for Learning Gain

Intervention   N   Mean  StDev  SE Mean
C              9   10.4   10.5      3.5
M             15  25.07   9.94      2.6


Difference = mu (C) - mu (M)
Estimate for difference:  -14.62
95% CI for difference:  (-23.84, -5.40)
T-Test of difference = 0 (vs not =): T-Value = -3.36  P-Value = 0.004  DF = 16
```

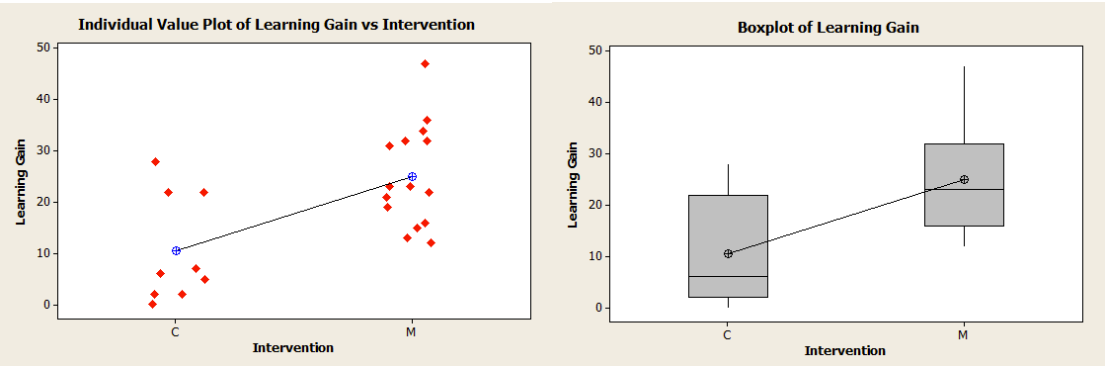


Figure M 34 - Learning Gain when Comparing Intervention Groups

On analysis of Figure M 34 above, there is a clear trend for those learners in the metacognitive support group to have a greater learning gain. However, it is difficult to separate this result from the previous analysis of the intervention. Indeed, while it may be that learners who received metacognitive supports reported greater learning gains because of the intervention, this result may simply be because of the interaction between the low prior ability and the experimental cohort to which they were assigned. In the Goby experiment, learners were assigned to experimental groups before completing the pre-test meaning that they were not stratified for prior-domain-ability. On examination of value plots to examine the differences between high (H) and low (L) prior-domain-ability, it appears as if this increase for those in the metacognitive groups (M) was seen in both plots (as shown in Figure M 35 below), particularly in the high ability learners.

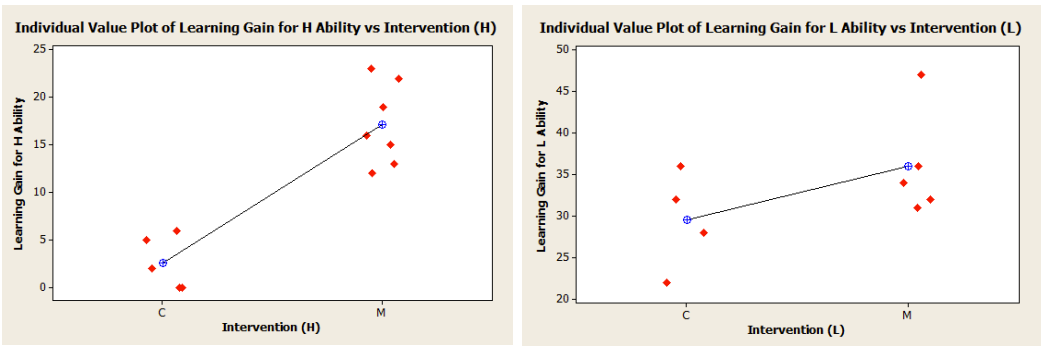


Figure M 35 - Learning Gain (M vs. C) - separating High (H) and Low (L) Prior-Domain Ability

Subsequent t-test analysis reported that this difference was significant for high ability learners (t= -7.10, *p*= 0.000 M diff = -14.54(95% CI (-19.18, -9.19)), but not for low ability learners (t= -1.57, *p*= 0.168 M diff = -6.50(95% CI (-16.65, 3.65)). This may be because the metacognitive supports helped those with higher prior ability to better overcome the ceiling effect. Indeed, it may be that those with higher ability were able to attend to the metacognitive supports and implement the strategies suggested because they were not as cognitively taxed as there lower ability peers. However, it is difficult to have confidence in these results because of the low number of participants meaning that these tests are not sufficiently powered. Indeed, in both cases these results may be due to random variability in the data.

Two-Sample T-Test and CI: Learning Gain for H Ability, Intervention (H)

```
Two-sample T for Learning Gain for H Ability

Intervention
(H)           N   Mean  StDev  SE Mean
C             5   2.60   2.79      1.2
M             7  17.14   4.30      1.6


Difference = mu (C) - mu (M)
Estimate for difference:  -14.54
95% CI for difference:  (-19.18, -9.91)
T-Test of difference = 0 (vs not =): T-Value = -7.10  P-Value = 0.000  DF = 9
```

Two-Sample T-Test and CI: Learning Gain for L Ability, Intervention (L)

```
Two-sample T for Learning Gain for L Ability

Intervention
(L)           N   Mean  StDev  SE Mean
C             4  29.50   5.97      3.0
M             5  36.00   6.44      2.9


Difference = mu (C) - mu (M)
Estimate for difference:  -6.50
95% CI for difference:  (-16.65, 3.65)
T-Test of difference = 0 (vs not =): T-Value = -1.57  P-Value = 0.168  DF = 6
```

Next, we examine prior-metacognitive ability by looking at each of the metacognitive factors individually and comparing the individual value plots for learning gains. Although the initial model[106] to examine learning gain did not indicate that these factors significantly influenced the learning gain outcome, it is interesting to examine these plots individually because examining such a range of conditions with such a small data set means that the test has limited power. Next, we will examine plots of

[106] Although the general linear model was re-run with only metacognitive factors, there was no difference seen in the significance ratings of the p-values.

the data to compare learning gain (low metacognitive ability vs. high metacognitive ability) for each metacognitive factor[107].

M.9.2 Change in Learning Gain when Comparing Prior Metacognitive Ability –Planning

As expected, there was no learning gain difference between learners with high (H) and low (L) prior-planning ability (t= -1.39, *p*= 0.182 M diff = -8.27 (95% CI (-20.85, 4.30)). On examination of the deviations of the gains and Figure M 36 below, it appears that regardless of prior-planning ability, learners reported a rage of gains.

Two-Sample T-Test and CI: Learning Gain, P Percentile

```
Two-sample T for Learning Gain

P Percentile   N  Mean  StDev  SE Mean
H             11  17.7   12.7      3.8
L              9  26.0   13.6      4.5


Difference = mu (H) - mu (L)
Estimate for difference:  -8.27
95% CI for difference:  (-20.85, 4.30)
T-Test of difference = 0 (vs not =): T-Value = -1.39  P-Value = 0.182  DF = 16
```

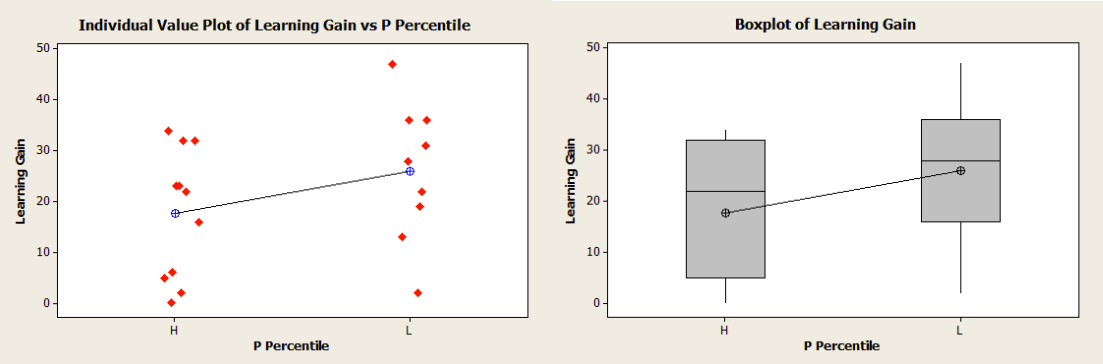


Figure M 36 - Learning Gain - Comparing low and high *planning* percentiles

M.9.3 Change in Learning Gain when Comparing Prior Metacognitive Ability –Information Management Strategies

There was no learning gain difference between learners with high (H) and low (L) prior-information management ability (t= -0.11, *p*= 0.912 M diff = -1.00 (95% CI (-20.58, 18.58)). On examination of the deviations of the gains and Figure M 37 below, it

[107] As discussed above, a sample size of 9 per group would provide sufficient power to assess a difference of 20 between groups.

appears that regardless of prior-information management ability, learners reported a wide rage of gains with only small difference in means.

Two-Sample T-Test and CI: Learning Gain, I Percentile

```
Two-sample T for Learning Gain

I Percentile   N  Mean  StDev  SE Mean
H             16  20.0   20.0      5.0
L              6  21.0   17.7      7.2


Difference = mu (H) - mu (L)
Estimate for difference:  -1.00
95% CI for difference:  (-20.58, 18.58)
T-Test of difference = 0 (vs not =): T-Value = -0.11  P-Value = 0.912  DF = 10
```

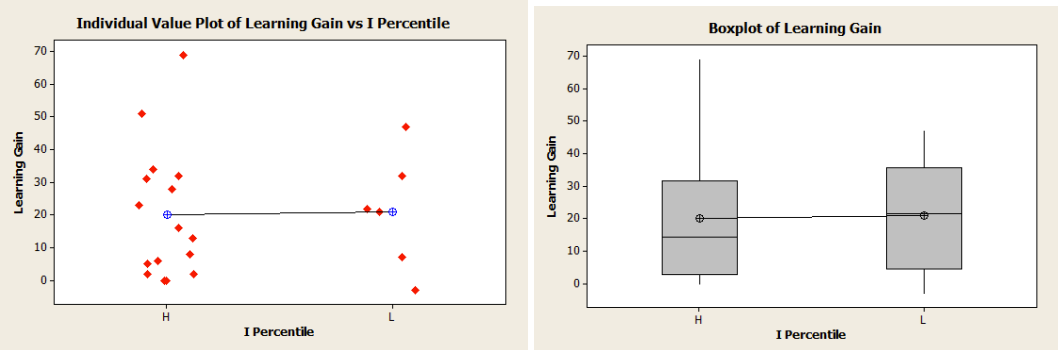


Figure M 37 - Learning Gain - Comparing low and high *information management* percentiles

M.9.4 Change in Learning Gain when Comparing Prior Metacognitive Ability –Comprehension Strategies

Again, there was no learning gain difference between learners with high (H) and low (L) prior-comprehension ability (t= 0.60, *p*= 0.555 M diff = 4.10 (95% CI (-10.20, 18.41)). On examination of the deviations of the gains and Figure M 38 below, learners reported a range of gains regardless of prior-comprehension ability.

Two-Sample T-Test and CI: Learning Gain, C Percentile

```
Two-sample T for Learning Gain

C Percentile   N  Mean  StDev  SE Mean
H             17  22.9   18.9      4.6
L              9  18.8   15.2      5.1


Difference = mu (H) - mu (L)
Estimate for difference:  4.10
95% CI for difference:  (-10.20, 18.41)
T-Test of difference = 0 (vs not =): T-Value = 0.60  P-Value = 0.555  DF = 19
```

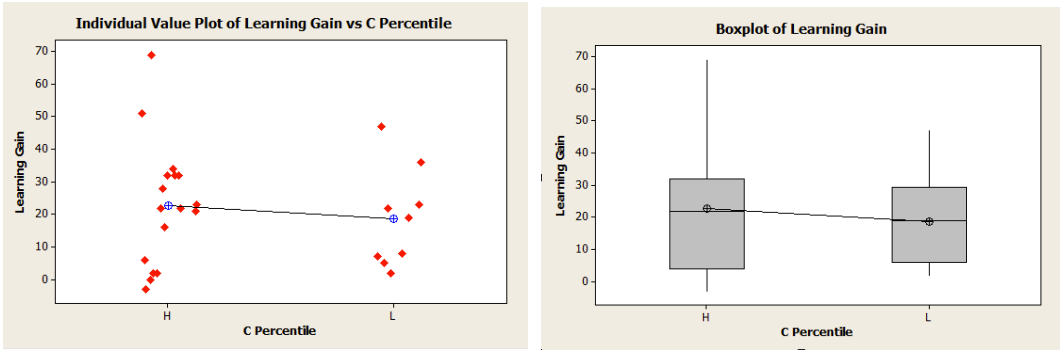


Figure M 38 - Learning Gain - Comparing low and high *comprehension* percentiles

M.9.5 Change in Learning Gain when Comparing Prior Metacognitive Ability –Debugging Strategies

As expected, there was no learning gain difference between learners with high (H) and low (L) prior-debugging ability (t= -1.16, *p*= 0.259 M diff = -7.84 (95% CI (-21.84, 6.17)). On examination of the deviations of the gains and Figure M 38 below, learners reported a rage of learning gains regardless of their debugging percentile.

Two-Sample T-Test and CI: Learning Gain, D Percentile

```
Two-sample T for Learning Gain

D Percentile   N  Mean  StDev  SE Mean
H             16  17.6   20.2      5.1
L             10  25.4   14.2      4.5


Difference = mu (H) - mu (L)
Estimate for difference:  -7.84
95% CI for difference:  (-21.84, 6.17)
T-Test of difference = 0 (vs not =): T-Value = -1.16  P-Value = 0.259  DF = 23
```

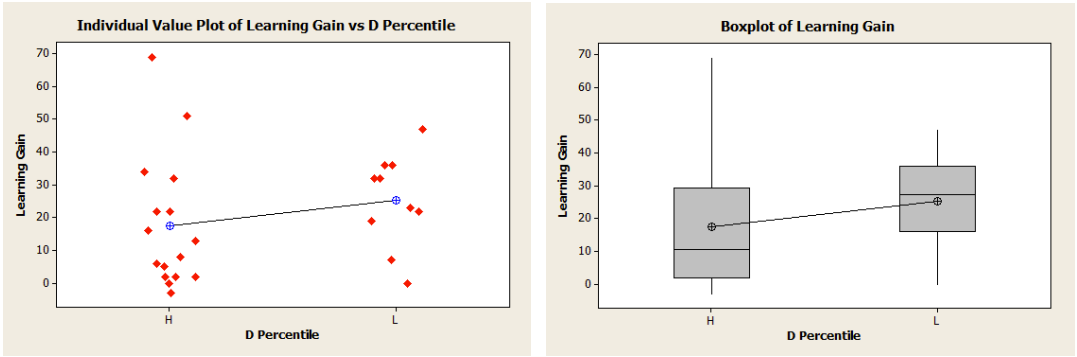


Figure M 39 - Learning Gain - Comparing low and high *debugging* percentiles

M.9.6 Change in Learning Gain when Comparing Prior Metacognitive Ability –Evaluation Strategies

Similarly, for prior-evaluation-ability, there was no learning gain difference between learners with high (H) and low (L) learners (t= -0.95, *p*= 0.358 M diff = -7.09 (95% CI

(-25.58, 9.78)). On examination of the deviations of the gains and Figure M 40 below, it a range of gains were reported regardless of the learners prior-evaluation ability.

Two-Sample T-Test and CI: Learning Gain, E Percentile

```
Two-sample T for Learning Gain

E Percentile   N  Mean  StDev  SE Mean
H             15  21.5   15.8      4.1
L             11  29.4   24.1      7.3


Difference = mu (H) - mu (L)
Estimate for difference:  -7.90
95% CI for difference:  (-25.58, 9.78)
T-Test of difference = 0 (vs not =): T-Value = -0.95  P-Value = 0.358  DF = 16
```

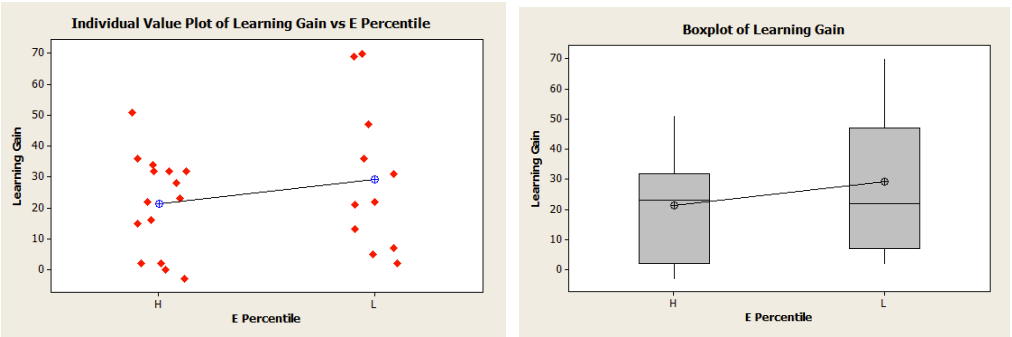
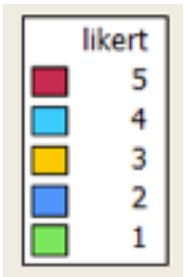


Figure M 40 - Learning Gain - Comparing low and high *evaluation* percentiles

M.10 Qualitative Feedback - Low vs. High (prior) Ability

This section describes a comparison of the low (L, n = 8) and high (H, n = 8) percentile learners[108] who received metacognitive supports. Participants were asked to rate a number of statements on a 5-point Likert scale (1 strongly disagree to 5 strongly agree). The figures in this section represent the number of response on this scale, with each response being assigned a colour. For example, in the key on the right, a response of '*strongly disagree*' is 1 on the scale and will be highlighted in a green colour. This section looks at questions that related to the three categories[109]:



- Motivation and learning support
- Relevancy of the prompts/questions to learning[110]
- Prompt/question interaction workload

[108] Here, quotes from learners who have been categorised into these percentiles (using the same data analysis method as described in Section 6.3.3) and participants are identified using their anonymised ID and a percentile identifier. Participants from Group A are identified with the letter P and those from Group B are identified with the letter Q. The letter L (low) and H (high) are then provided to identify whether they fell within the low or high prior-ability percentile. For example (Px, H) indicates that the learner was in Group A and the higher percentile.

[109] An overview of these three categories is described in Section 6.3.3.

[110] Here, when re-examining *relevancy,* it is not interesting to assess these Goby specific questions, as the relevancy was ratified previously (c.f. Section 6.3.3).

M.10.1Motivation and Learning Support

Q1. "Were you motivated by the popup content?"

Participants were asked, "*Were you motivated by the popup content?*" Overall both sets of learners (high ability (motPop H) and low (motPop L) ability groups) reported that they were motivated as can be seen in Table M 1.

Ability Group	Mean	Median	StDev
High Ability	3.125	3.5	1.356
Low Ability	3.222	4	1.202

Table M 1 - Were you motivated by the popup content?

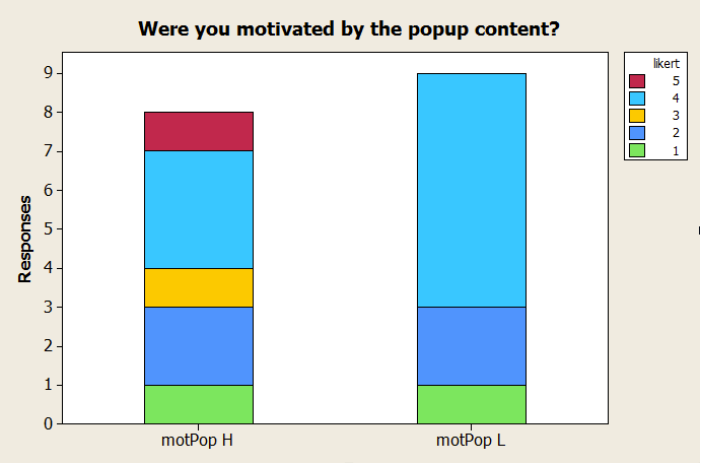


Figure M 41 - Were you motivated by the popup content?

However, despite the overall agreement, as can be seen in Figure M 41, there were a range of responses. Four participants in both groups indicated no motivation. These results are in line with the initial qualitative analysis, which compared the different experiment groups (Group A and Group B comparison were carried out in Section 6.3.3). The type of the supports provided (prompts and questions) may be helpful but not necessarily be motivational; "*Got me thinking, but wouldn't describe it as motivational*" – (P13, H) and "*Only as far as breaking information down and diagrams*" (P14, L)." Thus, different types of learners, regardless or prior capabilities, may have different needs when it comes to creating motivation metacognitive supports.

Q2. "Did the Goby prompts/questions help you while learning?"

Participants were asked, *"Did the Goby prompts/questions help you while learning?"* Here, there was some difference between the two groups – with low ability learners (prLearn L) reporting greater perceived help than higher ability (prLearn H) as can be seen in Table M 2.

Ability Group	Mean	Median	StDev
High Ability	3.125	3	0.835
Low Ability	3.444	4	1.014

Table M 2 - Did the Goby prompts/questions help you while learning?

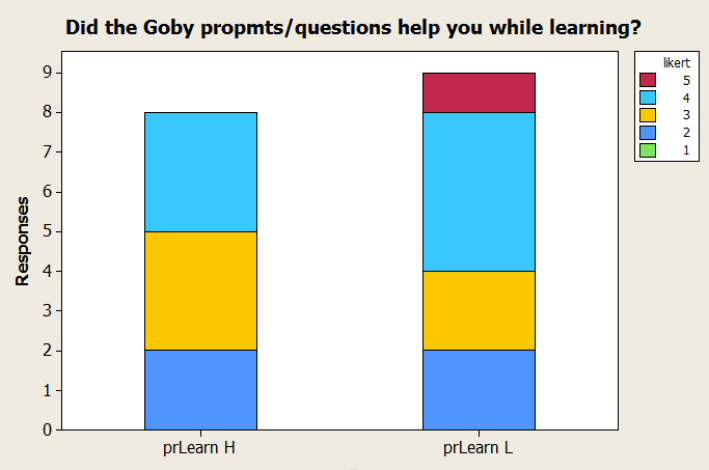


Figure M 42 - Did the Goby prompts/questions help you while learning?

As illustrated in Figure M 43, results from higher ability (prLearn H) learners were similar to the lower ability (prLearn H) learners. There was a mix of indifference, positive and negative feelings for the benefit from the dialog supports. Again, these results are in line with the previous comparison of the different experimental groups. Responses from the low (e.g. "*They served as little pauses in the information and refresh the learning process*" - (P6, L), "*Yes they provided a good interactive feature which helped me keep on track*" (P7, L)) ability learners were more positive than those with greater prior ability (e.g. *"...may not be so relevant to me as I have some experience with the material*" = (P16 H)). This suggests that those with lower ability may be more open to using these supports. However, similar to the results from the motivation questions above, regardless of their prior ability, different learners probably require different types of support.

Q3. Question - "Did you think about the prompts and questions?"

Participants were questioned, *"Did you think about the prompts and questions?"* Here, there was some difference between the two groups – with low ability learners (thinkPr L) reporting greater perceived help than higher ability (thinkPr H) as can be seen in Table M 2.

Ability Group	Mean	Median	StDev
High Ability	3.375	3.5	0.744
Low Ability	4	4	0

Table M 3 - Did you think about the prompts and questions?

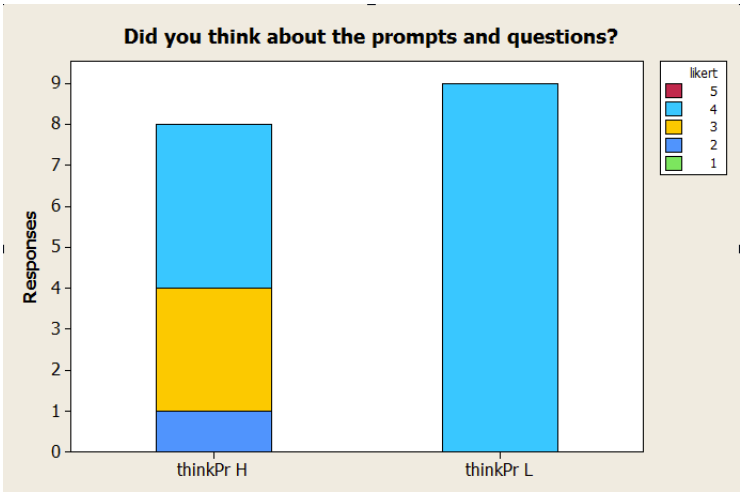


Figure M 43 - Did you think about the prompts and questions?

In this case, each of the response from the low (thinkPr L) ability group reported that they thought about the Goby dialog. As can be seed in Figure M 43, results from higher ability (thinkPr H) learners were mixed, however overall this did not result in a large difference, with only one H learner reporting that they did not think about them. All the responses in the lower group reported that they did think about the dialog (e.g. "*Yes I tried to use the methods the prompts suggested at all times.*" - (P7, L), "*I did stop and reassess my learning after reading the prompts & questions.*" - (P6, L)), with two of those reporting that they did so less over time – "*Yes, although towards the latter sections I started paying less attention*" - (Q14, L). Those in the higher ability group also reported that the "*effect varied over time*" – (P16, H). Although they thought about them initially, they did so less over time, "*Yes at the start. less so, towards the end.*" - (P4, H). While these results are similar to those where the two experimental conditions were compared, here there is a clear tendency for lower ability learners to think about the prompts, whereas those with greater prior ability look to have thought less about the dialog supports. This may be as a result of their own awareness of their novice capabilities, which meant that they tried to help themselves while learning by giving thought to the dialog supports. Also, regardless of the group or ability, the type of support can be time dependent – thus, it is not enough to simply map the content of the dialog to the status of the learner within their task (e.g. planning supports at the beginning).

Q4. Question - "Did you feel as though you used the prompts and questions to help you organise your time?"

The participants were also asked, *"Did you feel as though you used the prompts and questions to help you organise your time?"*

Ability Group	Mean	Median	StDev
High Ability	2.875	3	0.835
Low Ability	2.444	2	0.882

Table M 4 - Did the prompts and questions help you to organise your time?

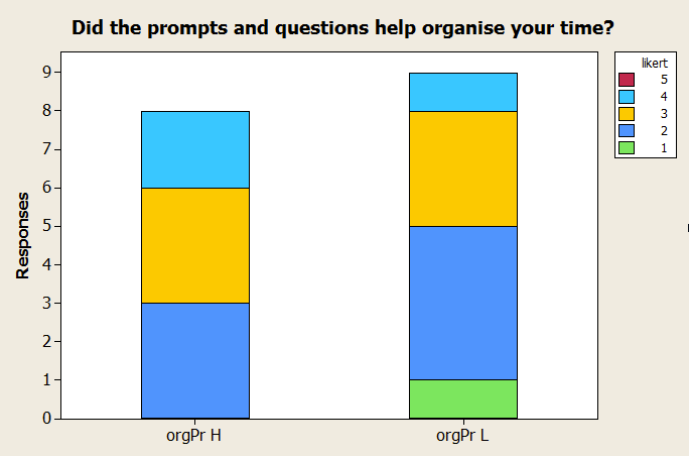


Figure M 44 - Did the prompts and questions help you to organise your time?

Overall, as seen in Table M 4 and Figure M 44, both sets of learners were indifferent or responded that the dialog supports had a negative effect on their ability to organise their learning time. Again this is line with the prior analysis of the experimental groups, where learners responded that although the supports did enable them to stop and take stock they did not provide strategies for organising their learning time. For instance, "*Sometimes the prompt did suggest 'taking stock' - this was useful*" – (P16, H) – however this response is not necessarily related to the task of organising the learning time. Similarly, learners in the lower ability category did not make changes to how they organised their time - "*no thought of time*" – (Q9, L), and "*No, I wasn't really managing my time, I just took the course at my own pace*" – (Q14, L). This suggests that regardless or prior ability, that different types of supports could be more useful for helping learners to organise their learning time and make learners aware of the need to organise their learning experience – while providing the supports can help them to take stock, additional supplementary supports (e.g. scheduler, calendar) could provide a richer scaffolding experience.

M.10.2Relevancy of the Prompt/Questions to Learning

Q5. Question - "Would Goby be useful while learning other Computer Science modules?"

Participants were questioned, *"Would Goby be useful while learning other Computer Science modules?"* Overall, as illustrated in Table M 5 below, there was agreement that Goby could be useful for other Computer Science modules and these results are

reflected in the initial analysis carried out between the experimental groups (illustrated in Section 6.3.3).

Ability Group	Mean	Median	StDev
High Ability	3.875	4	0.835
Low Ability	3.889	4	0.333

Table M 5 - Would Goby be useful while learning other Computer Science modules?

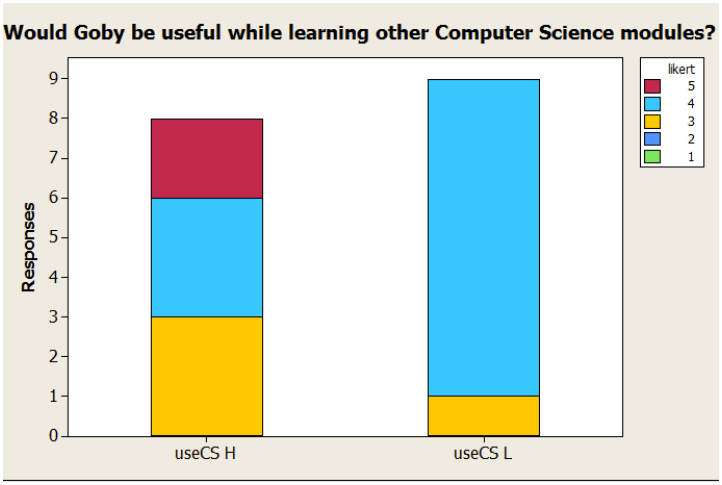


Figure M 45 - Would Goby be useful while learning other Computer Science modules?

As can be seen in Figure M 45, there were no negative responses from learners in either group – while it appears that the lower ability learners were more positive, overall the groups can be considered on par. Both categories reported that Goby has "*the potential, very much so*" – (Q8, L) and that it could benefit from tweaks – "*toned down a bit when there is no advantage to displaying a popup*" (P4, H). This is in line with the earlier results regarding motivation and learning, whereby learners gave less of their attention to the dialog supports over time. Again, regardless of prior ability, learners agreed – here that there was potential uses for Goby in the Computer Science domain however the supports provided would need to be fine-tuned and tweaked to better suit their needs.

Q6. Question - "Would Goby be useful for other domains?"

They were also asked, *"Would Goby be useful for other domains?"* Overall, as illustrated in Table M 6 below, there overall agreement that Goby could be useful for other domains.

Ability Group	Mean	Median	StDev
High Ability	4	4	0.756
Low Ability	3.778	4	0.667

Table M 6 - Would Goby be useful for other domains?

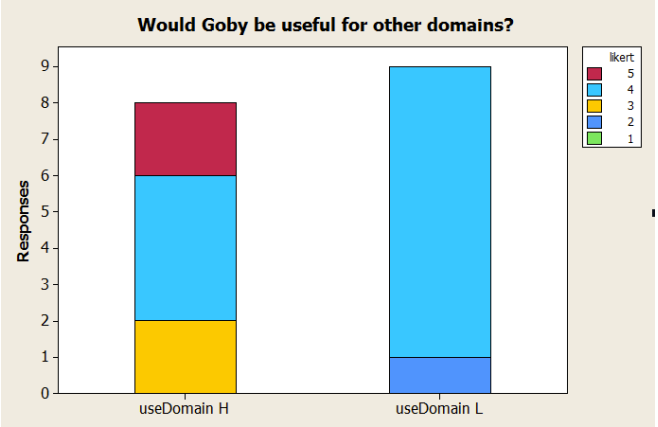


Figure M 46 - Would Goby be useful for other domains?

Here, as shown in Figure M 46, most of the lower ability learners agreed, while one learner disagreed that it could be useful in another domain. They reported "*as it stands no"* because it would "*have to be tailored for different modules*[111]*"* (P14, L). The higher ability cohort were indifferent or believed that it could have potential applications outside of the SQL and Computer Science domain. For instance, they reported that it "*would be useful in any learning situation*" - (P6, L) and suggested, "*Goby should be part of the Moodle course offerings*" - (P1, H). Again, these results are similar to the initial analysis – there were no reported differences between the lower and higher ability learners.

M.10.3Prompt/Question Interaction Workload

Q7. Question - "Did you feel that the Goby prompts added to the workload?"

Participants were questioned, *"Did you feel that the Goby prompts added to the workload?"* Overall, both lower and higher ability learners believed that the prompts added to the workload, as exemplified in Table M 7.

Ability Group	Mean	Median	StDev
High Ability	3.250	4	1.165
Low Ability	3.889	4	1.054

Table M 7 - Did you feel that the Goby prompts added to the workload?

[111] The second quote here from P14 refers back to their comments regarding the questions – "Would Goby be useful while learning other Computer Science modules?"

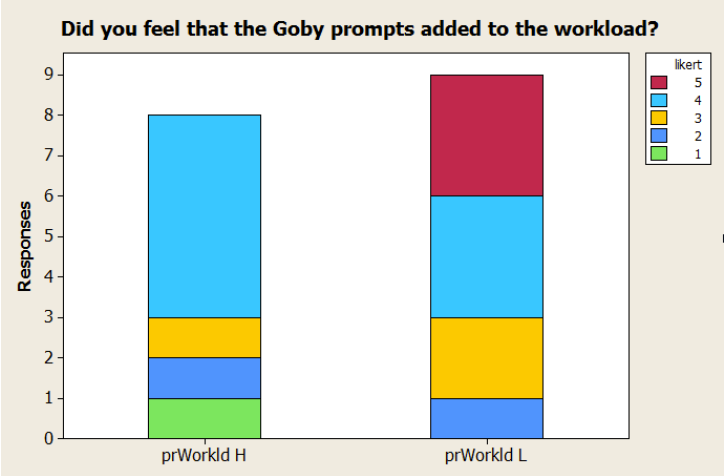


Figure M 47 - Did you feel that the Goby prompts added to the workload?

Although some participants did not believe that it added to the workload (three of the higher ability and lower ability learners, as shown in Figure M 47) overall they agreed with this statement – this is in line with the previous examination of the different experiment groups (Group A vs. Group B). As we have seen, some participants (regardless of prior ability or group) gave less thought to the dialog over time. As the dialog supports were an add-on to the traditional learning course, it is expected that they would add to the workload if they required the learner to stop and reassess their learning. For instance, one learner reported that, "*yes*", they did, "*if I did all the prompts it gave like drawing and revising*" – (Q9, L). Those who reported that they did not add to the workload may have done so because, "*The prompts did not interrupt me as there was no deciding process required, just a glance and confirmation*"- (P6, L). Here, regardless of the prior-ability of the learners, they saw they prompts as being either– a useful addition to the workload, no addition because they were useful, or else an addition that "*interrupted flow of thought at times*" – (Q10, H).

Q7. Question - "Did you feel that the Goby questions added to the workload?"

Participants were also asked, *"Did you feel that the Goby questions added to the workload?"* Overall, as illustrated in Table M 8, the higher ability learners tended to see the questions as an addition to the workload, whereas lower ability learners were did not feel as strongly about this statement.

Ability Group	Mean	Median	StDev
High Ability	3.500	4	0.926
Low Ability	3.111	3	0.928

Table M 8 - Did you feel that the Goby questions added to the workload?

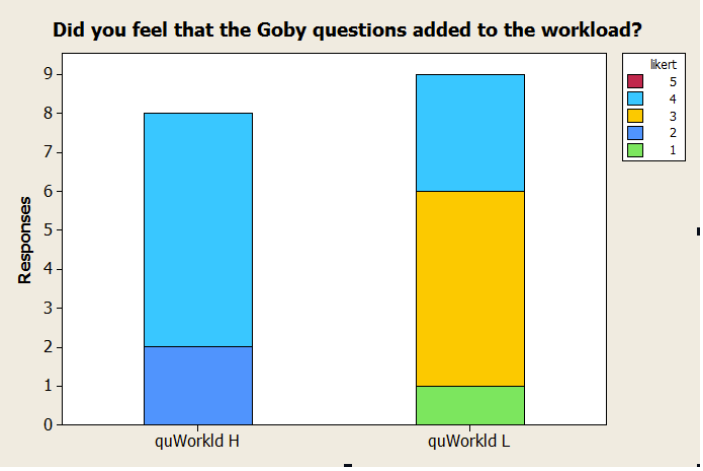


Figure M 48 - Did you feel that the Goby questions added to the workload?

As illustrated in Figure M 48 above, again there are variations within the responses – here in the lower ability cohort (quWorkld L) a number of neutral responses were reported. For instance, they replied, "*It was a bit distracting from time to time but the positives balance out the negatives*" – (P7, L) and "*no once you got (sic) acustomed to them*" – (Q9, L). Response from the higher ability learners (quWorkld H) were similar, "*No they were good where (sic) aplicable*" - (P8, H).

Q8. Question - "Did you feel that the Goby prompts interrupted the flow of the work?"

Participants were asked, *"Did you feel that the Goby prompts interrupted the flow of the work?"* As shown in Table M 9 below, the higher ability learners believed that the prompts interrupted the flow of the work, whereas overall, the lower ability learners were neutral.

Ability Group	Mean	Median	StDev
High Ability	4	4.5	1.309
Low Ability	3.556	3	1.014

Table M 9 - Did you fell that the Goby prompts interrupted the flow of the work?

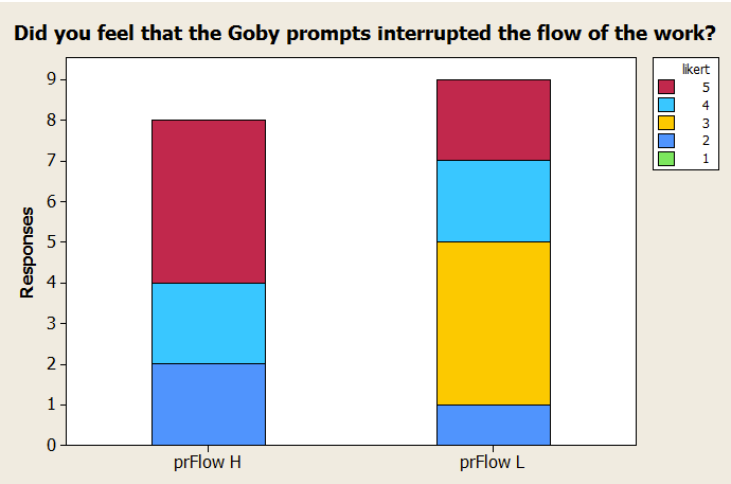


Figure M 49 - Did you fell that the Goby prompts interrupted the flow of the work?

Here, a range of responses was reported from both categories, as shown in Figure M 49 above. In particular, the high ability learners (prFlow H) agreed, with only two learners disagreeing. They reported that they, "*Felt like I was multi-tasking, instead of just being able to concentrate solely on the learning material*" – (P9, H) and "*strongly agree because there were too many of them. 1 in 3 would have been better*" – (P4, H). Responses from the lower ability category (prFlow L) were somewhat more positive – "*The prompts did not interrupt me as there was no deciding process required, just a glance and confirmation"* – (P6, L) and "*Somewhat due to quantity … but they were also helpful and helped pacing and encouraged contemplation*" – (Q14, H). Again, regardless of the prior ability, the timing and type of support offered is of importance – while richer supports may offer learners better tools with which to improve their regulatory strategies, here even prompts can result in the learner feeling as they are breaking their concentration.

Q9. Question - "Did you feel that the Goby questions interrupted the flow of the work?"

They were also asked, *"Did you feel that the Goby questions interrupted the flow of the work?"* As shown in Table M 10 below, overall there was no difference reported between participants with different prior abilities.

Ability Group	Mean	Median	StDev
High Ability	3.625	4	1.506
Low Ability	3.667	4	1.118

Table M 10 - Did you feel that the Goby questions interrupted the flow of the work?

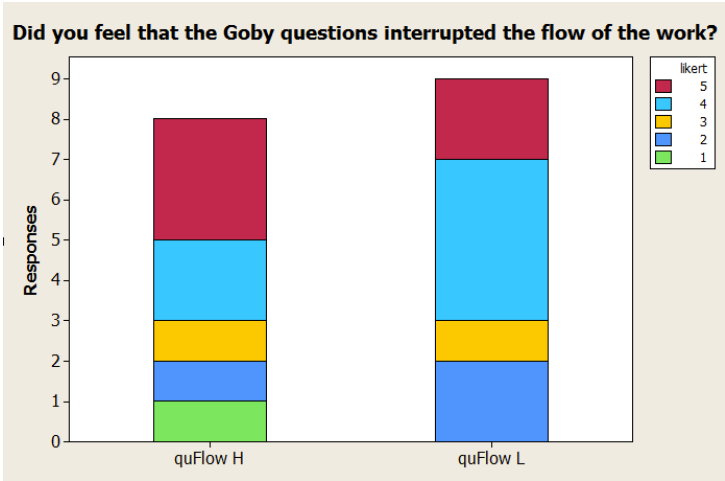


Figure M 50 - Did you feel that the Goby questions interrupted the flow of the work?

However, a range of responses was reported from both categories, as shown in Figure M 50 above. These participants indicated that, "*At first I did as I tried to answer everything as applicable to the section I was reading. After time I took them to serve as reminders and used them as needed.*" – (P6, L) "*One offs that were good. Repeating*

them again and again not needed although this may work for other people!" - (Q8, L). As the dialogs did add an extra element to the learning environment, it is expected that this type of add-on can create interruptions to the flow in the work. In line with the prior question (regarding prompts), regardless of the prior ability, the timing and type of support offered is of importance.

Q10. Question - "Did interactions with the Goby popup box add time to the learning task?"

Finally, participants were also asked, *"Did interactions with the Goby popup box add time to the learning task?"* Here there was overall agreement, as shown in Table M 11 below, however there was some difference within these groups, particularly within the lower ability group (time L).

Ability Group	Mean	Median	StDev
High Ability	4.125	4	0.354
Low Ability	3.889	4	1.054

Table M 11 - Did interactions with the Goby popup box add time to the learning task?

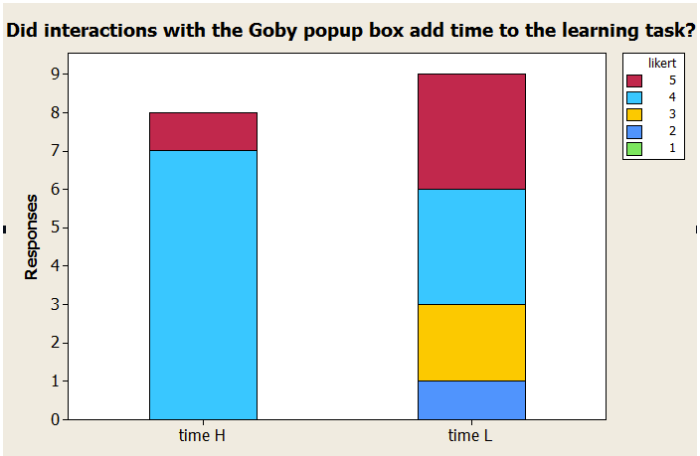


Figure M 51 - Did interactions with the Goby popup box add time to the learning task?

As shown in Figure M 51 above, the higher ability group (time H) were in agreement that the dialog interactions added to the overall time taken. They reported, "*Yes, but was time well spent*" - (P1, H) and "*I started ignoring them towards the end.*" (P4, H). Similarly, the lower ability group reported that, "*Only as the popup suggestions made me study the information more and in different ways.*" - (P7, L), "*No, the popup box was part of the learning process*" - (P14, L) and "*Yes, but not to a large extent and it didn't really bother me*" - (Q14, L). While there was agreement that time was added, particularly if the participants attended to the dialog and integrated their suggestions, in many cases they were seen as added benefit that supported the learners to study the information in ways that they would not have otherwise considered.