# Investigating accuracy of trade-off and its neural correlates, how well can we trade apples for oranges?

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# Declaration

I declare that this thesis has not been submitted as an exercise for a degree at this or any other university. This thesis is the result of my own work and includes nothing which is the outcome of work done in collaboration. This thesis contains less than 65,000 words including appendices, bibliography, footnotes, tables and equations. I agree to deposit this thesis in the University's open access institutional repository or allow the Library to do so on my behalf, subject to Irish Copyright Legislation and Trinity College Library conditions of use and acknowledgement.

Marek Bohacek
12/07/2018

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## Summary

As humans, we perform trade-off of incommensurable concepts on daily basis. For example, many of purchase decisions, especially those involving complex products with multiple incommensurable attributes, require us to trade qualities of two or more attributes against each other like in: ‘trading apples for oranges’. But, how does human brain maps these concepts of different currencies on each other has not been directly investigated even though literature from consumer research, various psychophysical tasks and decision-making models suggest that our ability to trade-off might be limited and prone to biases. Two experiments combining the Surplus-identification task with the random dot-motion-task, using colour and motion direction discrimination as its two attributes, investigate this question. Experiment 1 investigates origins of potential cognitive bottleneck by focusing on both the precision and biases of trade-off while Experiment 2 investigates neural correlates of trade-off with aim of isolating decision variable representing accumulation of evidence, as suggested by sequential sampling models, during trade-off. It was discovered that large decrease in precision results from mapping incommensurate attributes on each other and not from need to assess quality of two attributes simultaneously. This mapping process is also prone to number of biases. The isolated decision variable differed from those reported in previous studies using perceptual decision tasks and was not modulated by trial difficulty. This suggests that mapping incommensurate attributes is more complex process to that of simple perceptual decisions possibly requiring additional cognitive processes. The highly approximate nature of trade-off involving incommensurate concepts draws parallel with research on cognitive capacity and it also raises a doubt about validity of decision making models assuming calculation of internal ‘value’ associated with each option.

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# List of abbreviations

| | |
|---|---|
| BSS | Blind source separation |
| CPP | Centro-parietal positivity |
| EDM | Economic decision making |
| EEG | Electroencephalography |
| EOG | Electrooculogram |
| ERP | Event related potentials |
| fMRI | Functional magnetic resonance imaging |
| IIR filter | Infinite impulse response filter |
| iJND | Ideal integration just noticeable difference |
| JND | Just noticeable difference |
| MEG | Magnetoencephalogram |
| PDM | Perceptual decision making |
| RGB | Red-Green-Blue |

# CHAPTER 1: Introduction

## 1.1 General Introduction

Decisions that require prior assessment and subsequent integration of information from a number of sources are common occurrences in our daily lives. In fact, such decisions are not only relevant to humans, but are also common in the animal world, such as in foraging or mating behaviours. As such, they play a key role in animal survival. Take, for example, a troop of monkeys that has to make a decision between two feeding sites. One is plentiful in monkey food, but also in a number of predators, while the other one has a low number of predators, but is also low in food. Take a different example, this time involving humans. Imagine you are going to buy shoes and the two things you care about are price and likability. However, when you come to the shoe shop, you discover that the shoes that you like are expensive, but you do not like the cheap ones. What do these examples have in common? They both require multi-attribute decision making involving a trade-off which requires assessment of qualities of incommensurable[1] attributes (predators and food; price and likability) from which the available options are made, and subsequent integration of these pieces of information so the best option can be selected.

These multi-attribute decisions are part of what is referred to in the literature as *Economic decision making* (EDM) because they require either a calculation of some sort of internal ‘value’ or ‘utility’  associated with each option under consideration or alternatively an ordinal comparisons of the options’ attributes (Vlaev, Chater, Stewart, & Brown, 2011). Please note that EDM does not require that money is involved even though it will often be the case. When thinking about an option or a product in the framework of EDM, the product becomes a bundle of its attributes, and, even though some products have only one attribute of interest (e.g., commodities), most products encountered in our lives have numerous attributes. This is especially true for products such as houses, contracts for services, or multifunctional electronic goods. The larger the number of attributes we care about, the higher the probability that an attribute trade-off will have to be resolved. In fact, such decisions are made on a day-to-day basis by most of us.

[1] Incommensurable refers to having no common standard of measurement.

This study aims to add to our understanding of the cognitive process of attribute trade-off by investigating the accuracy with which information can be integrated, and the underlying brain processes involved. It will also test whether patterns of brain activity found during unidimensional *Perceptual decision making* (PDM) can also be found in multi-attribute EDM. If so, then there is scope to apply several theoretical models, originally devised to explain PDM, to the economically-meaningful context of multi-attribute consumer choice.

The study of attribute trade-off has implications for experimental psychology and neuroscience as investigating people's ability to combine information from multiple attributes into a single value judgment can provide new insights into human information-processing capacity, and an advance in our understanding of the brain processes involved in EDM and or PDM. The current study does not test the concrete predictions of the decision making theories developed from empirical findings of PDM and EDM. However, if limitations to the domains (e.g., the ability to trade incommensurable attributes) to which such theories can be applied are discovered, a number of implications for those theories will arise. For example, the similarities between PDM and attribute trade-off would imply an overlap between EDM and PDM processes. On the other hand, differences, such as the additional cognitive constraints that are present during attribute trade-off only would imply the existence of additional cognitive processes involved in EDM, but not PDM. This would further imply that an important component, or bottleneck, of EDM is not accounted for by the existing models, which mostly ignore cognitive limitations (for a comprehensive review of decision making models, see below).

In addition to the potential implications to decision making theories, the study of attribute trade-off is also pertinent to consumer research in the area of consumer behaviour and how it varies across markets. Following from this, it is relevant to policymakers concerned about the potential consumer detriment that markets with complex products could have, as such complexity is more likely to require trade-off between attributes. By better understanding consumers' cognitive limitations in multi-attribute decision making, it is possible to design consumer aids aimed at counteracting the identified limitations. It further enables policymakers to introduce empirically-informed policies. Moreover, the study of attribute trade-off has implications for neoclassical economic theories and those derived from them. The majority of such theories assume that consumer decisions can be approximated by the optimization of utility functions defined over an unconstrained number of attributes. A final area that requires mentioning is expert judgement. This includes, for example, decision making among clinicians, military officers, judges, traders, pilots, etc. Experts are often required to evaluate and combine information from multiple sources, and often make decisions under time stress. A better understanding of human caveats in multi-attribute decision making will lead to reduced risk and improved safety in many of those areas.

This chapter will introduce the theoretical models of PDM[2] followed by a review of the key empirical findings that have played crucial roles in the development of these models. Secondly, it introduces EDM models from three separate research fields: Economics, Psychology and Neuroscience, exploring key differences between the models, which largely come about as a result of underlying assumptions regarding whether the brain calculates internal value or employs purely comparative processes during decision making. The pros and cons of the EDM models are then discussed while drawing upon empirical findings. Thirdly, literature from the fields of economics, psychophysics, decision-making and consumer research with relevance to the study of a multi-attribute trade-off will be reviewed. This section will discuss the current understanding of how well people can perform such decisions, focusing on cognitive ability and identified limitations. This chapter will conclude by arguing that progress is possible from the combination of a behavioural task designed specifically to measure the accuracy of information integration in EDM and neuroscientific approaches previously employed to explore the process of information accumulation in PDM.

## 1.2 Perceptual decision-making

### 1.2.1 General

The prevalent approach used in studying EDM focuses on how options are selected based on their reinforcement history. The vast majority of EDM models is based on behavioural

[2] The distinction between PDM and EDM models followed in this thesis is based upon a review paper of decision making models by Summerfield and Tsetsos (2012). Most of the research in EDM explores how options are selected based on their reinforcement history, often manipulating reward probabilities, whereas PDM research is concerned with the detection, discrimination and categorization of noisy perceptual information. However, it should be stated that the boundaries between PDM and EDM are not as clear, which has been highlighted by the authors. Both types of decisions share common ground, as all decisions require an answer to two questions: What is it, and How much is it worth? It could also be argued that PDM models focus on explaining the physical level, inner workings of the cognitive system, while EDM models try to explain the algorithmic/representational level; in what way the cognitive system achieves its goals (Marr, 1982).

findings of biases, heuristics, or context effects that people display during decision making. However, this led to the development of mostly descriptive models of EDM. These best fit the currently-available behavioural data, but offer little towards our understanding of the underlying cognitive process. This is in sharp contrast to PDM, which is concerned with how people detect, categorize and discriminate noisy sensory information. PDM adopts tasks based on psychophysics, which is a branch of psychology that studies the relationship between sensory inputs and their consequences for subjective experience. In contrast to EDM, PDM research has explored the effects of deliberation time on decision making, leading to the explanation of the time-accuracy trade-off observed in data. This approach has led to the development of a large number of dynamic process theories of PDM. While static theories of EDM assume that decisions are made on the basis of a single sample of information, the dynamic approach prevalent in PDM assumes a sequential sampling.

Before describing theories of PDM, it should be clarified that the sequential sampling models have been applied in many contexts and to a variety of cognitive tasks, including lexical memory, for example. Hence, sequential sampling models are not limited to only PDM. However, the literature has mostly focused on elementary perceptual decisions because they are simple and afford easy experimental control. Moreover, elementary perceptual decisions allow for easier isolation of relevant signals in neurophysiological research because the initial area in which to search for the signals is known. Please note that terms ‘sequential sampling models’ and ‘PDM models’ are used interchangeably within this thesis. The fact that sequential sampling models are applied to variety of cognitive tasks also highlights the importance of those models to the study of multi-attribute economic decisions.

### 1.2.2 Theories of PDM

The sequential sampling models of PDM are based on statistical analyses of the sequential probability ratio test (Wald, 1947), which was developed to maximise the speed of quality control decisions. It uses the minimum possible amount of evidence to generate categorical decisions given noisy inputs (pieces of sensory evidence). This is achieved by updating the log likelihood ratio of evidence at each sampling step given the two competing hypotheses. This process continues until the pre-defined threshold is reached and the decision favouring the hypothesis with a larger likelihood is executed. However, the sequential probability ratio test assumes that distributions of evidence are known. Hence, PDM models have attempted to approximate this process in psychologically-plausible manners, which has, led to the development of the following three broad categories of PDM models: *Race, Diffusion,* and *Leaky competing accumulator* models. Race models (e.g., Brown & Heathcote, 2008; Townsend & Ashby, 1983) assume independent integration of evidence by separate accumulators, each being associated with particular choice. By contrast, Diffusion models (e.g., Ratcliff, 1978; Ratcliff & McKoon, 2008) assume only one accumulator that represents the net difference in evidence of the two competing alternatives. Note that Race models assume an absolute input of evidence, whereas Diffusion models assume relative input. Finally, Leaky competing accumulator models (e.g., Usher & McClelland, 2001; Wang, 2002), like Race models, assume separate accumulators but, as with Diffusion models, allow for competition between the alternatives. This competition is hypothesised to be achieved via lateral inhibition.

The advantage of dynamic PDM theories is their ability to model fundamental aspects of human choice such as a speed-accuracy trade-off, which is the finding that increased time deliberation leads to more accurate choices, and vice versa (Johnson, 1939). In addition, these theories make it possible to model any prior bias towards one of the options, as well as those towards early or late evidence. They further allow for the estimation of reaction time distributions of error-and-correct responses, and the disambiguation of decision time (the time required to accumulate evidence) from non-decision time (e.g., the time associated with the processing of motor response). They also allow for an estimation of the quality of input information (the level of ambiguity of sensory input) and response conservativeness (the level of the pre-set decision threshold) that a person employs (Wagenmakers, 2007). The main distinction between the different classes of PDM theories lies in the assumption of whether incoming evidence is accumulated in relative (Diffusion models) or absolute terms (Race models). While the advantage of Race models is the simplicity with which they can be extended beyond the application to decisions requiring only binary choice, their disadvantage lies in poorer approximations of statistically-optimal choice behaviour when compared with approximations of Diffusion models (Summerfield & Tsetsos, 2012).

The serial sampling shared by the reviewed PDM models provides a natural mechanism for decision optimization when categorizing noisy evidence. This is done by averaging out noise-driven fluctuations, and hence enhancing the signal-to-noise ratio. EDM, however, is characterized by static and perceptually-unambiguous evidence. Thus, if a similar accumulation process is involved in EDM, the question of what is being accumulated arises. A growing body of literature suggests similarities of benefits caused by increased processing time during the choice in both PDM and EDM tasks (Summerfield & Tsetsos, 2012). It has been suggested that during EDM, participants accumulate internal representations of value, rather than averaging out noise-driven fluctuations. For example, the subjective internal values associated with each option might be stochastically sampled from long-term memory (how good an option is in relation to previously-encountered options; Milosavljevic, Malmaud, & Huth, 2010), or sampled from the immediate context (how good an option is compared to other alternatives in the choice set; Stewart, Chater, & Brown, 2006). Whether EDM and PDM sampling processes are governed by similar principles remains an open question.

### 1.2.3 Empirical findings of PDM

One piece of evidence in support of sequential sampling PDM models comes from (Roitman & Shadlen, 2002), who recorded from neurons in the middle temporal visual area of monkeys while they were performing a *random-dot motion* task. This task consists of a circular aperture occupied by randomly-moving dots, and dots moving in particular direction; the ratios of the two groups of dots are under experimental manipulation. The aim is to identify the overall direction of motion. The researchers made two important discoveries. Firstly, the accuracy of the single-neuron response predicted the accuracy of the choice. Secondly, the trial-to-trial variability of the neuronal responses, which represents the level of noise within the signal, correlated (albeit weakly) with the variability of a monkey's choices. This suggests that the monkeys were either basing their decisions on small number of neurons, or, as is more likely, on a large number of neurons that share some part of their variability. This finding has been replicated in various studies, including tasks such as vibrotactile frequency discrimination induced both by mechanical and electric stimulation (Romo, Hernández, Zainos, & Salinas, 1998; Salinas, Hernandez, Zainos, & Romo, 2000), and heading direction discrimination tasks using a random-dot motion flow field (Heuer & Britten, 2004). Further support also comes from microstimulation studies (Salzman, Britten, & Newsome, 1990). Stimulation of neurons tuned to one of the two competing directions induced a systematic bias in the behaviour of the monkeys.

The key to understanding the organization of the decision making system in the brain is to dissociate the signals of *sensory* evidence and *decision variable* that represent the fundamental principles of the theoretical framework of the sequential-sampling approach (Gold & Shadlen, 2007). The sensory evidence is a momentary representation of the sensory evidence. In contrast, the decision variable represents a temporally-extended accumulation of sensory evidence characterized by a rate of build-up that triggers action upon reaching the threshold level. Neuronal recordings from the *lateral intraparietal area* (LIP) while monkeys performed a random-dot motion task revealed neurons that behaved exactly as the decision variable (e.g., Roitman & Shadlen, 2002; Huk & Shadlen, 2005). During periods of decision, these neurons increased their firing rate in a ramp-like fashion, and their discharge rate predicted the monkeys' decisions. A steeper rise was associated with a stronger motion signal and shorter reaction time.

Non-invasive approaches such as electroencephalography (EEG), magnetoencephalography (MEG) and functional magnetic resonance imaging (fMRI) used in human studies afford a global view of brain function. This allows the study of decision making processes at a system level and provides additional information about the hierarchical levels of sensorimotor areas, and system interactions of the main area with other supporting areas such as those representing attention.

A large portion of non-invasive PDM studies on humans have been conducted with fMRI. In line with neurophysiological studies of monkeys (Britten, Newsome, Shadlen, Celebrini, & Movshon, 1996) the perceptual reports of motion direction by human subjects can be predicted from activation patterns in hMT+ (Serences & Boynton, 2007), the human equivalent of the middle temporal visual area. The decision variable has also been investigated, but it is harder to identify with standard fMRI designs because of its low temporal resolution, making it difficult to observe such dynamic aspects like breaching a threshold. Early studies implicated the left dorsolateral prefrontal cortex as the candidate for the decision variable (Heekeren, Marrett, Bandettini, & Ungerleider, 2004). However, their underlying assumption that greater *blood-oxygen-level dependent* (BOLD) activation resulting from stronger evidence is reflected in steeper accumulation has been questioned by other researchers, who suggest the exact opposite prediction (Liu & Pleskac, 2011). An alternative approach to overcome the low temporal resolution of fMRI has also been developed. For example, applying additional or alternative criteria to identify the decision variable, including covariation with reaction time (Binder, Liebenthal, Possing, Medler, & Ward, 2004), earlier onset latency for stronger evidence (Ho, Brown, & Serences, 2009), and greater activation for correct-versus-incorrect trials (Pleger et al., 2006). However, given the large number of approaches it is not surprising that different numbers and locations of areas involved in decision making have been implicated by the literature (Kelly & O'Connell, 2014).

Human neurophysiological research (EEG and MEG) in PDM has been conducted over the past 50 years. The *event-related potential* (ERP) technique has been used readily, as it provides high temporal resolution, promising to isolate the distinct processing stages of PDM. A prominent component of ERP, the centro-parietal *P300* has been associated with PDM, as it has been observed across various tasks requiring decisions (Sutton, Braren, Zubin, & John, 1965). It has also been shown to display characteristics such as being larger for the sensory stimuli that were detected compared to those missed (Hillyard, Squires, Bauer, & Lindsay, 1971), and a temporal variation that corresponds closely with reaction time data (Ritter, Simson, & Vaughan, 1972). This makes it an ideal candidate for the decision variable. However, the application of EEG and MEG to the sequential sampling of sensory evidence is problematic for traditional ERP paradigms due to the poor spatial resolution of EEG/MEG. This makes it difficult to disambiguate overlapping sensory (task relevant or otherwise), decision and motor signals. A variety of powerful data transformations have been used to disentangle the overlapping signals using task-specific, functionally-grounded approaches (for more details, please see; Kelly & O'Connell, 2014). An alternative approach has been proposed by O'Connell, Dockree and Kelly (2012). The researchers used a clever paradigm adaptation. First, they eliminated task non-specific sensory responses (often elicited by stimulus onset) by using a continuously-ongoing stimulus with a gradual trial onset using seamless transition. Second, the response was unimanual, in order to explore lateralized motor preparation. Third, a flicker with about 20 Hz frequency was introduced to elicit steady-state visual evoked potential, making it possible to isolate the sensory evidence signal. With this adaptation, they were able to isolate centro-parietal positive potential, which displayed a gradual built-up consistent with the temporal integral of the evidence, as well as predicting the timing and accuracy of decision reports.

## 1.3 Economic decision-making

### 1.3.1 Theories of EDM

A large number of EDM models have been proposed in Economics, Psychology and Neuroscience. A classification framework proposed by Vlaev et al. (2011) categorizes these models according to whether they assume that the brain computes an internal value for each option in order to guide the decision (a product with a highest internal value is selected over products with lower values), or whether the decision is determined by the simple notion of ordinal comparison (products are compared against each other and the one that wins most of the comparisons is selected). Based on this notion, decision making theories can be classified into three types: *Value-first decision making* (Type 1), *Comparison-based decision making with value computation* (Type 2) and *Comparison-based decision making without value computation* (Type 3; Vlaev et al., 2011). The major distinction between the three types is that Type 1 theories consider each option from a choice independent of other available options, whereas Type 3 theories inherently explain decisions in terms of the entire choice set. Type 2 theories assume value computation, but allow for value adjustments driven by the comparison process.

Type 1 theories assume that in order for a person to choose between two or more options, the brain computes the internal value (also referred to as utility) associated with each option independently of the other available options. The next stage involves selection of the product with the highest value. A classic example is *Expected utility theory* (Von Neumann & Morgenstern, 1944). Newer approaches in Economics propose that this process is somewhat stochastic, leading to occasional selection of products with lower value (e.g. *Stochastic expected utility theory*; Blavatskyy, 2005). However, long-standing psychology research into decision making under uncertainty has identified a number of limitations to Expected utility theory and other economic approaches, including the *Allais paradox* (Allais, 1953; preference for a small 100% probability gain to a larger 50% probability gain, while also preferring a larger 5% probability gain to a small 10% probability gain); loss aversion (people prefer to avoid losses more strongly to acquiring gains); and the diminishing sensitivity of value functions (e.g., an increase from €10 to €20 is seen as larger than an increase from €40 to €50 Vlaev et al., 2011). These findings led to the development of *Prospect theory* and *Cumulative prospect theory* (Kahneman & Tversky, 1979; Tversky &

Kahneman, 1992), which depart significantly from Expected utility theory in assuming that internal values are assigned to movements (e.g. gaining or losing) from a relative reference point, usually the starting point prior to the occurrence of the movement. This theory further predicts concave and convex value functions for gains and losses, respectively, and that people overweigh high-probability outcomes and underweigh low-probability ones.

Type 2 theories still assume a value computation for options or attributes of options but allow for additional between-and-within option comparisons that re-adjust the internal values associated with each option. For example, *Inequity aversion theory* (Fehr & Schmidt, 1999) suggests that decisions are driven by motives of fairness and therefore people undervalue options perceived as inequitable. It is based on findings from game theory experiments such as the Ultimatum game, in which one player decides how to split a reward between her and another player. If the split is accepted by the second player, both players receive their allocated shares, but if it is refused, both receive nothing. According to Expected utility theory, the first player should offer the second player as little as possible to maximize utility, and the second player should accept this offer, since it is better than nothing. However, it has been found that a large portion of people resort to 50/50 splits. Inequity aversion theory explains this in terms of each outcome's internal value being adjusted by the level of inequity associated with it. The level of inequity is brought about by individuals' history of social interactions and social norms (Fehr & Schmidt, 1999).

In psychology, two subclasses of models within Type 2 theories have been proposed. The first sub-class of models assumes an internal value computation for the entire option, but this computation is affected by attributes from other options. The choice is therefore made in absolute terms. The second sub-class of models only assumes a utility computation for the different attributes that make up the options and the choice is a result of relative comparisons between different attributes. Hence, the choice is achieved in relative terms. An example of the first sub-class is the *Componential-context model* (Amos Tversky & Simonson, 1993), which proposes a two-stage valuation process. Each attribute of an option is associated with an internal value that depends entirely on the magnitude of that attribute. The first stage represents a contingent-weighting model. During this process, attribute utilities are combined as a weighted sum of each attribute that makes up that option, but their internal values are modified according to the level of attribute trade-off experienced during previous choice sets. The second component is a binary comparison model that evaluates each option against other options in the immediate set, and the winner is the option that wins most of the comparisons. The comparisons from the two stages are combined in additive fashion. An example of the second subclass is the *Stochastic difference model* (González-Vallejo, 2002) inspired by the *Thurstonian law of comparative judgment* (Thurstone, 1927). The model assumes that a decision maker normalizes differences of attribute internal values, or, to put it simply, they compare attributes across different options, and the resulting overall difference is represented as a ratio. Multi-attribute products are therefore not compared against each other, but their attributes are. The decision is achieved when the attributes difference ratio crosses the decision threshold, which varies across individuals, plus the stochastic error resulting from the decision process itself.

Type 3 theories are based only on the principle of ordinal comparison. In this sense, judgement can be seen as being based on a balanced scale which moves left or right in accordance with which side is heavier, but does not indicate the actual weights. This comparative approach assumes that each judgement involves a new comparison of attributes and/or options brought about by the available context rather than consulting stable internal value scales. *Decision by sampling* (Stewart et al., 2006) is a well-known example of a Type 3 model. It assumes that attribute values are compared in binary fashion against each other and the resulting outcome of those comparisons is bigger, smaller or equal. The information of those binary comparisons is tracked. This process is terminated and the option with the highest 'score' selected when the pre-selected threshold is reached. The value is never calculated, as only ordinal comparisons are tracked. The evaluation draws upon samples from memory or immediate perceptions. The decision is therefore influenced by the context in which it is performed, such as the perceived ranges of attributes of other offerings as well as memories about these ranges. The memories from which the samples are drawn are representative samples of the environment. For this reason, Decision by sampling is able to account for many patterns of economic behaviours, such as underestimating large probabilities and overestimating small ones, hyperbolic temporal discounting, loss aversion, etc. Another group of Type 3 theories is that of *Lexicographic semi-order* models (Amos Tversky, 1969). According to these models, preferences are formed by sequential comparison of the difference in attributes across two options against a criterion. In other words, if option A is better on attribute X than option B by at least a pre-selected amount, it is selected. If it is not, a less important attribute is used next, and so on. Thirdly and lastly, a further family of Type 3 models is that of *Reason-based* models (Vlaev et al., 2011), which assume a memory retrieval- and reasoning-based decision making process. The options are evaluated by comparing a number, and an ordering of pros and cons associated with each alternative.

### 1.3.2 Empirical findings of EDM

The appeal of value-based theories lies in their ability to incorporate various domains, solving the problem of how the brain compares incommensurable attributes, i.e., comparing apples with oranges. However, Type 1 theories struggle to explain empirically-observed context effects such as *preference reversals* (Amos Tversky, Slovic, & Kahneman, 1990), *prospect relativity* (Stewart, Chater, Stott, & Reimers, 2003) or *memory effects* (Ungemach, Stewart, & Reimers, 2011). An example of a preference reversal is when a decision maker that prefers option A over B reverses his preference (option B over A is now preferred) when an inferior option C is introduced to the option set. In line with preference reversals, prospect relativity refers to the effects that other prospects in the choice set have on a decision. This has been shown in a series of experiments that borrowed methods from psychophysics (Stewart et al., 2003). It has also been shown that peoples' perceptions of differences between two monetary values, risks and delays are altered by incidental everyday experiences, suggesting that subjective preferences are not stable but vary as a result of memory effects (Ungemach et al., 2011). As such, these findings of context effects question whether EDM is resolved by a utility-based computation process.

In comparison to purely value-based theories, comparative approaches including both Type 2 and 3 generally account well for various context effects (Vlaev et al., 2011). Additional evidence for comparison-based models comes from psychophysics. It has been shown that the perceived magnitude of a stimulus (e.g., loudness, frequency, luminance, force, etc.) is a function of comparison between other available stimuli. For example, a judgement of luminance of varying grey patches is not a function of absolute luminance, but rather a ratio of the luminance comparison of the patch in question to the brightest patch in the scene. This implies that a person presented with a scene consisting of only grey patches will perceive the brightest patch as being pure white (Wallach, 1948). Similar findings have been observed in other modalities as well. The subjective sweetness of sucrose concentration is context-dependent and affected by the distribution of the preceding concentration levels presented (Riskey, Parducci, & Beauchamp, 1979). In fact, the context-dependency of the subjective magnitude judgements for a wide variety of sensory stimuli follows a predictable pattern, as supported by findings from Neurophysiology of the sensory pathways. The system normalizes absolute sensory values in the earliest stages of sensory processing, possibly to enhance information coding efficiency (Barlow, 1961). Those findings clearly support the existence of a comparative process at least at the earlier stages of decision making.

On the other hand, neurophysiological studies on primates support the existence of neurons that code for internal value. In one such study, monkeys chose between pairs of juices of different quantities and types (Padoa-Schioppa & Assad, 2006). Based on the monkeys' choices, the researchers were able to model subjective utilities associated with each juice option, finding a linear correlation between the activity of certain neurons in the orbitofrontal cortex and the modelled utility. Hence, those neurons were named *value neurons* as they appear to represent the subjective internal value associated with each option. Importantly, a follow-up study found that these value neurons were menu invariant, as the neuronal activity associated with each option was not affected by the other option in the pair (Padoa-Schioppa & Assad, 2008). Other studies found the existence of value neurons in striatum (e.g., Lau & Glimcher, 2008), but, most importantly, it appeared that these value neurons encoded the subjective value of actions on a common scale (Samejima, Ueda, Doya, & Kimura, 2005). In all, neurophysiological studies of primates have identified three distinct types of decision making neurons; *value neurons* which track each option regardless of whether it is chosen; *chosen value neurons* that track the chosen option, and *choice neurons* that produce categorical responses when an option is chosen. The activity of value and chosen value neurons peaks early in the trial, whereas choice neurons are active late in the trial.

As highlighted above, the theoretical and empirical literature concerning EDM research is vast. Various approaches to studying EDM have been adopted by researchers from different fields, resulting in a multitude of different research questions being developed and, consequently, in the development of a large number of distinct theories, each concerned with the specific part of EDM that it is trying to explain. This hints at the possibility of the existence of multiple decision making process systems. Perhaps the brain uses a range of systems depending on the task at hand. Alternatively, the different models could represent different levels of the same process and hence could complement each other (for more detail on theory categorizations based on the level of information processing, see Marr, 1982). One thing that all of the reviewed EDM models have in common is that none directly address such aspects of decision making as deliberation, attention, conflict and cognitive limitations. Note that sequential-sampling PDM models make explicit assumptions about these cognitive processes.

A notable exception among EDM models is a small number of sequential sampling approaches such as *Decision field theory* (Busemeyer & Townsend, 1993), a stochastic random walk (diffusion) choice model of decision under uncertainty and its multi-alternative neural network implementation (Roe, Busemeyer, & Townsend, 2001). These models propose that sampling of competing options is biased by the size of the expected reward associated with particular options (those with larger rewards are sampled more often or over a longer time) and the process of sampling is guided by attention as it fluctuates across attributes.

## 1.4 Cognitive limitations and trade-off

From the review of EDM models, it is clear that very little has been done towards incorporating concepts such as deliberation, attention, conflict and cognitive limitations into these models. Considering that most EDM requires a trade-off of incommensurable attributes, the current thesis argues that understanding cognitive limitations resulting from this trade-off is essential for the development of valid EDM models, as well as for the advancement of our understanding of the ability to make economic decisions in general. The research that is most relevant to the study of the cognitive ability to trade-off incommensurable attributes comes from four areas of psychophysics. These include the literature on *Function learning*, *Categorization tasks*, *Magnitude estimation* and *Identification tasks*. The psychophysical literature is reviewed next, followed by a short review of the biases in product valuations identified in consumer research.

### 1.4.1 Function learning

Function learning literature, which has its origins in work of Carroll (1963), investigates how people learn a relationship between continuous variables. Those include causal relationships between stimulus-and-response variables such as how pressing accelerator pedal influences a car’s velocity, or relationships between two variables such as the difference between linear and exponential growth. In a typical Function learning experiment, participants are shown a stimulus (cue) variable and are asked to estimate the output magnitude, which is followed by a feedback. The key interest in these experiments is how well participants can learn various functional relationships, including linear, exponential, logarithmic, etc. Most of the research has focused on the relationship between two continuous variables, but multiple-cue function learning tasks have also been used. In the latter task, participants are required to estimate output magnitude based on the values of two-or-more input variables. For example, in one such experiment, participants learned the complex relationship between two cues, the varying lengths and angle orientations of lines, and a response duration (Koh, 1993). In such experiments, the relationship between cues and response is determined by functional forms between each cue and the response, the relative weighting of each cue, and the combination of the cues (additive, multiplicative, etc.).

An extensive review of single-cue Function learning by Busemeyer, Byun, Delosh and McDaniel (1997) found a number of biases. When the functional relationship is unknown, participants assume a linear relationship. Simple relationships are learned more efficiently compared to complex ones; presumably as participants are required to estimate fewer functional parameters. Participants also learn some relationships faster compared to others. For example: continuous compared to arbitrary categorical; increasing functions compared to decreasing functions; monotonic compared to non-monotonic; non-cyclical compared to cyclical; and linearly-increasing compared to non-linearly-increasing are learned faster. Moreover, participants are biased towards predictions about functional form made at the beginning of the training and are more accurate in interpolating than extrapolating. Similar finding have also been reported for multiple-cue Function learning (Klayman, 1988).

Several Function learning models have been proposed, and similar to EDM models, they can be classified as parametric or non-parametric types. Parametric models assume that people represent functions explicitly and estimate function parameters from available observations (e.g., Koh & Meyer, 1991). As such, people are readily able to form representations that go beyond the observed values of the variables involved (ability to extrapolate). These models resemble Type 1 EDM models that assume computation of internal utility. In contrast, non-parametric models assume associative learning. People learn by forging associations between observed variable pairs and are able to generalize these rules to newly-presented cues (e.g., Busemeyer et al., 1997). These models resemble Type 3 EDM models that assume comparison-based decision making. Moreover, hybrid Function learning models have also been proposed. For example, an *Extrapolation-association* model that combines a linear regression specification and instance based learning was proposed by Delosh, Busemeyer and Mcdaniel (1997). These types of models are comparable to Type 2 EDM models which assume comparison-based decision making with value computation. A review by McDaniel, Dimperio, Griego and Busemeyer (2009) provides an empirical assessment of proposed models. They conclude that neither purely parametric nor non-parametric models account well for empirical findings, while hybrid models provide the best account of the available data. Moreover, they suggest that the cognitive mechanism responsible for mapping attributes appears to be very flexible, but approximate.

The Function learning literature provides a good account of how people learn a relationship between continuous variables. However, the cognitive ability with focus on the precision with which people map the continuous variables onto each other once a relationship is learned has received less attention. One notable exception comes from Hammond and Summers (1972), who has proposed that accuracy in cognitive tasks is determined by the acquisition of knowledge and a subsequent ability to apply it. They argue that poor performance in cognitive tasks is due to the failure to apply acquired knowledge rather than the lack of it. This is of interest to the current investigation, which focuses on the cognitive ability to trade-off incommensurable continuous attributes.

### 1.4.2 Categorization Tasks

Categorization tasks are similar to Function learning tasks. The main distinction is in the nature of input-output mapping. While in Function learning, a continuous function maps cues onto criteria, in Categorization tasks a discontinuous mapping from cues to categories is used (Busemeyer et al., 1997). In a standard Categorization task, a participant is presented with a stimulus varying in X number of continuous dimensions, much like in a Function learning task, but the aim is to classify the stimulus into one of the two categories. The Categorization literature is enormous, including both animal and human studies (for review, see: Ashby & Maddox, 2005). The Categorization tasks in humans further include four different kinds of tasks, of which two are relevant to the current investigation. These are: *Rule-based* tasks and *Information integration* tasks.

Rule-based tasks are those in which categories can be easily described verbally, and hence the categories can be learned via an explicit reasoning process. These tasks mostly include one-dimensional stimuli, but can include stimuli with more dimensions, as well. An example of a two-dimensional version would be a task that incorporates a conjunctional rule requiring response A when a stimulus is small on dimension X, and small on dimension Y, for example. In contrast, Information integration tasks require integration of two-or-more continuous dimensions. This is similar to EDM, where a multi-attribute trade-off must be solved during the predecisional stage. The integration of incommensurable sources of information represented by these continuous dimensions can take many forms. For example, the human brain could compute a weighted linear combination of the dimensional values like in Type 1 theories of EDM, or treat the whole stimulus as gestalt (this is similar to Type 3 theories of EDM). The decision rules in these tasks are difficult to describe verbally. However, the distinction between Rule-based and Information Integration tasks is somewhat fuzzy, with Information integration tasks being complex Rule-based tasks whose rules are difficult to put into words.

Many theories of human category learning have been proposed. *Prototype* theories assume that category learning requires a comparison of presented stimuli to internal representations or prototypes, and the stimulus is assigned to the relevant category based on the similarity to a particular prototype (e.g., Smith & Minda, 1998). Prototype theories can be viewed as parametric theories assuming a linear decision bound. However, these theories were mostly discredited because humans can learn complex nonlinear decision bounds (Ashby & Maddox, 1992).

In contrast, *Exemplar* theories suggest that humans are able to learn complex categories given enough practice. These theories assume that each category is represented by many examples and a novel stimulus is compared to all retrieved examples from every relevant category (e.g., Nosofsky, 1986). One of the most developed theories applied to Rule-based tasks is the *Competition between verbal and implicit systems* model. It assumes that learning is mediated by an explicit, hypothesis-testing system that depends on attention and working memory (Ashby, Alfonso-Reese, Turken, & Waldron, 1998). People generate rules that are stored within working memory and any given rule is used until new evidence discredits it, at which point a new rule is generated. The shift from the old to the new rule is driven by attention. However, Exemplar theories assume almost no limits to the complexity of decision bounds that can be learned. This contradicts findings from complex Information integration tasks where subjects failed to learn to respond optimally (Ashby, Waldron, Lee, & Berkman, 2001).

Finally, *Decision-bound* theories, which are based on the findings from Information integration tasks, assume that stimulus space is partitioned into various response regions and novel stimuli are placed into their associated region. People either learn the regions (non-parametric), or their boundaries (parametric; e.g., Maddox & Ashby, 1993). A study by Ashby and Waldron (1999) experimentally tested whether category learning is parametric or nonparametric. Statistical information such as means, variances, and covariances that could be estimated from stimuli examples signalled a linear decision bound. However, the optimal bound to perform the task was quadratic. They found that participants were closer in their performance to a quadratic bound than to a linear bound, supporting the idea that non-parametric processing takes place during information integration in Categorization tasks.

While theories from both the Rule-based and Information integration tasks point towards the existence of non-parametric processing, they also suggest that human category learning is mediated by a multiple of qualitatively-distinct systems. Moreover, a review by Ashby and Maddox (2005) concluded that accuracy in Categorization tasks reduces with increased complexity in decision bounds between categories. This might have implications for the multi-attribute decision making involving trade-off, suggesting firstly that it might be quite inaccurate, and secondly, it raises a possibility that it might also be governed by multiple cognitive systems. However, similar to Function learning literature, the Categorization tasks focus mostly on learning rather than on accuracy once the relationship has been learned.

### 1.4.3 Magnitude estimation

Magnitude estimation has been developed to measure judgements of sensory stimuli. In its basic form, subjects assign numbers in proportion to the magnitude of the tested stimulus. The stimuli can be anything from the brightness of a light, or the loudness of a tone, to the length of a line, for example. Magnitude estimation is similar to valuing products because subjects must assess the quality of the stimulus dimension before they assign a numeric value to it. According to Steven's *Power law*, there is a relationship between stimulus magnitude and perceived intensity. The general form of the law is: $S = kI^{\alpha}$, where $S$ defines the magnitude of the perceived sensation, $k$ is a scaling constant which depends on the units used, $I$ is the stimulus magnitude, and $\alpha$ is an exponent dependent on the type of stimulus being used. Stevens (1957) has conducted a series of experiments with various sensory continua and estimated the corresponding $k$ and $\alpha$.

However, numerous studies have reported considerable inter-individual variation of exponents in a number of sensory systems (Verrillo, 1983). Furthermore, a low temporal stability of individual power functions has also been reported (Teghtsoonian & Teghtsoonian, 1971). These findings raise a question of the validity of the magnitude estimates. This long-standing controversy has been summarized by Laming (1997), who questions the implicit assumption that people have internally-consistent scales for mapping commensurate magnitudes of stimuli across modalities. Moreover, research of Magnitude estimation in relation to consumer evaluations suggests the evaluation of a single product yields a different relationship between magnitude and value to evaluation of the same product in the presence of a second product because the latter case facilitates cross-product comparison (Hsee et al., 2005). Hsee & Rottenstreich (2004) have conducted an experiment in which participants were asked to donate money to save either one or four endangered pandas. The number of pandas was depicted either by a cute picture or by a dot/dots. The researchers found that people donated more to save one panda when a picture was used but to save four pandas when dots were used. The above findings show that internal value is not independent of the process, discriminability and the mode of evaluation.

Nevertheless, there is a similarity between the Magnitude estimation and the trade-off of incommensurable attributes. In both cases, people must map incommensurable attributes onto one another. To solve a trade-off between two products, the difference in magnitude of attribute A between two products is compared against the difference in magnitude of attribute B. In the case of magnitude estimation, the magnitude of an attribute is mapped onto a continuous numerical scale. However, there is also a crucial distinction between those two examples. To resolve a trade-off, people are not necessarily required to generate a numerical value by using a computational strategy. They can just select the product with a greater combination of two attributes, inducing a response based on their gut feeling. Nevertheless, the Magnitude estimation literature suggests that valuation is a noisy process, prone to errors and systematic biases. Whether similar patterns are also present during trade-off, which would suggest that valuation and trade-off share the same cognitive process, remains an open question.

### 1.4.4 Absolute identification

Absolute identification is concerned with identifying the cognitive limit to processing information. In a typical task, participants are presented with a set of stimuli that vary systematically along one dimension (e.g., nine weights of different weights; eight lines of different lengths). Each stimulus from the set is associated with a label, often a digit. The goal is to correctly identify (assign the correct label) randomly-presented stimuli from the set. Intriguingly, performance in such tasks is fundamentally limited no matter how extensive the practice. A seminal work by Miller (1956) identified information processing constraints to be limited to 7±2 reliably-identifiable stimuli. An extensive literature review of a variety of both memory and Absolute identification tasks (Cowan, 2001) has concluded that the information processing constraint is the result of mental storage capacity, which is limited to only four *chunks of information*. Considering that products in EDM tend to fall into a larger number of distinct groups, this suggests that accuracy during EDM might be limited.

A radically different interpretation of the findings from Absolute identification tasks to that of mental storage capacity has been proposed by Lockhead (2004), who questions the theoretical assumption that people judge the intensities of stimulus elements in isolation. He also questions the assumption that averaged data from Absolute identification tasks demonstrate this theoretical view. Firstly, he argues that perception of any stimulus does not happen in isolation. For example, the fur of a moving tiger emits different intensities of light as it moves in and out of shadows, but the tiger's appearance changes little. Hence, the perception of brightness is a function of energy differences over time and space.

Secondly, he argues that findings from Absolute identification tasks are confounded by varying stimulus ranges within the task and sequential effects that result from randomly presenting different stimulus intensities from the set. For example, when a stimulus of the same intensity is presented in a consecutive trial, the judgment of this stimulus is biased towards the intensity presented two trials earlier. In other words, judgment of the current stimulus is affected by the memory of previous intensities. The memory of the first trial is assimilated by the memory of the previous trial, and the response to the next trial is partially determined by the previous events (Laming, 1997). The effects of the varying stimulus ranges have been demonstrated in a three-stimulus study conducted by Gravetter and Lockhead (1973), in which subjects judged tones of different intensities. The intensity of two tones was held constant throughout the study while the intensity of the third tone varied between experimental conditions. The researchers found that confusion between the two tones that were held constant increased in conditions where the intensity of the third tone was more different. This suggests that the cognitive system attunes to the stimulus range roughly delineated by recent trials, and that there is a trade-off between range and precision.

The reviewed literature on Absolute identification tasks suggests that people do not identify a stimulus in absolute terms, but rather identify its relationship to other stimuli either from within the scene or current memories, many of which depend on preceding events. People judge the relationships, not the absolutes, in Absolute identification tasks. These findings support the existence of non-parametric processing during judgment of the absolute quality of a stimulus. Such processing might have poorer precision compared to parametric processing, but it is highly flexible. If the same cognitive mechanism operates during EDM, it is possible that many of the identified biases in *Consumer choice* literature, which are reviewed next, are the result of this flexibility.

### 1.4.5 Consumer choice literature

A myriad of context effects have been identified by empirical studies of Consumer choice. The main focus has been on the heuristics people use and the resulting biases prevalent in their choices. While the research has been heavily influenced by the approach of Tversky and Kahneman (1974), who have focused on judgements under uncertainty, a large number of studies have also focused on the investigation of biases in consumer evaluations that have no dimension of uncertainty. A number of biases in consumer choice literature have been identified, including, for example: *attribute range effects*; *extremeness aversion* and *attribute balance*; *focussing illusion* and *familiarity effects*; *attribute averaging* and *dilution*; and *sequential effects*.

Research into attribute range effects dates back to *Range frequency* theory (Parducci, 1965), which posits that the perceived quality of an attribute is influenced by the internal representation of the attribute range, as well as the internal representation of the frequency that a particular attribute magnitude (value) is encountered (presented). The quality of the attribute is then determined by a trade-off between the perceived range and frequency. This suggests that valuations during EDM are not performed independently (in absolute terms), but depend on internal representations of attribute distributions, while these distributions are a result of the previous attribute encounters.

These range effects have been investigated in number of studies. For example, Stewart et al. (2003) demonstrate that options are not valued independently of other options within the choice set. Similarly, an experiment in which subjects rated the attractiveness of an apartment based on two or three attributes (price, distance, and recommendation from a friend) found that a varying range of one of the attributes altered the preference ordering of the stimuli (Cooke & Mellers, 1998). By increasing the range, the value assigned to the attribute increments was reduced. In another experiment involving apartments, the ranges of both attributes were manipulated, which resulted in a large variation in preferences; these were especially pronounced for apartments, with a large trade-off between price and distance. For example, apartments closest to a campus ranged from the $28^{th}$ to $80^{th}$ percentile depending on the range context. This suggests that valuations are approximate and prone to systematic errors.

Extremeness aversion is a bias against products with a large trade-off between attributes, and has been observed in many choice experiments. It has been suggested that the *compromise effect* (the overvaluation of the middle option after adding an inferior third choice to a choice set) is caused by extremeness aversion (Simonson, 1989). Simonson and Tversky (1992) explain extremeness aversion in terms of loss aversion, whereby disadvantages, poor attributes, are weighted more heavily than advantages and good attributes. This results in a desire for attribute balance, where products with comparable attributes are preferred (Chernev, 2005). However, in the light of findings from the psychophysical literature reviewed above (e.g., Absolute Identification and Magnitude estimation), and the range effects found in Consumer choice literature, extremeness aversion could be attributed to the relativity of value judgment. An efficient cognitive system which values products with extreme attributes less precisely could undervalue such products as a result of a compensating strategy.

Judgments can also be biased by altering the saliency of an attribute, which is referred to as focussing illusion. For example, Schkade and Kahneman (1998) have found that people disproportionally overvalue salient attributes. Similarly, Goldstein and Gigerenzer (2011) have reported that familiar attributes are overweighed. The researchers argue that this familiarity effect is a result of a recognition heuristic, which is an adaptive strategy of the cognitive system to make inferences from patterns of missing knowledge. Another somewhat unusual finding is that people seem to derive a product value by averaging its attributes, which results in preference for a product with high-quality attribute A over a product with high-quality attribute A and good-quality attribute B (Weaver, Garcia, & Schwarz, 2012). Consumers also struggle to ignore irrelevant attributes (the dilution effect), demonstrated in a series of experiments by Meyvis and Janiszewski (2002), who found that the inclusion of irrelevant information systematically altered product valuations.

Finally, a number of sequential effects identified in psychophysical tasks (Laming, 1997) were also reported in the Consumer Choice literature. In a series of experiments, Matthews and Stewart (2009) have found that when participants judged the prices of a sequence of products, their judgments were biased towards the previous response (*assimilation*), but away from the actual value of the previous product (*contrast*). Moreover, the researchers reported that judgments were biased towards the centre of the range (the *regression effect*), a finding reported in Magnitude estimation tasks. The fact that some of the biases found in psychophysical tasks are also present in complex judgements of product quality is intriguing, raising the possibility that same cognitive mechanism might be involved. However, it is unclear whether same biases are manifested during the trade-off of incommensurable attributes.

## 1.5 The current study

This section outlines the main research questions of this thesis, while the following chapters focus on specific questions: The ability to trade-off incommensurable attributes (Chapter 2), and exploration of neural signatures during this trade-off (Chapter 3). However, some common themes are explored throughout the chapters.

The review of empirics and models from Function learning, Categorization, Magnitude estimation and Absolute identification suggest that the human ability to perform an absolute judgement is limited because people make use of relative judgement to derive the qualities of precepts. These relative comparisons are performed against attributes from the current scene or stored internal representations, which are in turn updated by recent experiences on an ongoing basis. As such, this cognitive process is highly flexible, but prone to biases. The literature from EDM and consumer research has mostly focused on biases, many of which have also been found in the reviewed psychophysical literature (Categorization, Absolute Identification, etc.). Furthermore, Type 2 and 3 models of EDM also suggest, at least in part, that decisions are derived via a relative judgement process.

As described at the beginning of this chapter, much of the EDM people perform on a daily basis requires some form of multi-attribute trade-off. Recall the example of buying shoes where the choice was narrowed down to one pair that is expensive but very appealing, while the other pair is cheaper but less appealing. The question that the cognitive system must answer is: Is it justifiable to pay the extra amount for the extent of how much more appealing the first pair of shoes is? When thinking about EDM in this way, it becomes obvious that for the cognitive system to resolve this multi-attribute trade-off, at least two things must happen. Firstly, the cognitive system must assess the quality of each attribute (the *Assessment stage*) which determines which product is better on which attribute. This is simply a series of relative judgments performed either in parallel or in sequence. The second part requires that the cognitive system maps in some way the inter product difference between attributes $A_1$ and $A_2$ onto the difference between attributes $B_1$ and $B_2$ (the *Mapping stage*; the numerical subscripts represent products 1 and 2). Note the similarity between an absolute judgement and the Mapping stage. In both circumstances, two scales are mapped onto each other, or compared against each other in some way. However, there is a crucial distinction between the two. During an absolute judgment, the value of the quality of a percept is generated, which is not necessarily required during the Mapping stage, where the product with a greater combination of its attributes is selected without the need to put an overall value on its quality.

The first main research question of this thesis is: How accurately can consumers trade off incommensurable attributes? In particular, is there any evidence for a cognitive bottleneck similar to the one identified by the reviewed psychophysical literature, and if so, is it the result of the Assessment or Mapping stage?

Secondly, none of the reviewed EDM models directly address the aspect of cognitive limitations, which is in stark contrast to PDM models which make specific assumptions about cognitive ability to make decisions. The main feature of most PDM models is the sequential sampling approach, stating that a decision is triggered only after a temporally-extended accumulation of sensory evidence has reached a predetermined threshold level. This process of evidence accumulation is referred to as the decision variable. To enhance the understanding of how the brain solves the trade-off of incommensurable attributes, this thesis proposes to borrow a methodological approach frequently used to study neural signatures associated with the decision variable in PDM research and apply it to a multi-attribute trade-off. This has the potential to isolate the decision variable during higher-order decision making. Furthermore, it could provide additional evidence in support of various EDM models.

The second main research question is: Can the decision variable be isolated during a multi-attribute trade-off, and if so, in what way will the trial difficulty modulate it? In particular, the focus will be on exploration of potential differences of decision variable characteristics between the current study and previous studies of PDM.

# CHAPTER 2: Investigating multi-attribute trade-off

## 2.1 Introduction

To study the underlying cognitive process of multi-attribute decision making involving trade-offs between incommensurable attributes in detail, the present investigation develops a new task. This task is based on a psychophysical approach allowing rigorous assessment of both bias and precision in order to get a measure of the accuracy[3] of such decisions. The developed task is also EEG-compatible, and importantly, allows stepwise assessment of decision-making stages. Imagine a decision involving an attribute trade-off between two products, such as when product X is better on attribute A, while product Y is better on attribute B. Each attribute is a different construct, and hence its quality is described in different units. Provided the person cares about both attributes, the brain must firstly assess the quality of each attribute on each product (the Assessment stage). Secondly, these pieces of incommensurable information must be integrated into some measure of 'internal value'[4] associated with each product (the Mapping stage) for a person to be able to say she prefers product X over Y, for example. To put it simply, the Mapping stage is like comparing apples and oranges.

To date, only a few psychophysical approaches (e.g., Function learning, Categorization tasks) have measured the precision of multi-attribute decision making. More recent developments in this area come from PRICE Lab (Lunn, Bohacek, Somerville, Ní Choisdealbha, & McGowan, 2016), which has developed the *Surplus-identification* task. This task is a 'two-alternative-forced-choice-with-feedback' task in which participants are required to identify a surplus. They initially learn how much a product is worth, which is determined by an objective function set by the experimenter. The function combines product attributes into the overall product value. In the most basic form of the task, participants are presented with two products and they must choose the product with the better overall value, or more simply, the product that has the best combination of its attributes. For example, in

[3] The difference between bias, precision and accuracy can cause confusion. For something to be 'accurate', it has to be both unbiased and precise. Imagine an archer shooting at a target. If all of her arrows miss the bullseye but are equally scattered around the target, the archer's aim is imprecise but unbiased. If, however, all the arrows are concentrated in a small spot below the bullseye, her aim is precise, but biased. Hence, for her aim to be accurate, it has to be precise and unbiased (all arrows in the bullseye).

[4] Pieces of information are integrated into 'internal value', or alternatively a series of ordinal comparisons between attributes of different options are performed; for detail, see section 1.3.

one experiment, Lunn and colleagues (2016) had participants value golden eggs whose value was determined by two attributes; the size of the egg and the fineness of the egg's texture. Larger eggs and those with finer textures were more valuable. Participants were initially taught how much of a change in size was equivalent to a change in texture through examples and a practice session. In the task, to assess the accuracy of the trade-off, one egg was always larger, while the other had a finer texture, so participants were in fact trading the two attributes against each other. It was found that participants were significantly less precise at this Surplus identification task compared to tasks where they had to judge size or texture only. However, it is not clear whether this decrease in precision was caused by the need to evaluate the quality of both attributes simultaneously (the Assessment stage) or to trade the attributes against each other (the Mapping stage).

A series of studies conducted by O'Connell and collegues isolated neural signatures that potentially represent the decision variable (e.g., Twomey, Kelly, & O'Connell, 2016). The researchers experimentally isolated the accumulation of evidence represented by centro-parietal positivity (CPP) during the random-dot motion task that has been extensively used to study PDM. A potential difference between CPP signals of PDM and that of attribute trade-off is of interest to the current thesis. It has been hypothesized that CPP represents the decision variable (O'Connell et al., 2012), which is expressed as the accumulation of evidence during decision formation, and hence ought to be present during all decisions. Therefore, a similar CPP that changes by task difficulty should be recorded during multi-attribute trade-off as well.

The dynamic nature of the PDM theories allows for the development of computational models that simulate the structure and behaviour of a complex system based on a mathematical model. When applied to PDM, such models describe how the decision maker processes the noisy perceptual input and reaches the decision. The computational modelling also allows for a comparison of actual participants' performance on PDM tasks and the simulated data that provide quantitative predictions of behaviour, which in turn provides feedback for the development of better and more accurate PDM theories. Some of the quantitative predictions provided by the models include an estimation of bias towards one of the options, an estimation of reaction time distributions, disambiguation of decision time from non-decision time, and many others (for more details, see Wagenmakers, 2007). The main advantage of computational modelling is its ability to decompose complex behaviour into mathematically tractable latent variables, which might not always be possible via direct experimental manipulation.

The overall objective of the current thesis is to investigate the underlying cognitive process or processes during multi-attribute decision making involving trade-off. To achieve this, a novel experimental paradigm that allows for the separation of the Assessment stage from the Mapping stage has been developed. This experimental paradigm, termed a Congruence-Value task, is partially based on the random-dot motion task and the Surplus identification task. It uses dot motion and colour from the random-dot motion task for its two attributes (for a detailed description of the Congruence-Value task, see section 2.2.1). The aims of the Congruence-Value task are twofold. Firstly, it allows for an estimation of accuracy at the Assessment stage and the mapping stage separately. This answers the question of whether the potential cognitive bottleneck during attribute trade-off identified by Lunn and colleagues (2016) is a result of the Assessment stage, the Mapping stage, or a mixture of both (Chapter 2). However, to allow for a comparison of the results of the Assessment and Mapping stage, a computational model of ideal integration is developed. This model simulates statistically efficient decision making during the Assessment and Mapping stages. Secondly, the Congruence-Value task also aims to isolate CPP patterns during multi-attribute trade-off and compare them to findings of accumulation of evidence during simple PDM tasks (Chapter 3).

## 2.2 Methods

### 2.2.1 Experimental paradigm design

The Congruence-Value task is a two-alternative-forced choice task, which means that on any given trial a participant has only two response options (two-alternative) and is required to make a response (forcedchoice) or the trial becomes voided. The task is actually comprised of four independent tasks, which are referred to as task stages (or stages for simplicity) in the remainder of the text. Those are: Motion (stage 1), Colour (stage 2), Congruence (stage 3) and Value (stage 4) conditions (Table 2.1). Please note that every stage is a two-alternative-forcedchoice task in its own right but each stage has its unique response options (described below).

Table 2.1: Outline of the Congruence-Value task

The Congruence-Value task was conducted over two experimental sessions. In the first session, participants performed two tasks involving simple perceptual discriminations of direction of motion (Motion stage) and colour discrimination (Colour stage). In the second session, participants also performed two tasks. These involved simultaneous discriminations of direction of motion and colour discrimination (Congruence stage), and simultaneous discriminations of direction of motion and colour discrimination involving trade-off of motion against colour (Value stage).

| **Congruence-Value task** | | | |
|---|---|---|---|
| Stage 1 | Judgment of motion direction of dots (Motion stage) | Order pseudo-randomized | 96 trials |
| Stage 2 | Judgment of greenness of dots (Colour stage) | | 96 trials |
| Stage 3 | Simultaneous judgement of motion and colour (Congruence stage) | Order pseudo-randomized | 144 trials |
| Stage 4 | Simultaneous judgement of motion and colour + attribute trade-off (Value stage) | | 72 trials |

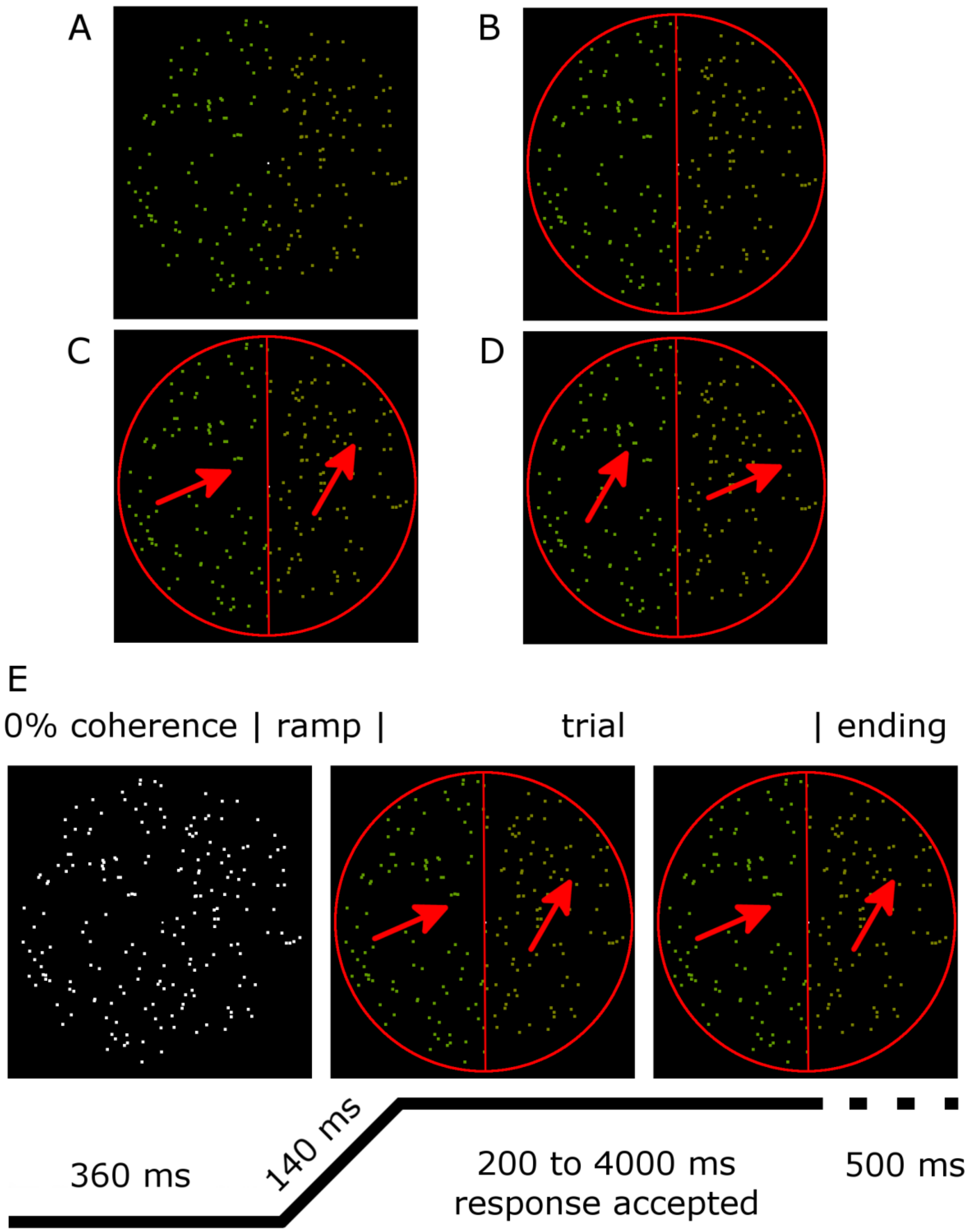


*Figure 2.1 Congruence-Value task schematic.*

*A) The actual task as it appeared during a trial. B) A schematic of the two semicircles representing the left and right product. C) A schematic representing the direction of motion and colour during an incongruent trial. The left product has a higher-quality colour but the right product has a higher-quality motion. D) A schematic representing the direction of motion and colour during a congruent trial. The left product has higher-quality colour and motion. E) A schematic representing the time development of a trial.*

The Congruence-Value task is similar in appearance to the Random-dot motion task but instead of one circular aperture populated by moving dots, the Congruence-Value task has two independent semi-circles joined along vertical axis (Figure 2.1A-D). Each semi-circle contains dots moving in a particular direction and of particular colour[5]. Hence, the colour and the motion represent two product attributes. In any given trial, during the task the participant is required to assess the direction of motion and/or the colour of dots in the left and right semi-circles, which represent the two products during EDM. In stage 1, the participant indicates which of the two semi-circles contains dots that are moving at a steeper angle (closer to the vertical axis), referred to as having a higher-quality motion, while in stage 2, the participant indicates which semi-circle has greener dots, referred to as having a higher-quality colour. In stage 3, the participant has to assess both the direction of motion and the colour, deciding whether a trial is congruent or incongruent. A congruent trial means that the same semicircle has greener dots as well as dots moving at a steeper angle in comparison to the other semi-circle. An incongruent trial means that one of the semi-circles has dots moving at a steeper angle, while the other semi-circle has greener dots[6]. In stage 4, the participant has to decide which semi-circle has a "better"[7] combination of motion and colour, referred to as having a higher value. The value of a semi-circle in any given trial was determined by Equation 1.

$$\mathrm{V}_t = \frac{M_t - M_{min}}{\Delta M} + \frac{C_t - C_{min}}{\Delta C} \qquad 1$$

*Value at a given trial ($V_t$); Level of Motion at a given trial ($M_t$); Level of Colour at a given trial ($C_t$); Minimum level of motion ($M_{min}$); Minimum level of Colour ($C_{min}$); Absolute range of Motion ($\Delta M$); Absolute range of Colour ($\Delta C$)*

Stages 1 and 2 served two important goals. Firstly, the results from these stages were used to set individualized ranges of colour and motion for Stages 3 and 4. This was achieved by fitting logistic regressions (Figure 2.2) to each participant's data with a logit link function

[5] In any given trial, all the dots contained within one semi-circle are of the same colour and are moving in the same direction in relation to each other.

[6] The response options in stage 3 are not determined by the difference between the left and right semi-circles. A congruent trial is both the trial where the left semicircle has a steeper motion and is greener, as well as a trial where the right semi-circle has a steeper motion and is greener. Similarly, an incongruent trial can be both a trial where the left semi-circle has a steeper motion while the right semi-circle is greener, as well as a trial where the right semi-circle has a steeper motion while the left semi-circle is greener.

[7] The word "better" refers to the semi-circle with a higher combined level of greenness and motion direction scaled by their corresponding absolute ranges to allow for mathematical addition of two incommensurate constructs (the colour and motion) that are naturally in different units.

(Equation 2) and generating individualized just-noticeable differences (JND; Equation 3a) for each attribute. Fitting logistic regression to a binary outcome variable is a standard procedure in psychophysics (for more details about the logistic regressions and JNDs, see section 2.2.5). Put simply, a JND represents the minimum amount of change in an attribute (motion, colour, etc.) required for the change to be detected with a statistical significance by a participant. Each participant's colour and motion range in Stages 3 and 4 contained 10 JNDs. Hence, the colour and motion ranges were standardised by the participant's discriminability. If a participant was poor at discriminating direction of motion but good at discriminating the colour at Stages 1 and 2, the motion range increased and the colour range decreased for Stages 3 and 4. Secondly, the results from Stages 1 and 2 were used to generate an 'ideal' integration variable for Stages 3 and 4. This is a hypothetical benchmark calculated for an observer who, given her single-attribute performance (Stages 1 and 2), performs the simultaneous 2-attribute judgment (Stage 3) efficiently (Equation 4) and/or integrates information from the 2 attributes (Stage 4) efficiently (Equation 5). Any disparity between the ideal integration and actual performance indicates a loss of statistical efficiency during cognitive processing.

$$p_{Rt} = \frac{1}{1 + \exp(-(\theta_0 + \theta_1 * \Delta_t))} \qquad 2$$

*Probability the right-hand-side semi-circle is selected ($p_{Rt}$); Slope of the logistic regression function ($\theta_1$); Intercept of the logistic regression function ($\theta_0$); Directional trial difficulty ($\Delta_t$)*

$$\text{a,} \quad \text{JND} = \frac{\pi}{\theta_1\sqrt{3}} \quad ; \text{ b,} \quad \text{bias} = -\frac{\theta_0}{\theta_1} \qquad 3$$

*Just-noticeable difference ($JND$); Slope of the logistic regression function ($\theta_1$); Intercept of the logistic regression function ($\theta_0$)*

$$p_{GMt} = \frac{1}{1+\exp(-\theta_{1M}*(\frac{M_{Rt}-M_{Lt}}{\Delta M}))}; \quad p_{GCt} = \frac{1}{1+\exp(-\theta_{1C}*(\frac{C_{Rt}-C_{Lt}}{\Delta C}))};$$
$$p_{Gt} = 1 - p_{GMt} - p_{GCt} + 2 * p_{GMt} * p_{GCt} \qquad 4$$

*Probability the participant views the right-hand-side semi-circle as higher-quality motion ($p_{GMt}$); Calculated slope of the logistic re-gression from stage 1/Motion ($\theta_{1M}$); Level of right-hand-side motion in a given trial ($M_{Rt}$); Level of left-hand-side motion in a given trial ($M_{Lt}$); Range of motion ($\Delta M$)*
*Probability the participant views the right-hand-side semi-circle as a higher-quality colour ($p_{GCt}$); Calculated slope of logistic regression from stage 1/Colour ($\theta_{1C}$); Level of right-*

*hand-side colour in a given trial ($C_{Rt}$); Level of left-hand-side colour in a given trial ($C_{Lt}$); Range of colour ($\Delta C$)*
*Probability the ideal integrator selects the right-hand-side semi-circle as congruent ($p_{Gt}$)*

$$\Delta_{tV} = \sum_{a=1}^{2} \frac{(A_{Rat} - A_{Lat})*10}{\Delta A_{Va}}; \quad \theta_{1\mathrm{V}} = \frac{\theta_{1\mathrm{C}}*\theta_{1\mathrm{M}}}{\sqrt{(\theta_{1\mathrm{C}}{}^{2}+\theta_{1\mathrm{C}}{}^{2})}}; \quad p_{Vt} = \frac{1}{1+\exp(-\theta_{1\mathrm{V}}*\Delta_{tV})} \qquad 5$$

*Directional trial difficulty in the Value condition ($\Delta_{tV}$); Level of right-hand-side attribute (colour or motion) in a given trial ($A_{Rat}$); Level of left-hand-side attribute (colour or motion) in a given trial ($A_{Lat}$); Range of attribute ($\Delta A_{Va}$)*
*Slope of ideal integration logistic function in the Value condition ($\theta_{1V}$); Calculated slope of logistic regression from stage 1/Motion ($\theta_{1M}$); Calculated slope of logistic regression from stage 2/Colour ($\theta_{1C}$)*
*Probability ideal integrator selects the right-hand-side semi-circle as more valuable ($p_{Vt}$)*

Equation 4 calculates a probability ($p_{Gt}$) that a participant who performs a simultaneous judgment of colour and motion without loss of statistical efficiency selects the response option congruent on a given trial. The probability of a participant reporting that a trial is congruent is derived from two combined probabilities. One, the probability that the participant has perceived that the right-hand-side semi-circle ($p_{GCt}$) has higher-quality colour. Two, the probability that the participant has perceived the right-hand-side semi-circle has higher-quality motion ($p_{GMt}$). These two probabilities ($p_{GCt}$ and $p_{GMt}$) are calculated from performance in stages 1 and 2. Hence, by comparing actual performance in stage 3 against the ideal integration probability ($p_{Gt}$), the question of whether a cognitive bottleneck during the attribute trade-off is a result of the Assessment stage can be addressed. Equation 5 calculates a probability ($p_{Vt}$) that a participant who trades-off colour against motion without loss of statistical efficiency selects the right-hand-side semicircle as being more valuable. This probability is given by the participant's performance on stages 1 and 2. Hence, comparing actual performance in stage 4 against the ideal integration probability ($p_{Vt}$) answers whether a cognitive bottleneck is present during the attribute trade-off of EDM. Moreover, by comparing the difference between ideal integration and actual performance in stage 3 against the difference between ideal integration and actual performance in stage 4 one can answer the question of whether a cognitive bottleneck during the attribute trade-off is a result of the Mapping stage.

### 2.2.2 Trial details and generation

Each semi-circle contained 100 dots of size 6 x 6 pixels. The circular aperture made of two conjoint semi-circles had a radius of 288 pixels and was centred in the middle of a black screen. The centre of the screen was marked by a white stationary fixation dot that was present for the duration of the trial. Each trial started with the onset of the fixation dot followed by a 360 ms period of 0% coherence of motion (dots appear at random positions) of dots of grey colour (Figure 2.1E). It was followed by the onset of a linear ramp that lasted for 140 ms. During this period, the dots gradually became coloured and the coherence of motion gradually reached 100%. This initial 360 ms period followed by the gradual onset of a stimulus has been used to avoid interference from the *Steady state visually-evoked potential* signal triggered by a sudden trial onset (Twomey et al., 2016). The trial stayed on for a duration of 4,000 ms, during which participants were required to respond by pressing one of two buttons on a Cedrus response box. This duration[8] was chosen to give the participants sufficient time to respond as accurately as possible while avoiding extremely long response times. If a participant did not respond within the 4,000 ms time window, pressed both response buttons simultaneously, or responded within 200 ms after the end of the ramp (which was considered too short a time for a decision to be reached), the trial was voided. Each voided trial was followed by an audible thud accompanied by an error message and a break of 2,800 ms. After a response, the trial continued for an additional 500 ms, after which participants received auditory feedback. Correct responses were followed by a ping, while incorrect responses were followed by a thud. A new trial was only initiated after the compression of both response buttons.

The colour of the dots varied from green to red, while saturation stayed constant at 100%. The quality of the attribute of colour was given by the level of greenness as determined by the RGB value that went from red (lowest quality) to green (highest quality) in steps of 1 unit of RGB. The RGB units were affecting the green component[9], while the blue component was set to 0 to avoid the presentation of grey dots in the centre of the range, and to minimize the influence of nonlinearities in chromaticity perception. The red component was calculated

[8] The duration of 4,000 ms appeared to be sufficient, as the median response time across all conditions and participants was 1,581 ms.
[9] The R,G and B components were reported on a scale of 0 to 255 using linear units of light energy.

as R = 255 - G. The direction of motion varied from horizontal rightward motion (lowest quality) to vertical upward motion (highest quality) in steps of 0.1 degrees.

**Stages 1 and 2**

The motion range went from -60 to -30 degrees and the range of colour went from 130 to 190 RGB units. At each stage, there were 96 test trials (Table 2.1) in blocks of 25 preceded by practice trials that lasted for at least two blocks. After each block there was a compulsory break of at least five seconds. Two stages were pseudorandomized across participants meaning half of the participants started with Motion while the other half started with the Colour condition. The directional trial difficulty ($\Delta_{tA}$ Equation 6) is in units of proportion of attribute range. An adaptive method of constant stimuli was used, which adjusted the difficulty of the task according to the participant's ongoing performance. Unbeknownst to participants, each run of 96 trials consisted of eight blocks of 12 trials. Within a block, a set of six possible $\Delta_{tA}$s, {-5σ, -3σ, -1σ, 1σ, 3σ, 5σ}[10], were each presented twice in a random order without replacement. The base σ had five possible levels, {0.05, 0.04, 0.03, 0.02, 0.01}[11]. If the participant responded correctly on more than 11 trials, the σ was reduced by 2 levels; more than 8, the σ was reduced by 1 level; exactly 8, the σ stayed at the current level; and less than 8, σ was increased by 1 level. All participants started at the second level (σ=0.04). For the responses, a left and a right button of a Cedrus response box were used.

$$\Delta_{tA} = \frac{S_{Rt} - S_{Lt}}{\Delta S} \qquad 6$$

*Directional trial difficulty in units of proportion of attribute range for stages 1 and 2 ($\Delta_{tA}$); Level of attribute (Motion or Colour) in right-hand-side semi-circle at a given trial ($S_{Rt}$); Level of attribute (Motion or Colour) in left-hand-side semi-circle at a given trial ($S_{Lt}$); Attribute range ($\Delta S$)*

**Stages 3 and 4**

To generate trials for the Congruence and Value stage the data from stages 1 and 2 had to be analysed (see section 2.2.5 for details of analysis) first so that correct ranges of Motion and

[10] A positive trial difficulty signifies that the right-hand-side semi-circle has a higher quality on a given attribute while negative trial difficulty means that the left-hand-side semi-circle has a higher quality. The absolute size of the trial difficulty determines how hard or easy the trial is, the smaller the value the harder the trial is.

[11] The easiest possible trial difficulty translates to the difference between right and left attributes as being 25% of an attribute range. The hardest trial difficulty translates to the difference between right and left attributes as being 1% of an attribute range.

Colour could be determined for each participant. Remember that each participant was presented with an attribute range containing 10 JNDs. This meant that each participant had different ranges of Motion and Colour. However, to minimize non-linearities in angle discrimination and colour perception, the centre points of both attribute ranges were anchored to the centre points of attribute ranges from stages 1 and 2[12].

All the trials for stages 3 and 4 were pre-generated, starting with the generation of Value stage trials. The directional trial difficulty, measured as a proportion of the combined attribute ranges ($\Delta_{Vt}$) was determined by Equation 7 using a simple linear addition with equal weighting between the attributes. Note that Equation 7 is just a multi-attribute version of Equation 6. Stage 4 used a method of constant stimuli with three negative and three positive levels $\Delta_{Vt} \in$ {-0.18, -0.1, -0.02, 0.02, 0.1, 0.18}[13]. In total, 72 trials were pre-generated for stage 4. To allow for attribute trade-off during Value stage all trials were, by design, incongruent. The trials for Stage 3 were created by combining two copies of the Stage 4 trials. One copy was unchanged and became the incongruent trials, while the other copy became the congruent trials. This was achieved by swapping the left for the right colour in half of the trials of that copy, and the left for the right motion in the other half. This resulted in matched trials in terms of colour and motion between Stages 3 and 4. So even though the task was different between the stages, the actual levels of colour and motion presented were precisely the same. Hence, any potential difference in performance between the stages could not have been caused by different attribute distributions; whether a participant could discriminate red colours more accurately than green colours, for example. However, this matching resulted in stage 3 having 144 trials.

$$\Delta_{Vt} = \sum_{a=1}^{2} \frac{S_{Rat} - S_{Lat}}{2\Delta S_a} \qquad 7$$

*Directional trial difficulty as a proportion of the combined attribute ranges ($\Delta_{Vt}$); Level of attribute (Motion or Colour) in right-hand-side semi-circle at a given trial ($S_{Rat}$); Level of attribute (Motion or Colour) in the left-hand-side semi-circle at a given trial ($S_{Lat}$); Attribute range ($\Delta S_a$)*

[12] The centre of Colour range was set to 160 RGB and the centre of Motion range was set to -45 degrees for each participant

[13] The negative values mean that the left semi-circle has higher value while positive values mean that the right semi-circle has higher value

The trials in both stages were presented in blocks of 25 trials. After each block there was a compulsory break of at least five seconds. Each stage was preceded by an extensive practice session of at least four blocks of trials to ensure that participants had become familiar with the task and responses. Due to the lack of a right vs left relationship during the Congruence stage, participants responded by pressing the top button on a response box with their right hand to indicate that a trial was congruent, and by pressing the bottom button to indicate that it was incongruent. For responses in the Value stage the left and right buttons were used.

### 2.2.3 Participants

The study was conducted with 20 participants (11 males and nine females) between 19 and 46 years of age, with a mean age of 30.5 years (*SD* 6 years). The participants were recruited via the School of Psychology and word-of-mouth. The inclusion criteria for the study were: no personal or family history of epilepsy or unexplained fainting; no sensitivity to flickering light; no personal history of neurological or psychiatric illness or brain injury; no personal history of colour vision deficiency; as well as the successful completion of six plates from the Ishihara colour-blindness test (Ishihara, 1917; for details see Apendix 1). Participants were incentivised with a tournament-style incentive and were informed that the best performer would receive a 50-Euro shopping voucher. Performance was assessed by fitting four psychometric functions (one to each experimental condition) to the data of each participant (for details, see section 2.2.3) to assess accuracy. The participant with the highest overall accuracy won the voucher. Students from the School of Psychology also received research credits for their participation. The participants gave written informed consent in advance of the study, which had been approved by the Trinity College Dublin School of Psychology Ethics Committee.

### 2.2.4 Procedure

After the initial assessment of eligibility, participants undertook the experiment, which was conducted across two experimental sessions separated by at least a week to allow for data from stages 1 and 2 to be analysed. The study used a within-subject design, so each participant conducted all four stages. There was no between-subject manipulation except for the pseudo-randomization of the order of stages within the session. The experiment was carried out in a darkened and sound-attenuated room. Each participant was seated comfortably, approximately 100 cm from a 29-inch LCD monitor with a 100 Hz refresh rate and a screen resolution of 1,920 x 1,080. To achieve an accurate colour display, the monitor was calibrated with a Spider4Pro calibration device and software. The visual angle of the circular aperture in which the stimulus was presented was approximately 5.7 degrees.

### 2.2.5 Data analysis

Analysis of the psychophysical data generates two main descriptive measures of accuracy. The *just noticeable difference* (JND, measure of precision) and the *bias* are standard measures in psychophysics. Both are generated by fitting binary-response data with a psychometric function that relates the size of the signal to be detected, such as the colour difference between the right and left semi-circles in Stage 2, to the probability of the right-hand-side semi-circle being selected.

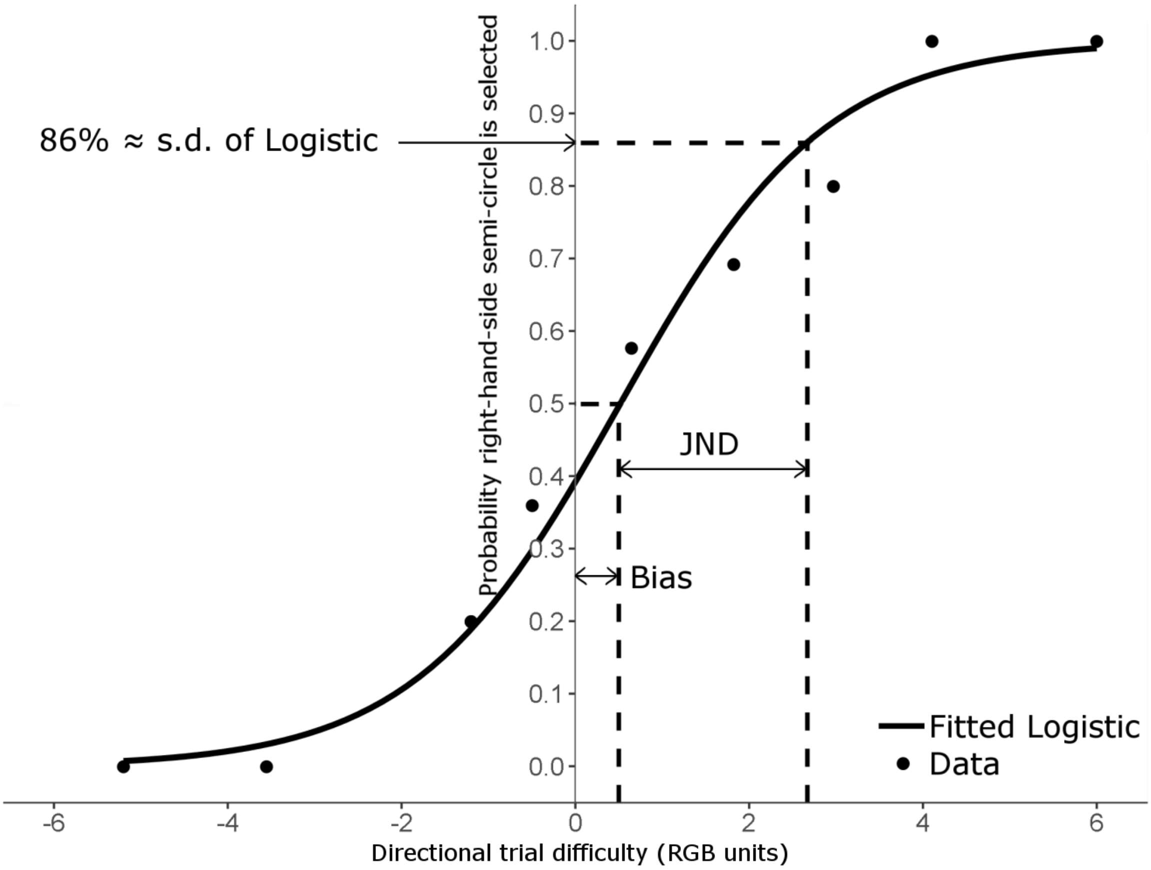


*Figure 2.2 Logistic curve example*
*An example of a logistic curve fitted to the probability that the right-hand-side semi-circle is selected (displayed on y-axis) arising from the binary data (participant's responses, outcome/dependent variable). The x-axis always represents directional trial difficulty (main predictor/independent variable). Here it is in the actual RGB units (for ease of explanation), but it could be in other units such as the proportion of colour range, or ideal integrator probability units, etc. The negative values on the x-axis always mean that the left-hand-side semi-circle has higher quality colour (greener colour) by the amount displayed on the axis in comparison to the right-hand-side semi-circle. The positive values mean the exact opposite – the right-hand-side semi-circle has higher quality colour. Bias is defined as the x-axis distance between the point where there is no actual colour difference between the right and left semi-circles (0 point on x-axis) and a point corresponding to where the participant is just as likely to select the right-hand-side semi-circle as the left as greener (0.5 probability). JND is defined as the x-axis distance between a point where the participant is just as likely (0.5 probability) to select the right-hand-side semi-circle as the left as greener, and a point at which the colour difference is large enough that the participant will select the correct response 86% of the time (0.86 probability).*

A logistic curve (Equation 2) is fitted to the probability that the participant decides that the right-hand-side semi-circle is greener, as a function of the colour difference measured in RGB units (Figure 2.2). Note that the x-axis goes from a large negative (the left attribute is much greener than the right one) to a large positive (the right attribute is much greener than the left one). The 'S' shaped curve (logit) is defined by two parameters: intercept ($\theta_0$) and slope ($\theta_1$). The intercept, which defines the location at which the logit intercepts y-axis, tells us about the probability of responding that the right-hand-side semi-circle is greener when the difference between the left and right colour is actually zero. The slope defines the steepness of the logistic curve. Bias is defined as the distance between the zero point on the x-axis (where there is no actual colour difference between the left and right semi-circle) and a point on the x-axis that corresponds to a probability of 0.5 on the y-axis (where the participant is just as likely to select the right semi-circile, as the left, as greener). Bias is therefore calculated as the intercept divided by the minus of the slope (Equation 3b). Hence, the bias tells us how much of a colour difference there is between the right and left semi-circles there is when a participant perceives the two semi-circles to have an identical colour. A positive bias equates to an overestimation of the greenness of the left attribute, while a negative bias equates to the overestimation of the quality of the right attribute. The JND is calculated from the slope of the psychometric function (Equation 3a). The JND is the size of the colour difference needed to raise the probability of correct discrimination[14] from 0.5 to 0.86. The value of 0.86 is somewhat arbitrary but the reason behind selecting is that 0.86 equates to one standard deviation of a logistic distribution. To put it simply, one JND is the size of the colour difference (or any x-axis units) needed for the participant to correctly identify the semi-circle which is greener 86% of the time, net of any bias.

All the outcome variables used in the logistic regressions for all of the stages are participants' binary responses of whether the right-hand-side semi-circle was selected (stages 1,2 and 4) and whether the congruent response was selected (stage 3). The main predictor variable (directional trial difficulty; displayed on x-axis in Figure 2.2) used, differed by stage. In stage 1 differences in the degrees of motion were used while in stage 2, differences in RGB units were used. In stage 1, the differences in the degrees of motion were calculated by subtracting the degrees of motion of the right-hand-side attribute from the degrees of motion of the left-hand-side attribute. In stage 2, the differences in the RGB units were calculated by subtracting the RGB units of the right hand side attribute from the RGB units of the left-hand-side. The directional trial difficulty units in Stage 3 are in ideal integration units (calculated from Equation 4) displayed as the ideal integrator selects right-hand-side semi-circle as congruent ($p_{Gt}$). In Stage 4, these units (calculated from Equation 5) are displayed

[14] Note that unlike bias JND is not directional. The correct discrimination means both identifying that right-hand-side semi-circle is greener as well as identifying that left-hand-side semi-circle is greener.

as the probability ideal integrator selects right-hand-side semi-circle as more valuable ($p_{Vt}$). By using probability units as the main predictor variables in logistic regressions in stages 3 and 4, this allows for a comparison of the Congruence and Value stages because otherwise incomparable units have been standardised by a common metric of ideal integration.

However, the ideal integration probability units do not offer an obviously intuitive interpretation when fitted to the binary data of actual responses. To simplify the interpretation of results of the logistic regressions of Stages 3 and 4, the probability units ($p_{Gt}, p_{Vt}$) are further transformed by the inverse of the logistic function (Equation 8) to ideal integration JND units (iJND), where the 86% probability equates to 1 iJND. Hence, if the Congruence and/or Value stage is performed efficiently, then the Congruence JND (cJND) and/or Value JND (vJND) equals to 1 iJND. Anything above 1 iJND implies a loss of statistical efficiency during cognitive processing, 1 iJND implies no loss, and less than 1 iJND implies that the performance is better than predicted by the ideal integration based on the ability to discriminate colour and motion. All data analysis in the current study uses iJND as the measure of directional trial difficulty, which is the main predictor variable[15] in all the models. For example, a -1 iJND in stage 3 means that an ideal integrator would correctly identify the trial as incongruent 86% of the time while +1 iJND means that the trial would be correctly identified as congruent by the ideal integrator.

$$\mathrm{iJND}_t = \ln\left(\frac{p_t}{1-p_t}\right) * \frac{\sqrt{3}}{\pi} \qquad 8$$

*Ideal integration JND unit at a given trial ($iJND_t$); Ideal integration probability units at a given trial ($p_t$) – calculated from Equation 4 (Congruence stage) and from Equation 5 (Value stage)*

According to traditional practice in psychophysics, researchers estimate separate psychometric functions across individuals and experimental conditions. The differences between the means of multiple measures of JND and bias across conditions are then typically assessed with a t-test. A more powerful technique is to fit a mixed-effect logit model to multiple individuals and conditions simultaneously. This allows for random variation of the intercept and slope at the individual level (random effects), while variation due to

[15] Predictor variable (x) refers to a variable that predicts the outcome variable (y) of regression. Hence, outcome is a function of the predictor: y = *f*(x). In psychology, predictor is referred to as the independent variable and outcome as the dependent variable.

experimental conditions is assessed by fixed effects after including conditions as predictor variables in the model. Moscatelli, Mezzetti and Lacquaniti (2012) have provided evidence for the increased statistical power of this type of mixed-effect logit model compared to the traditional approach. Moreover, mixed-effect logit models allow the inclusion of additional predictor variables as well as interactions between them. For example, a variable for the size of the *within-product attribute trade-off* can be added to the model to test whether the intercept and slope are affected, as would be predicted by extremeness aversion (Simonson & Tversky, 1992). The basic form of the mixed-effect logit model used for the data analysis can be seen in Equation 9, with two predictor variables of directional trial difficulty ($\Delta_{it}$; in units of iJND) and condition ($cond_{it}$; dummy variable for Stages 3 and 4). Different individuals are denoted by *i*, and the trial is denoted by *t*. The model estimates three random effects parameters, $u_i$, $v_i$ and the correlation ($u_i$, $v_i$), where $u_i$ corresponds to the change of the intercept by participant and $v_i$ corresponds to the change of the slope by participant. Importantly, the model estimates four fixed effects parameters $\theta_0$, $\theta_1$, $\theta_2$ and $\theta_3$. The crucial ones are the latter two which reveal how much the intercept ($\theta_0$) and slope ($\theta_1$) of the logistic function vary by condition. To interpret the model, the average JNDs and biases for each condition (Congruence and Value stage) can be computed from model coefficients (where intercepts = $\theta_0 + \theta_2 * cond$ and slopes = $\theta_1 + \theta_3 * cond$ for the two conditions), according to the Equations (3a and 3b).

$$y_{it} = \frac{1}{1 + e^{-(\theta_0 + u_i + (\theta_1 + v_i) * \Delta_{it} + \theta_2 * cond_{it} + \theta_3 * (\Delta_{it} * cond_{it}) + \epsilon_{it})}} \qquad 9$$

*Outcome variable at a given trial t for a given participant i ($y_{it}$); Intercept of the model/logistic function ($\theta_0$); Slope of the model/logistic function ($\theta_1$); Random effects parameter determining change of intercept for a given participant ($u_i$); Random effects parameter determining change of slope for a given participant ($v_i$); Directional trial difficulty for a given participant at a given trial in units of iJND ($\Delta_{it}$); Dummy variable for condition (stage 3 or 4) for a given participant at a given trial ($cond_{it}$); Change of the intercept by condition ($\theta_2$); Change of the slope by condition ($\theta_3$); Error term for a given participant at a given trial ($\epsilon_{it}$)*

## 2.3 Results

### 2.3.1 Statistical analysis of Stages 1 and 2

Each stage consisted of 1,920 trials (20 participants x 96 trials). Twelve trials in the colour stage (<1%) were excluded due to erroneous responses (11 too late; 1 too early). Similarly, 18 trials (<1%) were excluded from the motion stage (17 too late; 1 too early). This low error rate suggests that the participants understood the tasks and had no problem performing them. For Stages 1 and 2, a separate psychometric function was fitted to the data for each participant and each condition. The models were simple (Equation 10), with only one predictor variable, directional trial difficulty ($\Delta_t$) in units of degrees (motion stage) or RGB (colour stage). The fits of all psychometric functions were assessed with deviance statistics by performing chi-squared tests (Brown, Durbin, & Evans, 1975), visual inspection of fitted logistic curves plotted over the probability of selecting a right-hand-side semi-circle (generated by binning responses into seven bins of equal number of observations), and by investigating half-normal plots of residuals (Atkinson, 1981). The residuals appeared to be normally-distributed and none of the chi-squared tests were significant at the 5% level. The mean *p* value was: 0.33 (*SD* = 0.19) for colour and 0.43 (*SD* = 0.25) for motion. The lower mean *p* value for colour indicated somewhat worse fits in the colour condition, which was confirmed by visual inspection of the fitted logistic curves. The models were re-run with the additional predictor variables of mean colour of the left and right attribute, and the interaction term of mean colour and directional trial difficulty. This revealed that some participants (five in total) were significantly worse at colour discrimination at the green end of the colour range used.

$$y_t = \frac{1}{1 + \exp -(\theta_0 + \theta_1 * \Delta_t + \epsilon_t)} \qquad 10$$

*Outcome variable at a given trial t ($y_t$); Intercept of the model/logistic function ($\theta_0$); Slope of the model/logistic function ($\theta_1$); Directional trial difficulty for a given participant at a given trial in units of degrees/RGB ($\Delta_t$); Error term at a given trial ($\epsilon_t$)*

The groups of estimates of slopes ($\theta_1$) and intercepts ($\theta_0$) by participant by condition from the models (Equation 10) were checked for violations of normality using Shapiro–Wilk tests (Royston, 1992), kernel density plots and quantile-quantile plots. All, with the exception of slopes in the Motion stage, were approximately normally distributed. The slopes in the

Motion stage were positively skewed and did not pass the Shapiro–Wilk normality test (W=0.89, *p*=.026). On closer inspection, it appeared that the skew was not severe and resulted from two participants with larger slope estimates (they performed well in the Motion task). However, when the same tests were performed on the JND and bias estimates instead, none of them were significant according to the Shapiro-Wilk test, and visual inspection of the plots confirmed that they were approximately normally distributed. This further supported the notion that psychometric functions fitted the data well and confirmed that there were no obvious outliers at the participant level. The mean colour difference needed to discriminate between the two semi-circles, i.e., the mean JND, was 6 RGB units (*SD* = 1.6 RGB units). The mean bias was 0.3 RGB units (*SD* = 1.7 RGB units). The mean direction of motion difference needed to discriminate between the two semi-circles was 2.2 degrees (*SD* = 1 degrees) and the bias was -0.1 degrees (*SD* = 0.8 degrees). One sample t-tests found that the overall biases in motion and colour conditions were non-significant. This is as expected unless there was some reason for the participants to perform better or worse when the right stimulus had better quality than the left one or pressing one response button more often than the other. A JND of 2.2 degrees in angle discrimination is consistent with previous studies (e.g., Orban, Vandenbussche, & Vogels, 1984). Similarly, a JND of 6 RGB when converted into a CIE 1931 xy chromaticity diagram is close to previous findings (e.g., Brown & MacAdam, 1949).

An initial clarification regarding the units in Equations 5 may be helpful before describing the main results from Stages 3 and 4. To calculate ideal integration probabilities for the Value condition (Equations 5) for each participant, the variables of the slope of Motion $\theta_{1M}$ and Colour $\theta_{1C}$ must come from models where the directional trial difficulty is in JND units and not in degrees or RGB units. The equation variables must always be in the same units. This is in contrast to Equations 4, where $\theta_{1M}$ and $\theta_{1C}$ come from models in which the directional trial difficulty is in degrees and RGB, respectively, because they are in two separate equations. To accomplish this, the directional trial difficulty was converted to motion and colour JND units (Equation 11; $A_{JND}$ is the size of one JND in units of degrees/RGB) based on individual performance of each participant, and the same models as described above were re-run with the re-scaled predictor variable. This does not alter the shape or goodness of fit of the psychometric functions. The only difference between these models and the ones described above is in the x-axis units. The change merely re-scales the $\theta_1$ and its standard error estimate but leaves all the other estimates identical (including $\theta_0$).

Also note that Equations 4 and 5 lack $\theta_0$. The reason for the exclusion is that there are no theoretical underpinnings for the existence of a left/right bias in judgment tasks of colour and the direction of motion discrimination, which is supported by the finding of a non-significant bias in these conditions in the present experiment.

$$\Delta_{tJND} = \frac{A_{Rt} - A_{Lt}}{A_{JND}} \qquad 11$$

*Directional trial difficulty on a given trial in attribute JND units ($\Delta_{tJND}$); Level of attribute in right-hand-side semi-circle in degrees/RGB units on a given trial ($A_{Rt}$); Level of attribute in left-hand-side semi-circle in degrees/RGB units on a given trial ($A_{Lt}$); Size of 1 JND for a given participant in units of degrees/RGB units ($A_{JND}$)*

### 2.3.2 Statistical analysis of Stages 3 and 4

There were 2,880 trials (20 participants x 144 trials) in the Congruence stage, of which 16 (<1%) were excluded due to erroneous responses (14, too late; and 2, both buttons pressed) and 1,440 trials (20 participants x 72 trials) in the Value stage, of which seven (<1%) were excluded (5 too late and 2 both buttons pressed). Median response time was 1,762 ms (Congruence) and 1,726 ms (Value). Based on these descriptive statistics, it appears that the participants understood and had no problem performing the tasks. In total, the participants responded incorrectly 400 times in the Congruent condition and 348 times in the Value condition.

As with Stages 1 and 2, each participant initially had a psychometric function fitted to their data in each condition. The assessment of the goodness of fit of the psychometric functions was carried out in exactly the same way as in Stages 1 and 2. Simple models (Equation 10) were used with the directional trial difficulty ($\Delta_t$) being in iJND units for both conditions. The mean $p$ values from the deviance statistics were: 0.95 (*SD* 0.08) for Congruence and 0.42 (*SD* 0.33) for Value. Out of 40 tests, one was significant at $p$=.02 for participant 5 in the Value condition, indicating a poor fit of the psychometric function. The same participant also had the lowest $p$ value in the Congruence condition[16]. The plotted psychometric functions can be seen in

[16] All reported Models were re-estimated after excluding Participant 5. However, it had minimal impact on the estimated coefficients. Hence, it was decided to include Participant 5 in all the analyses. Also, note that one poor fit out of 40 tests conducted ought to be expected purely due to chance.

Figure 2.3 for the Congruence and Figure 2.4 for Value conditions. From the assessment of the deviance statistics, it appeared that directional trial difficulty (in iJNDs) predicted participants' actual responses in the Congruence condition much better than in the Value condition.

The estimated slopes and intercepts were also checked for violations of normality with Shapiro–Wilk tests (Royston, 1992), kernel density plots and quantile-quantile plots. None of the tests were statistically significant. Visual inspection also suggested that the slopes and intercepts were approximately normally distributed. The estimates of slopes and intercepts were strongly positively correlated, $r(20) = .56$, $p=.01$, for Congruence and appeared moderately correlated (not significant) for Value, $r(20) = .24$, $p=.3$. This supported the use of a mixed-effect logit model with random effects on both coefficients, allowing for a correlation between the two.

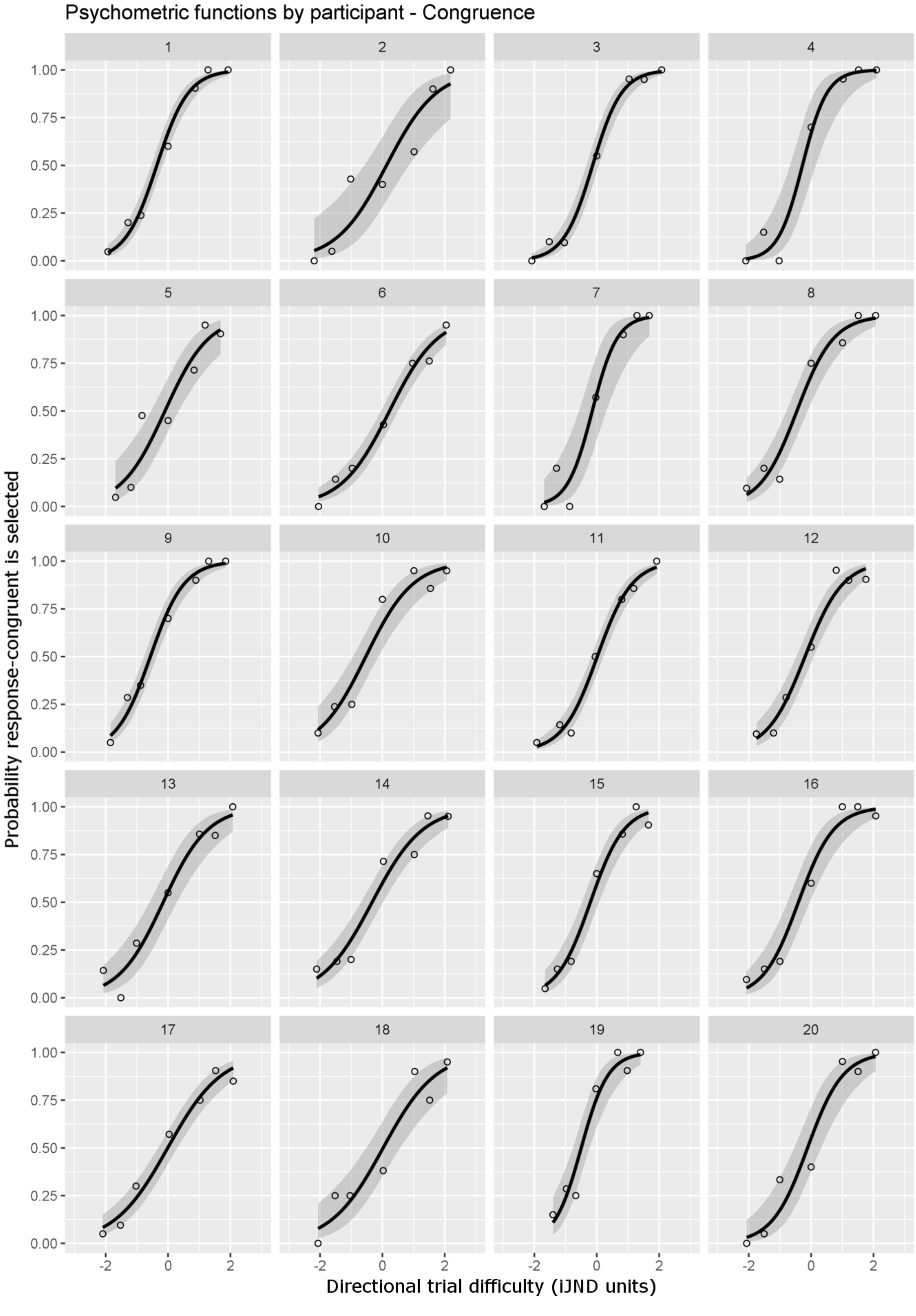


*Figure 2.3 Logistic curves by participant – Congruence.*

*Fitted logistic curves plotted over the probability of selecting the congruent response (y-axis) generated by binning responses into seven bins of equal number of observations. The x-axis is in iJND units. The large negative value means the trial is incongruent and easy while large positive value means the trial is congruent and easy. The small values mean the trial is difficult.*

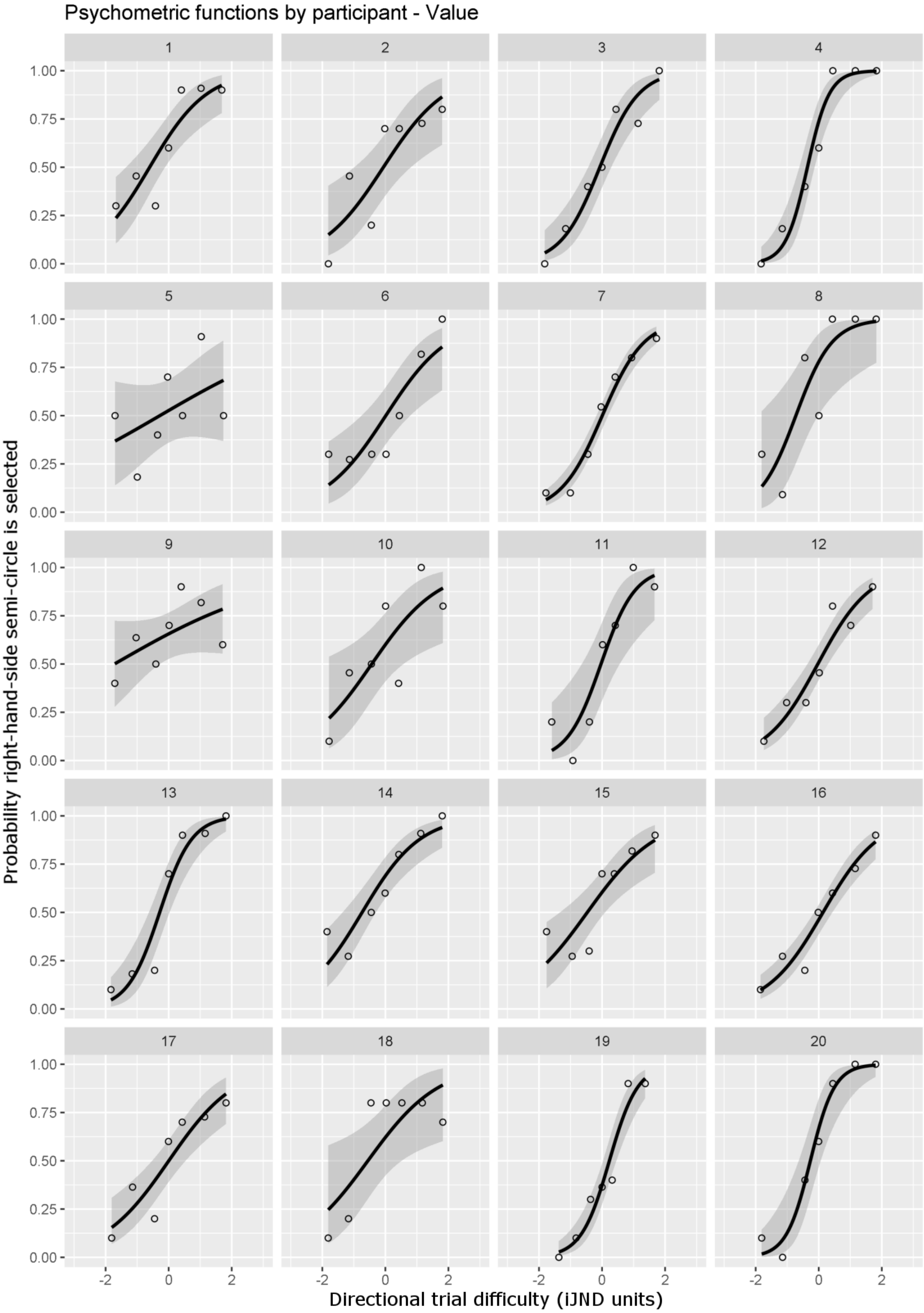


*Figure 2.4 Logistic curves by participant – Value.*
*Fitted logistic curves plotted over the probability of selecting right-hand-side semi-circle/product as having higher value (y-axis) generated by binning responses into seven bins of equal number of observations. The x-axis is in iJND units. The large negative value means the left-hand-side semi-circle has higher value and the trial is easy while large positive value means the right-hand-side semi-circle has higher value and the trial is easy. The small values mean the trial is difficult.*

Table 2.2: Model output Exp. 1 – Congruence.

Outputs (model coefficients and standard errors in parenthesis) from four Mixed Effects Logit models estimated on Congruence stage data given for a mean participant. Intercept represents $\theta_0$; Trial diff is directional trial difficulty and represents $\theta_1$; Trials 37-77 tests for effect of learning on Intercept while Trials 37-77 interacted with Trial diff tests for effect of learning on slope; Within trade-off is within-product attribute trade-off and tests for effect on intercept while Within trade-off interacted with Trial diff tests for effect on slope; Between trade-off is between-product attribute trade-off and tests for effect on intercept while Between trade-off interacted with Trial diff tests for effect on slope

| Model | (2.1) | (2.2) | (2.3) | (2.4) |
|---|---|---|---|---|
| Intercept | 0.380*** | 0.443*** | 0.381*** | 0.361*** |
| | (0.091) | (0.109) | (0.092) | (0.094) |
| Trial diff (iJND) | 1.647*** | 1.618*** | 1.656*** | 1.650*** |
| | (0.085) | (0.099) | (0.086) | (0.087) |
| *Leaning* | | | | |
| Trials 73-144 | | -0.122 | | |
| | | (0.115) | | |
| Trials 73-144*Trial diff | | 0.056 | | |
| | | (0.102) | | |
| *Within product trade-off* | | | | |
| Within trade-off | | | -0.002 | -0.003 |
| | | | (0.018) | (0.018) |
| Within trade-off*Trial diff | | | 0.019 | 0.018 |
| | | | (0.013) | (0.013) |
| *Between product trade-off* | | | | |
| Between trade-off | | | | -0.025 |
| | | | | (0.037) |
| Between trade-off*Trial diff | | | | 0.008 |
| | | | | (0.033) |
| Observations | 2864 | 2864 | 2864 | 2864 |
| Individuals | 20 | 20 | 20 | 20 |

Standard errors in parentheses
 * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 2.3: Model output Exp. 1 – Value.
Outputs (model coefficients and standard errors in parenthesis) from four Mixed Effects Logit models estimated on Value stage data given for a mean participant. Intercept represents $\theta_0$; Trial diff is directional trial difficulty and represents $\theta_1$; Trials 37-77 tests for effect of learning on Intercept while Trials 37-77 interacted with Trial diff tests for effect of learning on slope; Within trade-off is within-product attribute trade-off and tests for effect on intercept while Within trade-off interacted with Trial diff tests for effect on slope; Between trade-off is between-product attribute trade-off and tests for effect on intercept while Between trade-off interacted with Trial diff tests for effect on slope

| Model | (2.5) | (2.6) | (2.7) | (2.8) |
|---|---|---|---|---|
| Intercept | 0.300*** | 0.217* | 0.277*** | 0.248** |
| | (0.084) | (0.108) | (0.084) | (0.088) |
| Trial diff (iJND) | 0.869*** | 0.829*** | 0.884*** | 1.011*** |
| | (0.085) | (0.093) | (0.082) | (0.089) |
| *Learning* | | | | |
| Trials 37-77 | | 0.165 | | |
| | | (0.129) | | |
| Trials 37-77*Trial diff | | 0.109 | | |
| | | (0.098) | | |
| *Within product trade-off* | | | | |
| Within trade-off | | | -0.106*** | -0.98*** |
| | | | (0.019) | (0.019) |
| Within trade-off*Trial diff | | | -0.017 | -0.010 |
| | | | (0.012) | (0.011) |
| *Between-product trade-off* | | | | |
| Between trade-off | | | | -0.056 |
| | | | | (0.039) |
| Between trade-off*Trial diff | | | | -0.115*** |
| | | | | (0.031) |
| Observations | 1433 | 1433 | 1433 | 1433 |
| Individuals | 20 | 20 | 20 | 20 |

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 2.2 and Table 2.3 present a series of mixed-effect logit models estimated on the Congruence and Value conditions, respectively. However, the model coefficients are not easily interpretable without conversion to bias and JND (Equation 3a and 3b). To calculate the overall bias, the intercept is divided by the minus of the slope (Trial diff representing directional trial difficulty; Equation 3a). Similarly, the overall JND is calculated from the 'Trial diff.' (Equation 3b). Models 2.1 and 2.5 reveal a bias, as indicated by the significant intercept in both conditions. A positive intercept translates to a bias towards the congruent response (the Congruence condition) and the right-hand-side-product[17]-is-more-valuable response (the Value condition). Unsurprisingly, the coefficient for directional trial difficulty is significant. The larger the absolute difference in iJNDs, the more likely a participant was to get the trial correct. Recall that the concept of JND is not directional which means that it describes the amount of change in iJND units required for a participant to correctly identify an incongruent trial as incongruent or a congruent trial as congruent (or correctly identify the left product as being more valuable when it is more valuable or the right product as being more valuable when it is more valuable). Model 2.1 (Congruence condition) reveals that the average participant required approximately 1.1 iJNDs (calculated from Equation 3b) to precisely perform simultaneous colour and motion judgements. It also reveals that the participants were biased towards selecting the congruent response by 0.23 iJNDs (calculated from Equation 3a). Model 2.5 (Value condition) reveals that participants required 2.09 iJNDs to precisely trade colour against motion. Furthermore, the participants had a bias of 0.35 iJNDs towards the right-hand-side product.

Models (2.2 and 2.6) test for learning effects by including a dummy variable for whether the trial was in the first or second half of the run. The reference category is the first half. The non-significant coefficients reveal no change in bias (intercept) or in precision (Learning interacted with Trial diff) from the first to the second half of the run in both conditions[18].

Models 2.3 and 2.7 test how performance was affected by the extent of *within-product attribute trade-off* by including a continuous predictor variable: within trade-off (*W*; Equation 12). This trade-off represents the level of attribute extremeness within a product

[17] Recall from section 2.2.1 that the terms product and semi-circle are referring to the same construct and are hence used interchangeably within this thesis

[18] The learning effects were also investigated by including other predictor variables in the model. These included: Trial number, Trial number squared, and log of Trial number. None of these predictor variables indicated a presence of significant learning effects.

compared with the level of attribute extremeness within the other product. For example if the left semi-circle has a poor quality colour and a good quality motion (extreme attributes), and the right semi-circle has a mediocre quality of both the colour and motion (balanced attributes) the within-product attribute trade-off will be large and negative. However, if both semi-circles have two mediocre attributes then the within attribute trade-off will be small. The coefficients from the models reveal that there are no significant changes to bias or precision in the Congruence condition. However, there is a significant change to bias in the Value condition (Model 2.7). The negative coefficient reveals that as the size of the $W$ increased from 0 to a large positive value (the right product has increasingly extreme attributes compared to the left product), the participants were increasingly biased against the right-hand-side product. The exact opposite was true for the $W$ decreasing from 0 to a large negative value. To better understand the changes in within-product attribute trade-off, Figure 2.5 plots the $W$ against bias. There was no significant effect of this within-product attribute trade-off on precision.

$$\mathrm{W}_t = |C_{Rt} - M_{Rt}| - |C_{Lt} - M_{Lt}| \qquad 12$$

*Within-product attribute trade-off at a given trial ($W_t$); Level of colour in right-hand-side semi-circle in colour JND units on a given trial ($C_{Rt}$); Level of motion in right-hand-side semi-circle in motion JND units on a given trial ($M_{Rt}$); Level of colour in left-hand-side semi-circle in colour JND units on a given trial ($C_{Lt}$); Level of motion in left-hand-side semi-circle in motion JND units on a given trial ($M_{Lt}$)*

Models 2.4 and 2.8 introduce a *between-product attribute trade-off* ($B$; Equation 13), where $B_{mid}$ is a constant that centres the mean of the $\mathrm{B}_t$ range on 0 ($B_{mid} = 4.651664$ ) to allow for an easier comparison between the Congruence models and Value models. The between-product attribute trade-off represents the level of difference between the attributes of the left and right products. For example, if the left product has good quality colour and poor quality motion but the right product has poor quality colour and good quality motion the between-product attribute trade-off will be large. If the colour difference as well as the motion difference between the left and right product is small then the between-product attribute trade-off will be small. There is no significant effect of between-product attribute trade-off on bias or precision in the Congruence condition. However, the precision significantly decreased with an increased between-product attribute trade-off in the Value condition (Model 2.8), as shown by the negative interaction term of between-product attribute trade-off and directional trial difficulty. To visualize this result, Figure 2.6 plots the between-product attribute trade-off against the JND. There was no significant effect on bias.

$$\mathrm{B}_t = |C_{Rt} - C_{Lt}| + |M_{Rt} - M_{Lt}| - B_{mid} \qquad 13$$

*Between-product attribute trade-off at a given trial ($B_t$); Level of colour in right-hand-side semi-circle in colour JND units on a given trial ($C_{Rt}$); Level of colour in left-hand-side semi-circle in colour JND units on a given trial ($C_{Lt}$); Level of motion in right-hand-side semi-circle in motion JND units on a given trial ($M_{Rt}$); Level of motion in left-hand-side semi-circle in motion JND units on a given trial ($M_{Lt}$); Mean of the $B_t$ range ($B_{mid}$)*

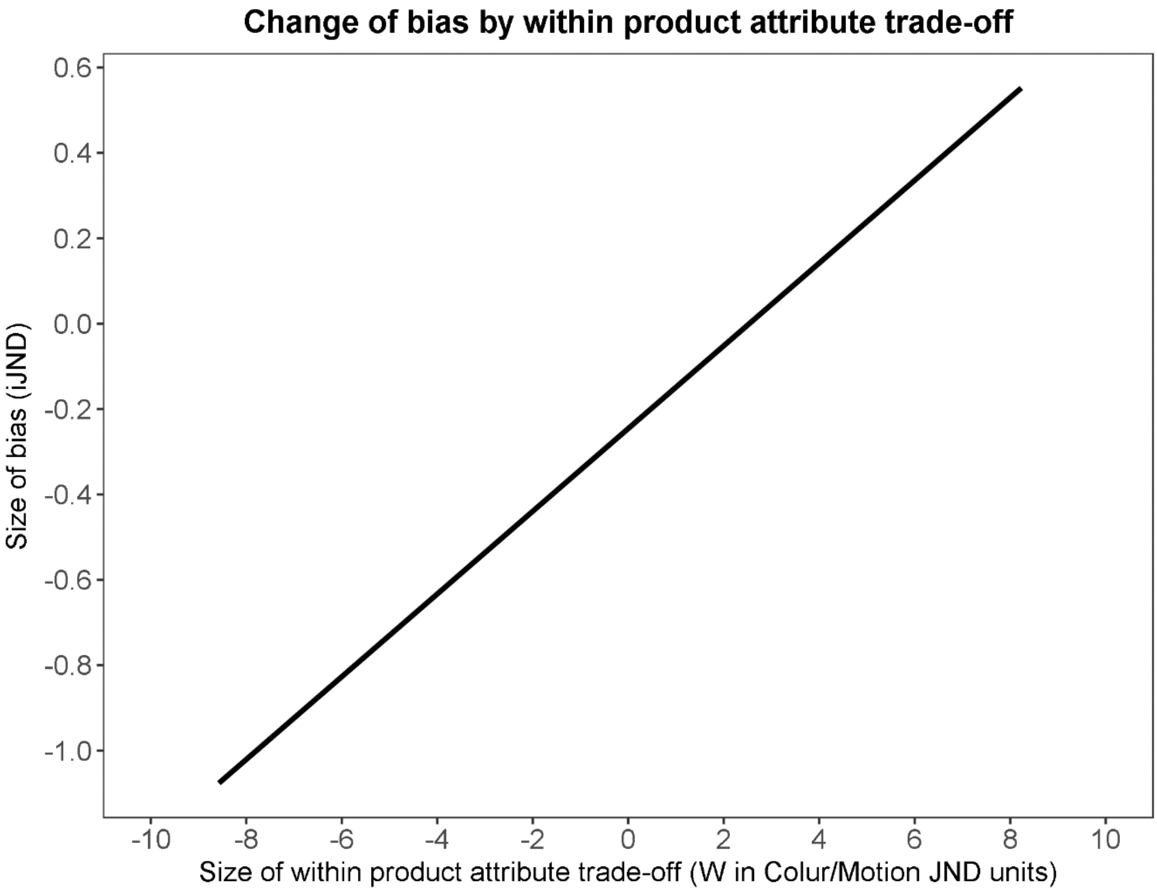


*Figure 2.5 Within-product attribute trade-off vs. bias – Value.*
*The size of bias change across the within-product attribute trade-off (W) displayed on x-axis in JND units of colour/motion. A large within-product attribute trade-off means that one of the products has more extreme attributes in comparison to the other product. A negative W means that the left product has larger attribute extremeness than the right product while positive W means that the right product has larger attribute extremeness. A negative bias is a bias against the left attribute. Hence, if the left product has extreme attributes, participants are biased towards the right product and vice versa. Put simply, the graph shows that products with large attribute extremeness are being under-valued.*

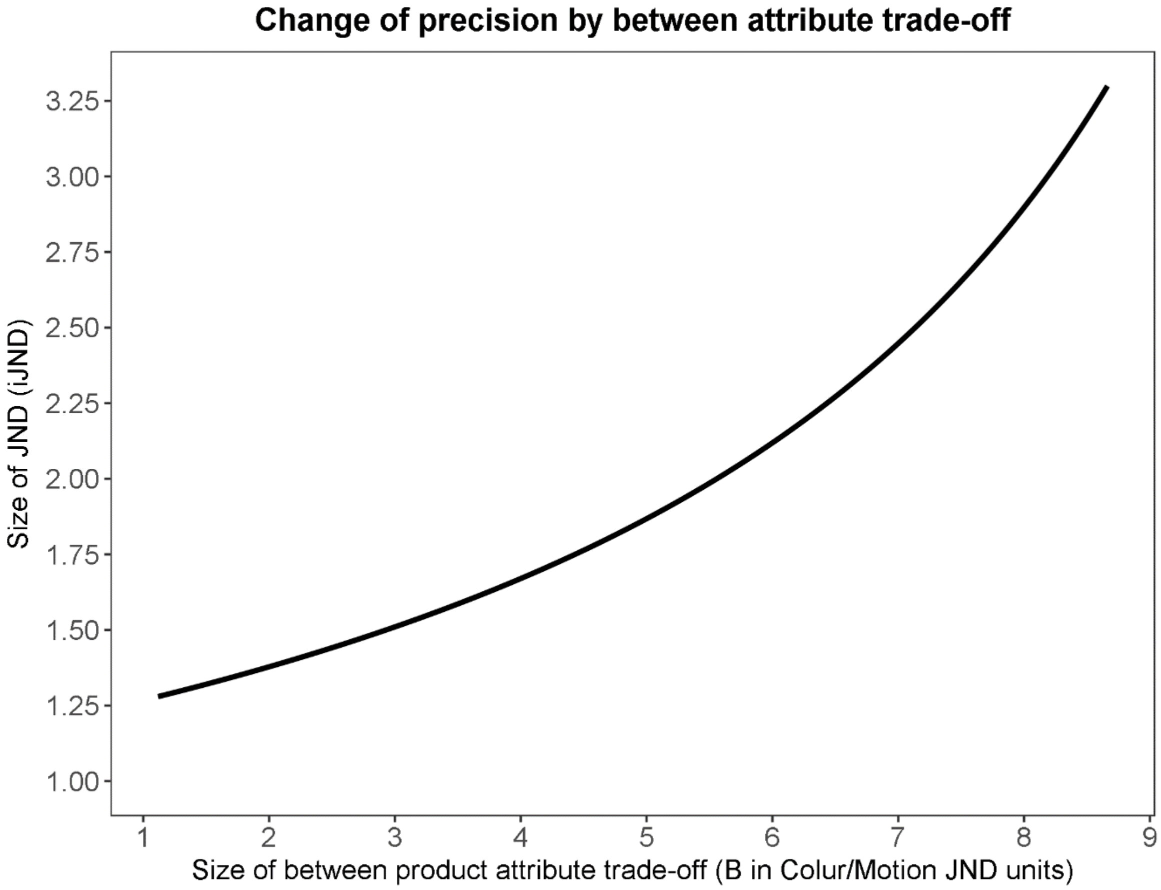


*Figure 2.6 Between-product attribute trade-off vs. JND - Value*
*The size of JND change across the between-product attribute trade-off (B) displayed on x-axis in colour/motion JND units. A large between-product attribute trade-off means that there is a large difference between the qualities of the left and the right Colour and/or Motion. For example, the left colour is green while the right colour is red, and the left motion is horizontal while the right motion is vertical. The larger the between-product attribute trade-off is, the larger the JND that is required for the participant to correctly identify which of the two products has higher value. In other words, the precision on the task decreases with increased between-product attribute trade-off.*

Based on the coefficients from the models, the participants were biased towards a congruent response by about 0.23 iJNDs (Congruence condition), and towards the right-hand-side product by about 0.25 iJNDs (Value condition), on average. However, the bias in the Value condition was affected by a within-product attribute trade-off ranging from -1 to 0.5 iJNDs. The precision in the Congruence task is around 1.1 iJNDs, and in the Value task it ranges from 1.3 to 3.2 iJNDs depending on the size of the between-product attribute trade-off. As previously stated, if the participants can perform these tasks with statistical efficiency, both their cJND and vJND should equal to 1 iJND. The models, hence, indicate a substantial deterioration in precision in the Value task and a smaller decrease in precision in the

Congruence task compared to the ideal integration. However, they do not reveal if these differences are statistically significant. An initial *one-way analysis of means* test (Welch, 1951) was carried out to compare the means of slope estimates of the three groups (Congruence, Value and ideal integration) across participants. This test does not assume equal variances between groups. Note that the ideal integration has no variance as all the estimates of $\theta_1$ were scaled by iJND. There were significant differences between the means according to the one-way test, $F(2, 25.33) = 5.51$, $p = .01$, $\eta^2 = 0.19$. Post hoc tests revealed a significant difference between the Value and ideal integration, $F(1, 19) = 10.69$, $p = .004$, $\eta^2 = 0.22$; between Value and Congruence, $F(1, 31.86) = 5.55$, $p = .025$, $\eta^2 = 0.13$; while the difference between the Congruence and ideal integration was not significant, $F(1, 19) = 0.62$, $p = .441$, $\eta^2 = 0.02$. However, these tests lack statistical power, given the small sample size. To address this issue, two strategies were adopted. First, a simulation analysis was conducted, in which extensive simulations of the ideal integrator were compared against the actual performance in the Congruence and Value conditions. Second, a mixed-effect logit model was fitted to all the trials to compare the actual performance between the two conditions.

The simulation of the ideal integration was created via an in-house MATLAB (The MathWorks) script. It tested whether the decrease in precision of the actual performance compared to the ideal integration was significant. It simulated ideal integration responses given probabilities $p_{Gt}$ (Congruence; Equation 4) and $p_{Vt}$ (Value; Equation 5) for each trial. In total, 1000 simulations per condition were conducted and each was analysed, generating 1000 estimates of slope of the average ideal integrator. Such distributions of $i\theta_1$s (ideal integrator slope) are compared to the actual estimates of $\theta_1$ from the best fitting Models (2.1 and 2.8). If the actual estimate is smaller than the bottom 5th percentile of a related distribution, the probability of it coming from that distribution is $p < .05$[19]. The results of this analysis are presented in Table 2.4. It was found that a median participant had a significantly higher JND in the Congruence and Value condition compared to the ideal integrator ($p < .05$). The last column shows that all but two participants in the Value condition were significantly worse compared to the ideal integrator. In the Congruence condition, 10 participants were significantly worse. However, eight participants were better

[19] The probability corresponds to a one-tailed test due to the directional nature of the hypothesis. It is assumed that the actual performance cannot be better than that of the 'ideal' integrator.

than the median ideal integrator in the Congruence condition compared to only one in the Value condition.

Table 2.4: Simulation output Exp. 1 – Congruence & Value.
Comparison of actual (Actual mean) estimates taken from the best-fitting models (2.1 – Congruence, 2.8 – Value) and the 50th percentile (Simulated $p_5$) and mean (Simulated mean) of the simulated distributions of estimates assuming the ideal integration. The last column displays the number of participants with a significantly higher JND ($p < .05$). That is a JND higher than 95th percentile of the simulated distributions of estimates assuming the ideal integration.

| | | *Actual mean* | *Simulated $P_5$* | *Simulated mean* | *No. of sig. participants* |
|---|---|---|---|---|---|
| **$\theta_1$ (JND)** | **Congruence** | 1.650 (1.10 iJND) | 1.727 (1.05 iJND) | 1.817 (1 iJND) | 10 |
| | **Value** | 1.011 (1.79 iJND) | 1.669 (1.09 iJND) | 1.819 (1 iJND) | 18 |

The results from the simulations should be considered with caution as they are not based on real data, but a simulated ideal integrator with low standard error estimates. By contrast, Model 2.9 (Table 2.5) compares the actual Congruence against the actual Value data with Congruence as a reference category. The significant positive coefficient on the intercept equates with a bias towards a congruent response, while the non-significant coefficient on 'Value' shows that this bias (the right-hand-side product is more Valuable) remained when the task changed. However, the significant interaction of Value with directional trial difficulty (Trial diff) shows that the precision deteriorated in the Value condition relative to the Congruence condition. The negative coefficient of the 'Value* Within trade-off' interaction reveals a bias against products with a large within-product attribute trade-off (Figure 2.7) in the Value condition only. Finally, the significant three-way interaction of 'Value * Between trade-off * 'Trial diff.' shows that a large between-product attribute trade-off was associated with a decrease in precision (Figure 2.8) in the Value condition only.

Table 2.5: Model output Exp. 1 – Congruence & Value.
Outputs (model coefficients and standard errors in parenthesis) from Mixed Effects Logit model estimated on Value and Congruence stage data given for a mean participant. The reference category is Congruence condition. The variable 'Value' tests for difference between Value and Congruence conditions. Intercept represents $\theta_0$; Trial diff is directional trial difficulty and represents $\theta_1$; Value tests for effects of Value condition on intercept in comparison to reference category (Congruence condition); Value*Trial diff interaction tests

for effect of Value condition on slope compared to reference category; Within trade-off is within-product attribute trade-off and tests for effect on intercept in Congruence condition; Value*Within trade-off interaction tests for effect of Within trade-off in Value condition on intercept; Between trade-off is between attribute trade-off and tests for effects of Between trade-off on intercept in Congruence condition; Between trade-off*Trial diff interaction tests for effects of Between trade-off on slope; Value*Between trade-off interaction tests for effects of Between trade-off on intercept in Value condition; Value*Between trade-off*Trial diff interaction tests for effect of Between trade-off on slope in Value condition.

| Model | (2.9) |
|---|---|
| Intercept | 0.336*** |
| | (0.082) |
| Trial diff. (iJND) | 1.633*** |
| | (0.185) |
| *Dataset* | |
| Value | -0.077 |
| | (0.091) |
| Value*Trial diff | -0.622*** |
| | (0.082) |
| *Within-product trade-off* | |
| Within trade-off | -0.009 |
| | (0.017) |
| Value*Within trade-off | -0.086*** |
| | (0.025) |
| *Between-product trade-off* | |
| Between trade-off | -0.043 |
| | (0.036) |
| Between trade-off*Trial diff | 0.002 |
| | (0.033) |
| Value*Between trade-off | -0.003 |
| | (0.052) |
| Value*Between trade-off*Trial diff | -0.107* |
| | (0.044) |
| Observations | 4297 |
| Individuals | 20 |

Standard errors in parentheses
$^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$

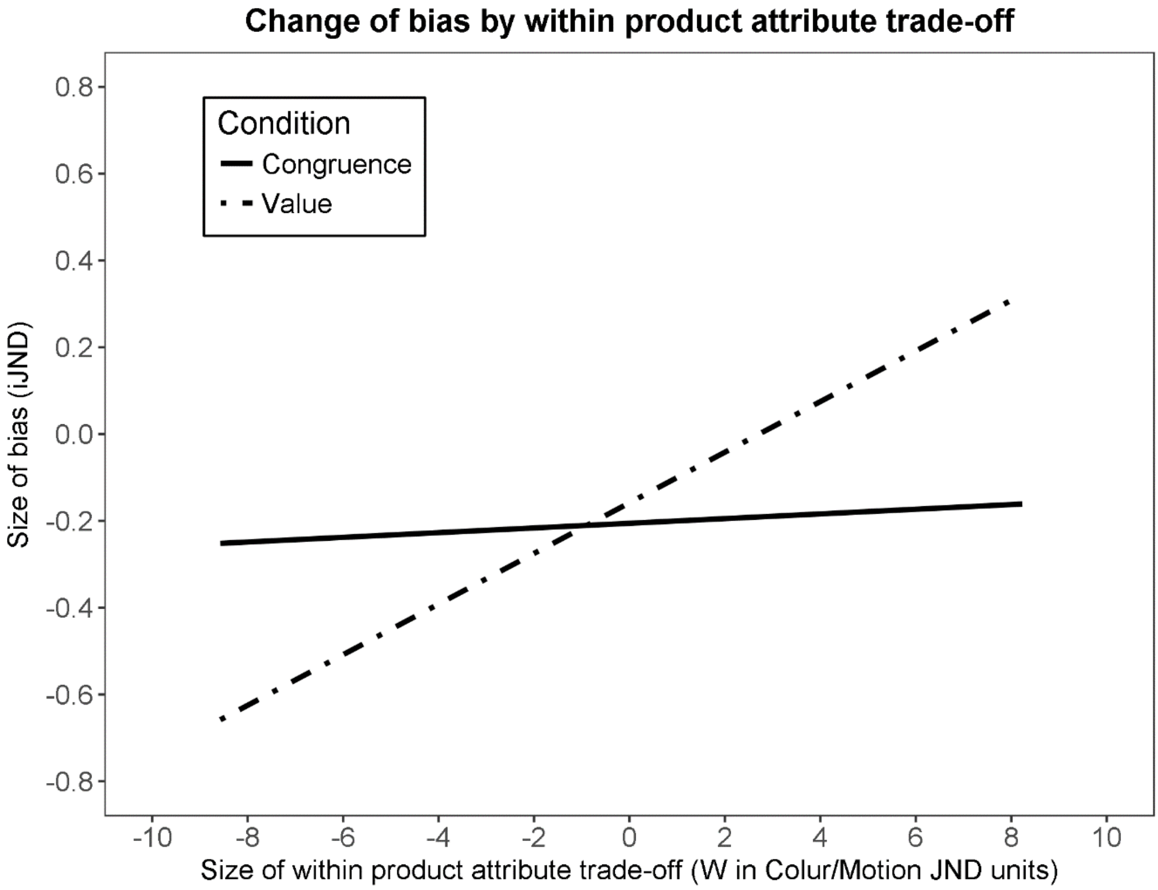


*Figure 2.7 Within-product attribute trade-off vs. bias – Congruence & Value*

*The size of change in bias across within-product attribute trade-off (W) by condition displayed on x-axis in colour/motion JND units. A large within-product attribute trade-off means that one of the products has more extreme attributes in comparison to the other product. A negative W means that the left product has larger attribute extremeness than the right product while positive W means that the right product has larger attribute extremeness. A negative bias is a bias against the left attribute. There is no effect of within-product attribute trade-off in the Congruence condition. However, in the Value condition, if the left product has extreme attributes, participants are biased towards the right product and vice versa. Put simply, the graph shows that the product with large attribute extremeness is being under-valued. The graph also shows a small consistent bias towards congruent responses (Congruence condition) and that the right-hand-side product is more valuable (Value condition).*

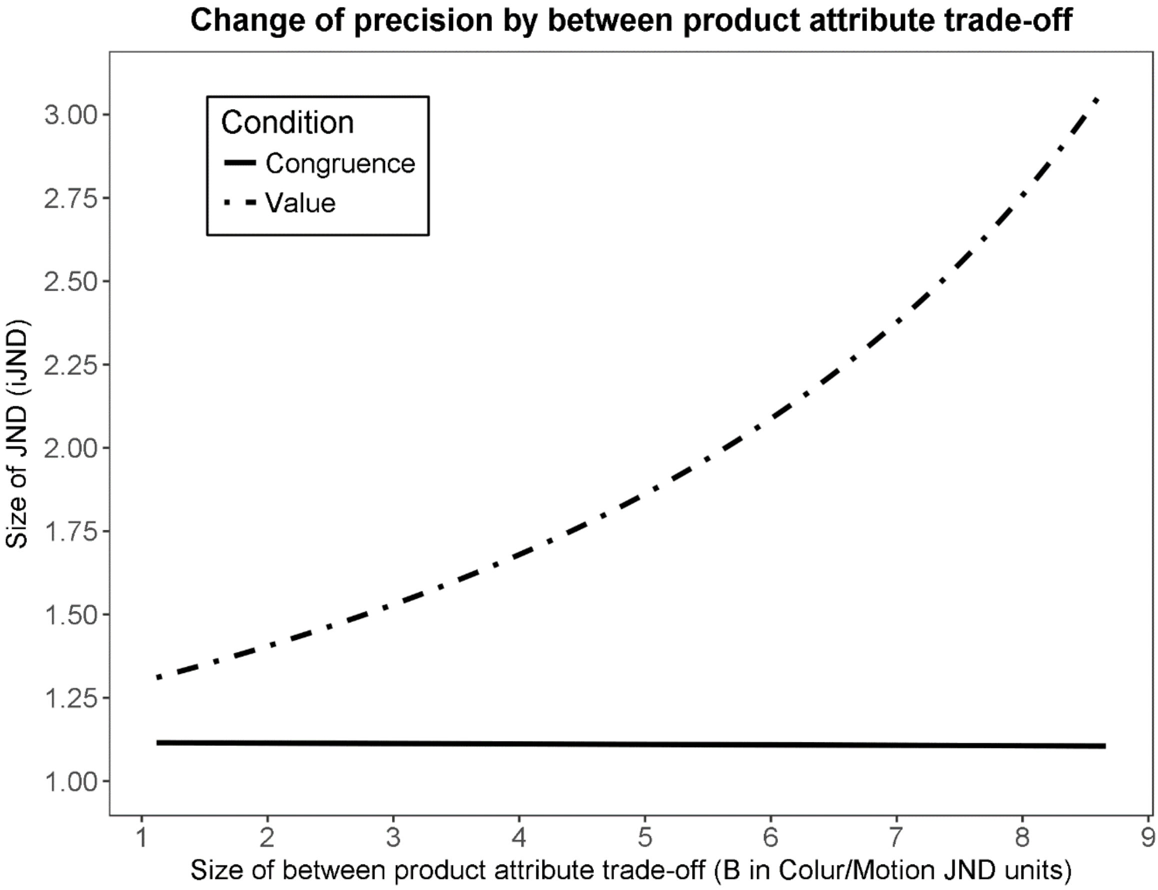


*Figure 2.8 Between-product attribute trade-off vs. JND – Congruence & Value*
*The size of the JND change across between-product attribute trade-off (B) by condition displayed on x-axis in colour/motion JND units. A large between-product attribute trade-off means that there is a large difference between the qualities of the left and the right Colour and/or Motion. For example, the left colour is green while the right colour is red, and the left motion is horizontal while the right motion is vertical. The graph shows no effect of between-product attribute trade-off on JND in the Congruence condition. However, in the Value condition, the larger the between-product attribute trade-off is, the larger the JND that is required for the participant to correctly identify which of the two products has the higher value. In other words, the precision on the task decreases with increased between-product attribute trade-off but this happens in the Value condition only.*

## 2.4 Discussion

The aim of Experiment 1 was to separate and assess the stages of multi-attribute decision making involving incommensurable attributes. Such decision making can be broken down into the Assessment stage (judgement of the quality of attribute, assessed by the Congruence task), and the Mapping stage (integration of assessed pieces of information onto a 'common scale', assessed by the difference in accuracy between the Congruence and Value task). The main research question was to determine at what stage of decision making previously reported cognitive limits (Lunn et al., 2016) manifest themselves. Experiment 1 demonstrated that the precision (given by iJND) during multi-attribute decision making is substantially reduced as a result of the Mapping stage (from 1.1 to 1.79 iJNDs). There was also a reduction, although a substantially smaller one, during the Assessment stage (from 1 to 1.1 iJNDs). The reduction in precision during the Mapping stage when compared to the Assessment stage equalled 39%, while comparison of the ideal integration (performance based on statistical efficiency) to the Assessment stage produced only a 9% reduction.

The small reduction in precision during the judgement of two attributes resembles the findings from absolute judgements of multidimensional stimuli. For example, Pollack (1954) has found that participants could accurately identify 2.5 bits[20] of pitch information and 2.3 bits of loudness information, but their accuracy on combined pitch and loudness judgement was 3.1 bits, which falls short of the 4.8 bits expected if the task was performed with statistical efficiency. However, absolute judgement tasks require comparison of a presented stimulus with stimulus exemplars stored in the long-term memory, which the Congruence task does not. It is, hence, unclear whether the reduction in accuracy found by Pollack (1954) is a result of having to retrieve exemplars from memory, or the simultaneous judgement of two dimensions (loudness and pitch). For this reason, it is not possible to draw any direct comparisons between the Congruence task and multi-dimensional absolute judgement tasks. There is also a possibility that the precision reduction in the Congruence task resulted from the nature of the task itself. The task requires the participants to ignore a spatial position of congruent (e.g., is the dominating product on left or right) and incongruent trials. This can potentially cause confusion resulting in erroneous responses, especially for congruent trials when the dominating product is on the left requiring a response with the right hand. Unfortunately, testing for this error within the existing dataset is not possible due to the infrequency of the error and the number of trials per participant available. Testing for this error would require a significant increase in the number of trials, which is not feasible.

Experiment 1 also reveals that precision during the Mapping stage is highly moderated by the size of the between-product attribute trade-off. In other words, it is much harder to compare two products with large attribute differences between them than two products with small attribute differences. An example of a large attribute difference is when one product

[20] Bit is a number of binary choices where 1 bit = 2 alternatives, 2 bits = 4 alternatives, 3 bits = 8 alternatives and so on.

is really good on colour but bad on motion, and the other is bad on colour and good on motion. When the between-product attribute trade-off is large, the precision reduces to 3.2 iJNDs, but increases to 1.25 iJNDs when the between-product attribute trade-off is small. However, the increase in precision at the left end of the between-product attribute trade-off spectrum could be attributed to, at least in part, the use of a potential heuristic during the Value task. When the differences between the left and right of one attribute became almost non-existent, that attribute could simply be ignored and the task effectively reduced to a judgment task in relation to the other attribute. However, while this heuristic represents a plausible influence on responses, it cannot explain the decrease in precision when the attribute trade-off was large.

The presented findings suggest the existence of a cognitive bottleneck during the Mapping stage. Moreover, the lack of a learning effect on precision found in this experiment supports the idea that this is a genuine capacity limit. The participants were able to discriminate only 7.4 distinct products from the entire iJND range, which is reminiscent of Miller's (1956) ‘magical’ number seven. Furthermore, Lunn and colleagues (2016), who conducted a number of Surplus identification task experiments in which participants mapped single-attribute products against monetary values also found that participants were able to discriminate about 7 distinct products. The researchers used various products, attributes and ranges. These results suggest that the mapping of incommensurable pieces of information is imprecise and appears to be determined by perceived attribute ranges or attribute distributions. One possibility is that the presented attributes on each trial are compared against the internal representations of the attribute ranges, but due to a limited cognitive capacity, or perhaps a limited working memory capacity, these ranges are represented by only a limited number of markers placed within them. Such comparisons could be achieved without the need to compute internal value, which resembles Type 3 theories (e.g., Tversky, 1969; Stewart et al., 2006).

However, the question arises as to what might be causing the increasingly-inefficient mapping when the absolute distance between attribute values increases. Decision by sampling theory (Stewart et al., 2006) postulates that attributes are compared within a decision context, as well as against attribute examples retrieved from long-term memory, where decision making is determined by the relative frequencies of these comparisons. If long-term memory examples represent the actual attribute distributions (truncated normal in this experiment) and presented attributes are from the tails of these distributions (large between attribute trade-off), most of the comparisons involve long-term memory samples from the centre of the distribution. This results in a decreased sensitivity for extreme attributes. Another possibility is that the cognitive system places markers within the internal attribute distribution to maximise discriminability around the mean, resulting in larger distances between markers in the tails of the distribution, which would also lead to a decreased sensitivity for trials that have large between-attribute trade-off. It is also possible that this comparison process is highly dynamic and the internal examples are drawn from recently-presented trials weighted as a function of time. Due to the shape of the actual attribute distributions, most of the markers would be placed around the attribute mean. This would be consistent with the findings of sequential effect literature (e.g., Laming, 1984), which suggests that the point of reference in relative judgements is given by the previous trial.

In addition to the findings of decreased precision, Experiment 1 also uncovered a bias towards the right response (congruent/ right valuable). However, compared to the decrease in precision, the overall average bias was relatively small (0.23 iJND - Congruence, 0.25 iJND - Value). Interestingly, this bias was present during both tasks, suggesting it originates from the Assessment stage. A potential reason for such a bias could be an attentional bias towards the participant’s dominant hand, possibly caused by the increased cognitive demand as two attributes had to be assessed in parallel. It has been found that handedness affects attentional bias in spatial coding (Rubichi & Nicoleti, 2006). Alternatively, the attentional bias could be the result of the direction of motion used in the task as the movement of dots was always from left to right. However, it is less likely as Lunn and colleagues (2016) reported a similar bias in their Surplus identification task.

The Value task revealed that the bias is moderated by the size of the within-product attribute trade-off originating from the Mapping stage. Participants preferred products with balanced attributes over products with extreme attributes. Similarly, findings from choice experiments have revealed that consumers are less likely to opt for products with extreme attribute magnitudes (Simonson & Tversky, 1992) and are more likely to choose products with balanced attributes (Chernev, 2005). However, these findings have generally been attributed to a genuine preference for balanced products. The current experiment suggests a different reason. The choices towards balanced attributes are the result of the cognitive system’s ability to trade incommensurable attributes. It is hypothesized that this bias is directly linked to the precision decrease moderated by the increase in between-attribute trade-offs. Hence, this bias represents an uncertainty weighting of the cognitive system, which compensates for such decreased precision by down-weighing products that have extreme attributes, and cannot be evaluated as precisely as products with balanced attributes. In other words, it is a precision bias trade-off. Recent evidence showing that multi-attribute context effects and reference-dependence are present in perceptual judgements as well as in consumer choice tasks (Trueblood, Brown, Heathcote & Busemeyer, 2013) supports this hypothesis.

# CHAPTER 3: An EEG investigation of multi-attribute trade-off

## 3.1 Introduction

The purpose of the study in this chapter is to assess the neural signals of multi-attribute decision making using the same Congruence-Value task as in Chapter 2, experiment 1. The results of experiment 1 showed significant deterioration in precision during the Mapping stage which did not result from the need to simultaneously assess the quality of two attributes. It was also revealed that the size of the trade-off matters for the mapping process. The larger the between-product-attribute trade-off, the greater the decrease in precision. This suggests that a separate cognitive mechanism which maps incommensurable attributes is involved during multi-attribute decision making. However, it is unclear whether this mechanism accumulates evidence in a similar manner to PDM. Is the evidence for multi-attribute value comparisons also integrated up to a specific threshold? Can a neural signature of such a decision variable (Gold & Shadlen, 2007) be isolated? The potential isolation of this signal would provide direct access to the neural decision process, informing how incommensurable attributes are being mapped onto each other. Moreover, it would give deeper insights into the strategies participants invoke during EDM.

Recent studies in neurophysiology have identified a domain general decision variable signal (Donner, Siegel, Fries, & Engel, 2009; O’Connell et al., 2012; de Lange, Rahnev, Donner, & Lau, 2013) which seems to represent decision formation during PDM independent of the specific motor response or sensory task used. This decision signal is referred to as centro-parietal positivity (CPP; O’Connell et al., 2012). During PDM tasks, the characteristics of CPP, such as the rate of the signal build-up, and the amplitude at response predict timing and accuracy of decisions. It has been suggested that onset latency, rate of rise, peak amplitude and peak latency appear to represent the start of the evidence accumulation, the rate of evidence accumulation, the threshold, and the cessation of evidence accumulation, respectively (Kelly & O’Connell, 2014). A number of experimental findings support this suggestion. The rate of rise of the CPP is positively correlated with directional trial difficulty (consistent with evidence integration) and reaches a fixed amplitude immediately prior to decision reports (consistent with a boundary crossing effect).

The Value condition in the Congruence-Value task uses three separate absolute trial difficulty levels (for detail, see section 2.2.2) designed to isolate the varying rate of rise of CPP. However, because the nature of the current study is exploratory, as it is unknown whether the CPP signal is even present during the Mapping stage. The aim is to replicate the findings from experiment 1 and answer the following questions. Is CPP present during the Mapping stage, and if so, is its rate of evidence accumulation correlated with the trial difficulty? In what way, if any, does the onset latency, the rate of rise, the peak amplitude and the peak latency of CPP during the Congruence condition differ from CPP during the Value condition?

## 3.2 Methods

The experimental design and the task used in this study were almost identical to that of experiment 1. Only the description of the changes made to experiment 2 are given below. Please refer to section (2.2 Methods) in Chapter 2 for additional details.

### 3.2.1 Participants

Twenty participants (13 males and 7 females) of ages between 18 and 46 years (*M* = 30.3, *SD* = 6.7) undertook the study. They were recruited in the same way as in experiment 1 and the same inclusion criteria were applied. Moreover, the best performing participant also won a 50-Euro shopping voucher, as assessed by the overall accuracy in four experimental conditions (refer to section 2.2.3 for details). Participants gave written informed consent in advance of the study, which had been approved by the Trinity College Dublin School of Psychology Ethics Committee.

### 3.2.2 Procedure

Small changes were made to the Congruence-Value task. The number of trials in the Motion and Colour stages in session 1 was increased from 96 to 180 trials to increase the quality of fits of psychometric functions to each participant. The colour range was adjusted to 105–165 RGB varied on the green gun, which shifted the range more towards the red end of the spectrum. The intent was to minimize the effects of colour discrimination nonlinearity especially pronounced at the end of the green spectrum (Wallach, 1948) found in experiment

1, where five participants were significantly worse at discriminating green dots. In session 2 participants had their brain activity recorded with EEG. To accommodate EEG data analysis, the number of trials in the Congruence and Value conditions was increased to 240. As in experiment 1, the trials for Value condition were generated first, and Congruence trials were created from them. Half of the duplicated Value trials had either their left colour swapped for the right colour (25% of the duplicated trials), or the left motion swapped for the right motion (25%). In this way, half of the trials became congruent while the other half stayed incongruent. The task was carried out in a darkened and sound-attenuated room under the same conditions and using the same equipment as in experiment 1.

### 3.2.3 EEG data acquisition and pre-processing

In session 2, participants' continuous EEG signal was recorded with ActiveTwo (Biosemi) from 128 scalp electrodes, digitized at 512 Hz. The electrodes were arranged according to a standard 10/20 setup. Eye movements were recorded with two electro-oculogram (EOG) electrodes placed above and below the left eye. To minimize the participant's movement during the EEG recording, their head was supported in a chin rest. Moreover, participants were instructed to keep still, focus at the fixation dot in the centre of the screen and try to avoid blinking during a trial. They were also advised that they were free to take a rest at any time between trials. All of these procedural instructions were applied in both sessions to achieve as similar an experimental setting between the sessions as possible. Data were analysed using in-house MATLAB (The MathWorks) scripts, drawing on EEGLAB (Delorme & Makeig, 2004) routines for reading raw data files and spherical spline interpolation of noisy channels.

Initially, the data were checked for bad channels, which were then interpolated using spherical interpolation (Delorme & Makeig, 2004). In total, 37 channels across six subjects were interpolated. The continuous data were then re-referenced to an average reference and low-pass filtered <35 Hz using a $2^{nd}$ order digital Butterworth Infinite impulse response (IIR) filter. The continuous recordings on all the channels were detrended to minimize the influence of slow drifts. Finally, the data were high pass filtered >0.05 Hz using a $2^{nd}$ order digital Butterworth IIR filter. For all of the analyses, the EEG data were segmented into epochs from -360 ms (from the start of the ramp) to 200 ms (from the response). The epochs were baseline-corrected relative to a 200 ms interval preceding the start of the ramp and later detrended. Trials were rejected when a difference between the absolute maximum and minimum of EOG signals exceeded 200 $\mu$V, or if any scalp channel exceeded ±100 $\mu$V at any time during the artefact rejection window, which started at -200 ms (from the start of the ramp) to 50 ms (from the response). The mean number of artefact-free trials across participants was $M$ = 215 ($SD$ = 32, $MIN$ = 167) in Congruence and $M$ = 221 ($SD$ = 22, $MIN$ = 117) in Value condition. Artefact-free trials were converted to current source density (Kayser & Tenke, 2006) to increase spatial selectivity and to decrease the spatial blurring effects of volume conduction. This transformation was applied to reduce the projection of fronto-central negativity to posterior centro-parietal electrodes (Kelly & O'Connell, 2013). For the purpose of analysis, the epochs were stimulus-aligned (aligned to the start of the ramp) going from -360 to 640 ms, and response-aligned going from -350 to 200 ms.

### 3.2.4 Measurement and analysis of electrophysiological signal

The CPP signal was measured at the single electrode location with maximum component amplitude within the centro-parietal area as given by an average response-aligned topography on the pooled data across the conditions. Separate topographies were used for each participant to allow for subtle individual differences in cap fit, scalp morphology, and cortical folding between participants. The time window used was -90 to 40 ms from response. For each participant, the topography plots identified the peak CPP as the region of maximum component amplitude no further than two electrodes from the standard site CPz (O'Connell et al., 2012). For a grand average topography, see Figure 3.1.

ERP waveforms were generated to analyse CPP by participant. The signal across individual trials grouped by the condition (Congruence, Value) and the trial difficulty group was averaged. Each ERP waveform was low-pass filtered with a <6 Hz zero-shift fourth order Butterworth IIR filter. The build-up rate was measured as the slope of a straight line fitted to the unfiltered ERP waveform of each subject, using an interval 150 to 310 ms (Congruence) and 135 to 310 ms (Value) for the stimulus-aligned CPP, and -120 to -40 ms (Congruence) and -90 to -40 ms (Value) for the response-aligned CPP. The intervals were selected by locating the onset and peak latencies of grand average of filtered ERPs for each condition, and selecting time points within proportions of 0.25 and 0.75 as given by the duration between the peak and onset. This creates a 25% buffer zone after the onset latency and before the peak latency, ensuring that the buildup of evidence was captured. Note that different intervals were used for Congruence and Value conditions, resulting from somewhat different ERPs between them. It is not an issue for the analyses as each condition is a different task and they are not being compared against each other in the EEG data analysis. The peak amplitude was measured at response for the response-aligned ERPs and at the identified peak latency, 390 ms (the same for both conditions) for the stimulus-aligned ERPs. A series of t-tests and anovas was conducted on various formats of trial difficulty bins.

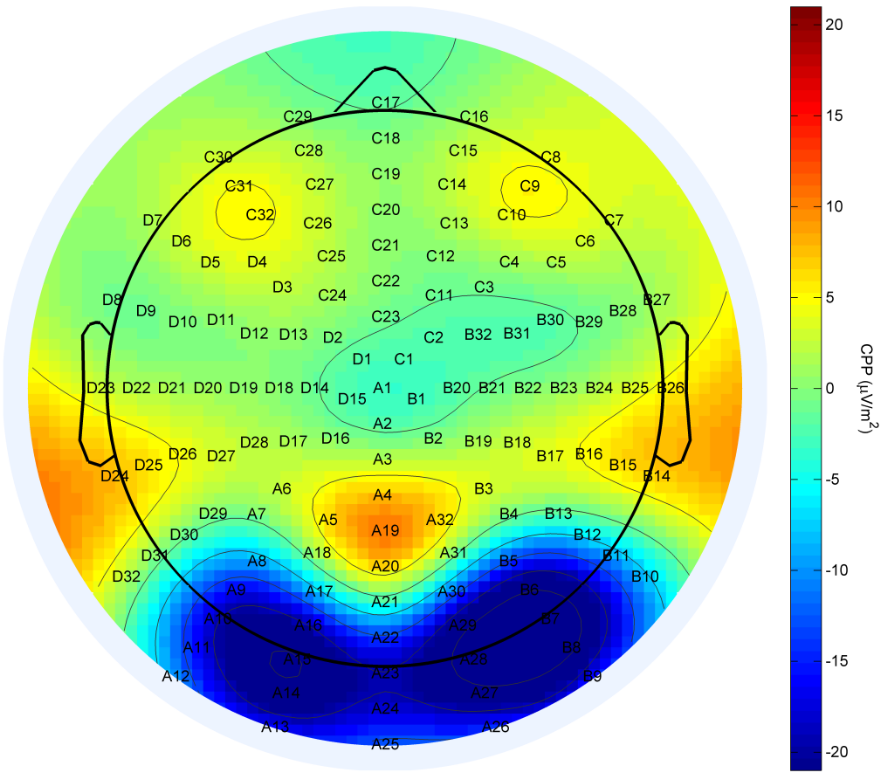


*Figure 3.1 CPP topographic map*
*A topographic plot of the mean CPP amplitude over a window of -90 to 40 ms from response from all participants' data pooled together. The peak CPP is identified as the region of maximum component amplitude and is located around the CPz (A19) electrode. Moreover, the plot also shows a bilateral frontal component around C32 and C9 electrodes present during the time window of the CPP. This component could represent attentional modulation during decision formation.*

To perform a single trial analysis, each epoch was initially low-pass filtered <6 Hz using a fourth order Butterworth IIR filter to limit the influence of alpha activity on the signal. The buildup rate was measured as the slope of a straight line fitted to the filtered data waveform of each trial, using an interval of -400 to -100 ms from response. This interval was informed by the fastest response time (Congruence: 460 ms; Value: 490 ms), which allowed assessment of the final stages of evidence build-up, excluding the last 100 ms before response. The peak amplitude was measured at response. The generated data of the peak amplitude and the buildup rate were fitted with mixed effects (ME) models with random effects of participant on intercepts and slopes.

## 3.3 Results

The results of behavioural data analyses, which are identical to those in Chapter 2, are described next, followed by the EEG data analysis.

### 3.3.1 Behavioural results of stages 1&2

A very small number of trials (16 Colour and 25 Motion) were excluded due to erroneous responses and an additional three Colour and five Motion trials were excluded on the basis of being significant outliers as identified by half-normal plots of residuals (Atkinson, 1981) from logistic regressions fitted to each subject by condition. In total, less than 1% of all the trials in each condition were excluded. The deviance statistics of fits of the psychometric functions revealed a mean *p* value (across participants) of *M* = 0.32 (*SD* = 0.22) for the Colour condition, and *M* = 0.38 (*SD* = 0.31) for the Motion condition. None of the tests were statistically significant. Visual inspection of the fitted logistic curves confirmed that all appeared to represent data well, with the exception of one participant in the colour condition whose data were a little noisier. All the estimates of slopes ($\theta_1$) and intercepts ($\theta_0$) across participants were checked for violations of normality using the Shapiro–Wilk test and visual inspection of kernel density plots, as well as quantile-quantile plots. The slopes in the motion stage were the only one that did not appear normally distributed, which was confirmed with the Shapiro–Wilk test ($W=0.90$, $p=.046$). Closer examination revealed that five participants performed better than the rest. The colour JND was 5.2 RGB (*SD* = 1.8), and the motion JND was 2.7 degrees (*SD* = 1.16). The one-sample t-test revealed a significant bias (*M* = -0.43, *SD* = 0.52) in the Motion condition $t(20) = -3.69$, $p = .0015$, while there was no bias in the Colour condition. The significant negative bias indicates that participants were consistently judging the motion on the right side as moving more upwards compared to the actual movement. The reasons are unclear, but the bias is not very large compared to the JND. Also, the actual motions in the Value and Congruence conditions presented on each trial are selected randomly, so the bias should have no effect on the performance in these conditions.

### 3.3.2 Behavioural results of stages 3&4

Seventeen trials in the Congruence and seven in the Value condition were excluded due to erroneous responses (<1% in each condition). The median response time was 1622 ms (Congruence) and 1512 (Value). The proportion of incorrect responses was 0.15 (Congruence) and 0.23 (Value). The deviance statistics of psychometric functions fitted to each participant (Simple models with one predictor variable; Equation 10) revealed a mean $p = 0.89$ ($SD = 0.29$) for the Congruence and $p = 0.52$ ($SD = 0.34$) for the Value condition. Out of 40 tests, one was significant for Congruence (participant 8), and three for the Value condition (participants 15, 7 and 4)[21]. A further inspection of the slopes of psychometric functions revealed that two participants (eight and 19) in the Congruence condition (Figure 3.2) had much lower slope estimates compared to the rest, and in the Value condition (Figure 3.3) participant six had a much higher slope than the rest. When normality tests were conducted on $\theta_1$ estimates, the Shapiro–Wilk tests indicated a deviance from normality in the Value condition, $W(20) = 0.80$, $p < 0.001$ caused by the identified outlier, participant six, whose performance was much better than that of the rest. Visual inspection of quantile-quantile plots of $\theta_1$ estimates in the Congruence condition also revealed a left skew combined with fat tails. Inspection of estimates of intercepts found no significant deviations from normality, as indicated by the Shapiro–Wilk tests, and visual inspections of quantile-quantile plots and kernel density plots.

[21] The findings from Experiment 1 revealed significant effects of between- and within-product attribute trade-offs in the Value condition. When models for each participant were re-run with these trade-offs included, deviance statistics improved and revealed that only one participant in the Value condition had a poor fit that was significant. All principal analyses on behavioural data were also conducted with two outliers (participant eight – Congruence and participant four - Value) excluded, with minimal impact on the estimated coefficients.

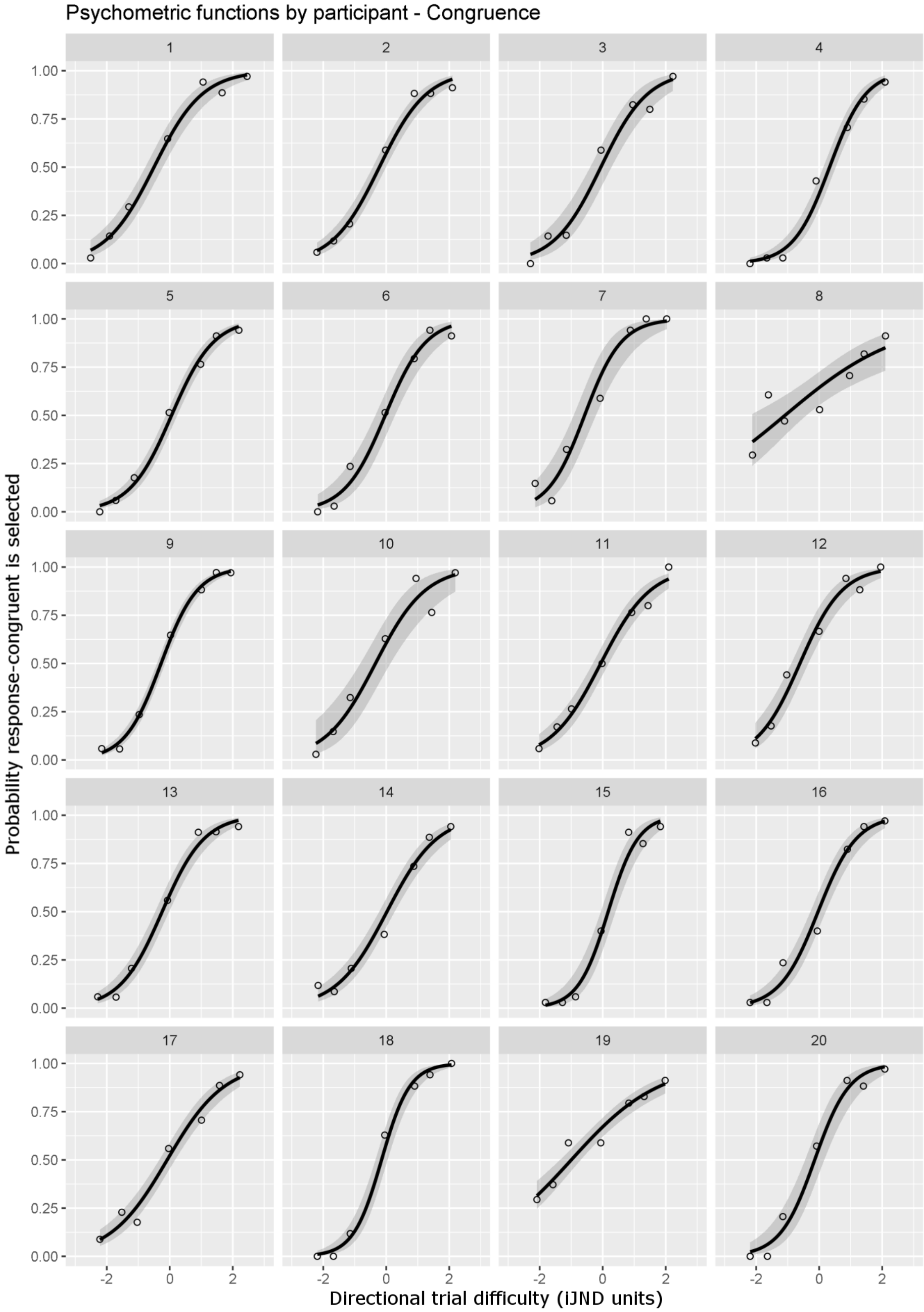


*Figure 3.2 Logistic curves by participant - Congruence*

*Fitted logistic curves plotted over the probability of selecting the congruent response (y-axis) generated by binning responses into seven bins of equal number of observations. The x-axis is in iJND units. The large negative value means the trial is incongruent and easy while large positive values means the trial is congruent and easy. Small values mean the trial is difficult.*

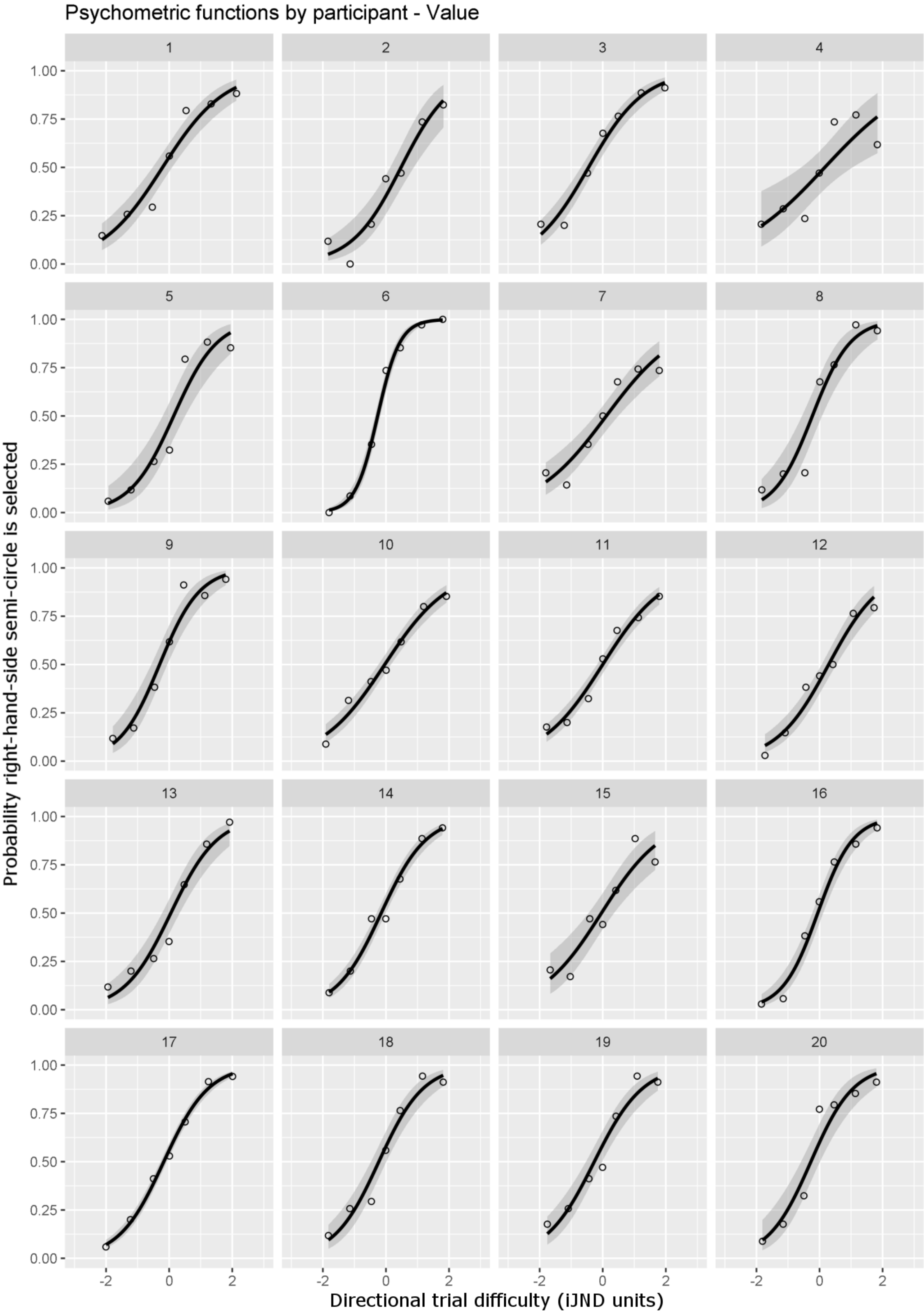


*Figure 3.3 Logistic curves by participant - Value*

*Fitted logistic curves plotted over the probability of selecting the right-hand-side semi-circle/product as having higher value (y-axis) generated by binning responses into seven bins of equal number of observations. The x-axis is in iJND units. The large negative value means the left-hand-side semi-circle has higher value and the trial is easy while large positive value means the right-hand-side semi-circle has higher value and the trial is easy. Small values mean the trial is difficult.*

The visual inspections, the statistical tests of fits and the $\theta_1$ estimates identified potential issues for mixed-effect logit models which assume a normal distribution of random effects. This could be especially problematic when fitting to the combined data sets of the Congruence condition with the left skew and the Value condition with the right skew. Hence, it was decided to use fixed effects for the estimates of slope and intercept instead of random effects, which meant fitting separate dummy variables for each participant plus interactions with trial difficulty. For the purpose of clarity, comparability to experiment 1 and space constraints within the model output table, only the estimates of intercept for a median participant, and slope for a median participant are reported.

Table 3.1 presents a series of models fitted to the Congruence data and Table 3.2 models fitted to the Value data. Models (3.1 and 3.5) reveal a significant effect of trial difficulty and a non-significant bias in both conditions. Models (3.2 and 3.6) found no learning effects on intercept or slope, which means that participants' bias and/or the JND did not change from the first half to the second half of the condition run. Models (3.3 and 3.7) test for the existence of a within-product attribute trade-off (Equation 12). It reveals a significant effect of the within-product attribute trade-off on intercept in the Value condition. Recall that the within-product attribute trade-off is the size of attribute extremeness of one product compared to attribute extremeness of the other product. The results indicate that participants are biased against a product with extreme attributes (Figure 3.4). Finally, Models (3.4 and 3.8) add a predictor variable of a between-product attribute trade-off (Equation 13). Note that the mean of the $\mathrm{B}_t$ range was different to Experiment 1, resulting in a different constant ($B_{mid} = 5.020945$). Recall that the between-product attribute trade-off represents the level of difference between the same attributes of left and right product. The findings revealed a significant interaction of between-product trade-off and trial difficulty in the Value condition. The negative coefficient indicates a decreasing JND with increasing between-product attribute trade-off (Figure 3.5).

Table 3.1: Model output Exp. 2 - Congruence
Outputs (model coefficients and standard errors in parenthesis) from four Fixed Effects Logit models estimated on Congruence stage data given for a median participant. The model outputs were calculated from the output of the regression with two additional predictor variables (dummy for each participant, and each participant interacted with directional trial difficulty). Intercept represents $\theta_0$; Trial diff is directional trial difficulty and represents $\theta_1$; Trials 121-240 tests for effect of learning on Intercept while Trials 121-240 interacted with Trial diff tests for effect of learning on slope; Within trade-off is within-product attribute trade-off and tests for effect on intercept while Within trade-off interacted with Trial diff tests for effect on slope; Between trade-off is between-product attribute trade-off and tests for effect on intercept while Between trade-off interacted with Trial diff tests for effect on slope

| Model | (3.1) | (3.2) | (3.3) | (3.4) |
|---|---|---|---|---|
| Intercept | 0.281 | 0.328 | 0.282 | 0.276 |
| | (0.219) | (0.223) | (0.219) | (0.220) |
| Trial diff (iJND) | 1.562*** | 1.519*** | 1.562*** | 1.552*** |
| | (0.184) | (0.187) | (0.184) | (0.185) |
| *Leaning* | | | | |
| Trials 121-240 | | -0.085 | | |
| | | (0.087) | | |
| Trials 121-240*Trial diff | | 0.080 | | |
| | | (0.068) | | |
| *Within-product trade-off* | | | | |
| Within trade-off | | | -0.005 | -0.004 |
| | | | (0.012) | (0.012) |
| Within trade-off*Trial diff | | | -0.006 | -0.007 |
| | | | (0.008) | (0.009) |
| *Between product trade-off* | | | | |
| Between trade-off | | | | -0.014 |
| | | | | (0.028) |
| Between trade-off*Trial diff | | | | 0.038 |
| | | | | (0.021) |
| Observations | 4783 | 4783 | 4783 | 4783 |
| Individuals | 20 | 20 | 20 | 20 |

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3.2: Model output Exp. 2 - Value
Outputs (model coefficients and standard errors in parenthesis) from four Fixed Effects Logit models estimated on Value stage data given for a median participant. The model outputs were calculated from the output of the regression with two additional predictor variables (dummy for each participant, and each participant interacted with directional trial difficulty). Intercept represents $\theta_0$; Trial diff is directional trial difficulty and represents $\theta_1$; Trials 121-240 tests for effect of learning on Intercept while Trials 121-240 interacted with Trial diff tests for effect of learning on slope; Within trade-off is within-product attribute trade-off and tests for effect on intercept while Within trade-off interacted with Trial diff tests for effect on slope; Between trade-off is between-product attribute trade-off and tests for effect on intercept while Between trade-off interacted with Trial diff tests for effect on slope

| Model | (3.5) | (3.6) | (3.7) | (3.8) |
|---|---|---|---|---|
| Intercept | 0.156 | 0.156 | 0.151 | 0.145 |
| | (0.178) | (0.182) | (0.179) | (0.182) |
| Trial diff (iJND) | 0.952*** | 0.953*** | 0.960*** | 1.101*** |
| | (0.124) | (0.127) | (0.123) | (0.123) |
| *Learning* | | | | |
| Trials 121-240 | | 0.000 | | |
| | | (0.072) | | |
| Trials 121-240*Trial diff | | -0.002 | | |
| | | (0.053) | | |
| *Within product trade-off* | | | | |
| Within trade-off | | | -0.062*** | -0.065*** |
| | | | (0.010) | (0.010) |
| Within trade-off*Trial diff | | | -0.003 | -0.001 |
| | | | (0.006) | (0.006) |
| *Between product trade-off* | | | | |
| Between trade-off | | | | -0.026 |
| | | | | (0.021) |
| Between trade-off*Trial diff | | | | -0.144*** |
| | | | | (0.017) |
| Observations | 4793 | 4793 | 4793 | 4793 |
| Individuals | 20 | 20 | 20 | 20 |

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

When JNDs are calculated from coefficients from the best-fitting models for the Congruence (Model 3.1) and Value (Model 3.8) conditions, they reveal that precision of the median participant is about 1.16 iJND (Congruence), and about 1.1 to 3.2 iJND in the Value condition. Recall from earlier that if participants can perform these tasks with statistical efficiency, both their cJND and vJND should equal to 1 iJND. This indicates a deterioration in precision in the Congruence task and a large deterioration in precision with increased between-product attribute trade-off in the Value task compared to ideal integration. To address whether the differences are significant, an initial one-way analysis of means (Welch, 1951) compared the means of slope estimates from individual models of three groups (Congruence, Value, and ideal integration). There were significant differences between means according to the one-way test, $F(2, 25.33) = 38{,}26$, $p < .0001$, $\eta^2 = 0.42$. A Post-hoc test revealed a significant difference between Value and ideal integration, $F(1, 19) = 63.6$, $p < .0001$, $\eta^2 = 0.63$; Congruence and ideal integration, $F(1, 19) = 14.9$, $p = .001$, $\eta^2 = 0.28$; and between the Value and Congruence conditions $F(1, 37.4) = 5.7$, $p = .022$, $\eta^2 = 0.13$. However, these tests lack statistical power due to the small sample size and do not allow for tests of interactions such as those of between-product and within-product attribute trade-offs.

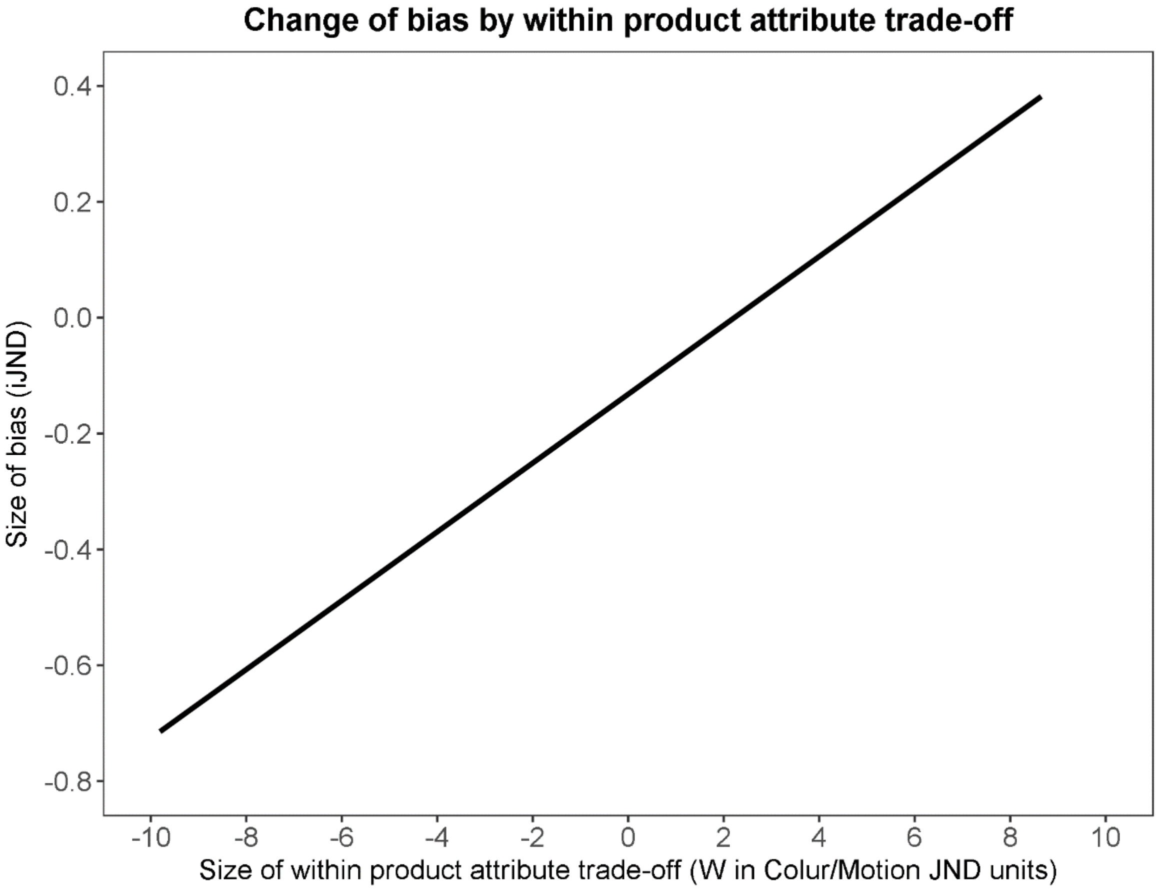


*Figure 3.4 Within-product attribute trade-off vs. bias - Value*

*The size of bias change across the within-product attribute trade-off (W) displayed on x-axis in JND units of colour/motion. A large within-product attribute trade-off means that one of the products has more extreme attributes in comparison to the other product. A negative W means that the left product has larger attribute extremeness than the right product while positive W means that the right product has larger attribute extremeness. A negative bias is a bias against the left attribute. Hence, if the left product has extreme attributes participants are biased towards the right product and vice versa. Put simply, the graph shows that products with large attribute extremeness are being under-valued.*

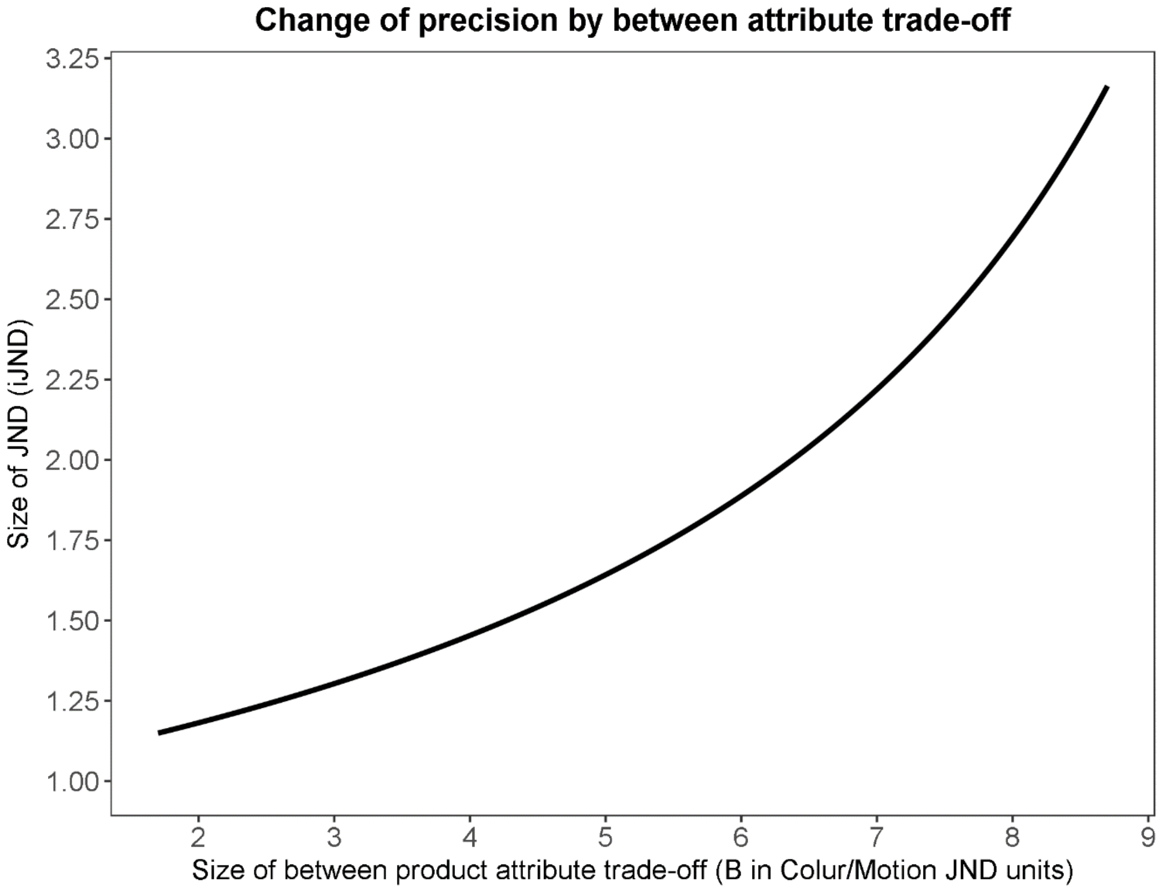


*Figure 3.5 Between-product attribute trade-off vs. JND - Value*

*The size of JND change across the between-product attribute trade-off (B) displayed on x-axis in colour/motion JND units. A large between-product attribute trade-off means that there is a large difference between the qualities of the left and the right Colour and/or Motion. For example, the left colour is green while the right colour is red, and the left motion is horizontal while the right motion is vertical. The larger the between-product attribute trade-off is, the larger JND is required for participant to correctly identified which of the two products has higher value. In other words, the precision on the task decreases with increased between-product attribute trade-off.*

Table 3.3: Simulation output. Exp. 2 – Congruence & Value.
Comparison of actual (Actual median) estimates taken from the best-fitting models (3.1 – Congruence, 3.8 – Value) and the 50th percentile (Simulated $p_5$) and median (Simulated median) of the simulated distributions of estimates assuming the ideal integration. The last column displays the number of participants with a significantly higher JND ($p < .05$). That is a JND higher than the 95th percentile of the simulated distributions of estimates assuming the ideal integration.

| | | ***Actual median*** | ***Simulated $P_5$*** | ***Simulated median*** | ***No. of sig. participants*** |
|---|---|---|---|---|---|
| **$\theta_1$ (JND)** | **Congruence** | 1.562 (1.16 iJND) | 1.740 (1.04 iJND) | 1.818 (1 iJND) | 16 |
| | **Value** | 1.101 (1.65 iJND) | 1.729 (1.05 iJND) | 1.818 (1 iJND) | 19 |

The same simulation as in experiment 1 simulated ideal integration in experiment 2. In total, 1000 simulations per condition were conducted and analysed to generate distributions of $i\theta_1$s. The comparison of descriptive statistics of those distributions and $\theta_1$s from the best-fitting Models (3.1 and 3.8) are presented in Table 3.3. It was found that the median participant had a significantly higher JND in the Congruence and Value conditions compared to the ideal integrator ($p < .05$). Moreover, the last column shows that majority of participants in the Congruence, and all except one in the Value condition had a significantly higher JND.

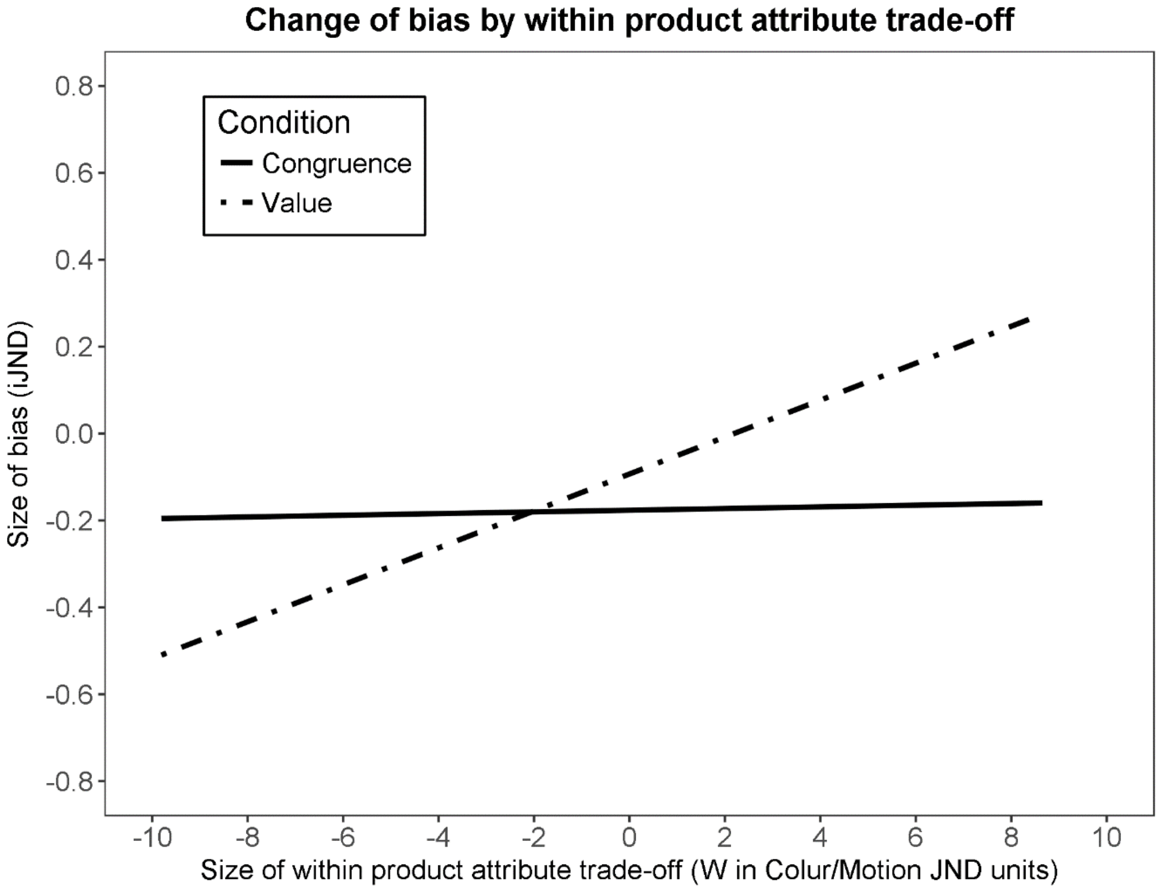


*Figure 3.6 Within-product attribute trade-off vs. bias – Congruence & Value.*
*The size of change in bias across within-product attribute trade-off (W) by condition displayed on x-axis in colour/motion JND units. A large within-product attribute trade-off means that one of the products has more extreme attributes in comparison to the other product. A negative W means that the left product has larger attribute extremeness than the right product while positive W means that the right product has larger attribute extremeness. A negative bias is a bias against the left attribute. There is no effect of within-product attribute trade-off in the Congruence condition. However, in the Value condition, if the left product has extreme attributes, participants are biased towards the right product and vice versa. Put simply, the graph shows that the product with the larger attribute extremeness is being under-valued. The graph also shows a small consistent bias towards congruent responses (Congruence condition) and that the right-hand-side product is more valuable (Value condition).*

To test for significant changes in accuracy resulting from the additional need to trade attributes against each other in the Value condition, a fixed-effects logistic regression was carried out on all the trials of combined datasets of the Congruence and Value conditions. Four sets of 20 dummy variables were used for: each participant; the interaction of each participant plus trial difficulty; the interaction of each participant plus condition; and the interaction of each participant plus condition plus trial difficulty. The reported coefficients (Table 3.4) of intercept, trial difficulty and their interactions with condition are estimates for the median participant. The lack of significance on intercept compared to Experiment 1 is most likely a result of model selection as a fixed-effect model will have larger standard errors compared to random effects. Note that the values of the actual coefficients are similar. It is revealed that the precision was significantly worse in the Value condition, and significantly more so with increased between-product attribute trade-off (Figure 3.7). Moreover, participants were biased against products with a large within-product attribute trade-off (Figure 3.6).

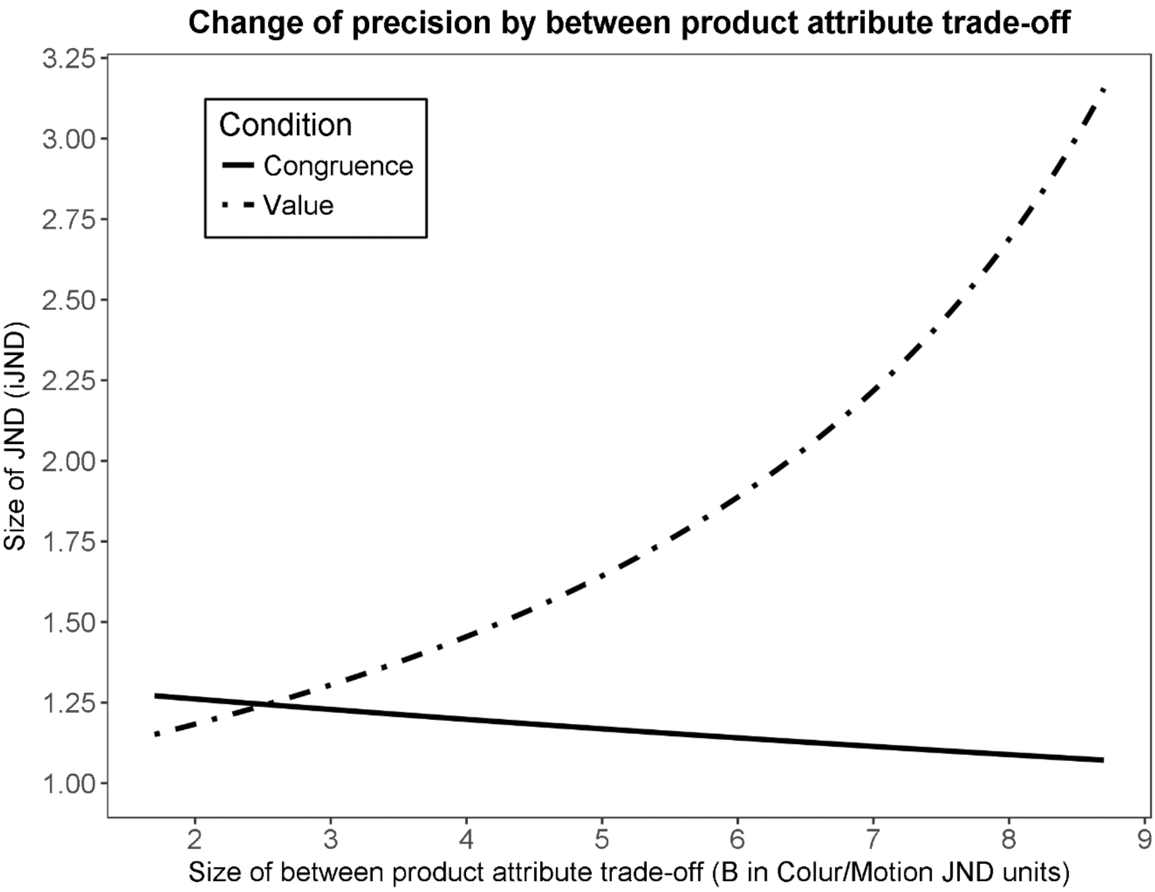


*Figure 3.7 Between-product attribute trade-off vs. JND – Congruence & Value*
*The size of the JND change across between-product attribute trade-off (B) by condition displayed on x-axis in colour/motion JND units. A large between-product attribute trade-off means that there is a large difference between the qualities of the left and the right Colour and/or Motion. For example, the left colour is green while the right colour is red, and the left motion is horizontal while the right motion is vertical. The graph shows no effect of between-product attribute trade-off on JND in the Congruence condition. However, in rhe Value condition, the larger the between-product attribute trade-off is, the larger the JND that is required for participant to correctly identify which of the two products has higher value. In other words, the precision on the task decreases with increased between-product attribute trade-off but this happens in the Value condition only.*

Table 3.4: Model output Exp. 2 – Congruence & Value.
Outputs (model coefficients and standard errors in parenthesis) from Fixed Effects Logit model estimated on Value and Congruence stage data given for a median participant. The model outputs were calculated from the output of the regression with two additional predictor variables (dummy for each participant, and each participant interacted with directional trial difficulty). The reference category is the Congruence condition. The variable 'Value' tests for difference between Value and Congruence conditions. Intercept represents $\theta_0$; Trial diff is directional trial difficulty and represents $\theta_1$; Value tests for effects of Value condition on intercept in comparison to reference category (Congruence condition); Value*Trial diff interaction tests for effect of Value condition on slope compared to reference category; Within trade-off is within-product attribute trade-off and tests for effect on intercept in Congruence condition; Value*Within trade-off interaction tests for effect of Within trade-off in Value condition on intercept; Between trade-off is between attribute trade-off and tests for effects of Between trade-off on intercept in Congruence condition; Between trade-off*Trial diff interaction tests for effects of Between trade-off on slope; Value*Between trade-off interaction tests for effects of Between trade-off on intercept in Value condition; Value*Between trade-off*Trial diff interaction tests for effect of Between trade-off on slope in Value condition.

| Model | (3.9) |
|---|---|
| Intercept ($\theta_0$) | 0.274<br>(0.191) |
| Trial diff (in iJND, $\theta_1$) | 1.553***<br>(0.185) |
| *Dataset* | |
| Value ($\theta_2$) | -0.130<br>(0.264) |
| Value*Trial diff ($\theta_3$) | -0.452*<br>(0.220) |
| *Within-product trade-off* | |
| Within trade-off ($\theta_4$) | -0.003<br>(0.012) |
| Value*Within trade-off ($\theta_5$) | -0.063***<br>(0.015) |
| *Between-product trade-off* | |
| Between trade-off ($\theta_6$) | -0.015<br>(0.028) |
| Between trade-off*Trial diff ($\theta_7$) | 0.038<br>(0.021) |

| | |
|---|---|
| Value*Between trade-off ($\theta_8$) | -0.011 |
| | (0.035) |
| Value*Between trade-off*Trial diff ($\theta_9$) | -0.181*** |
| | (0.027) |
| Observations | 9576 |
| Individuals | 20 |

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

### 3.3.3 Statistical analysis of EEG data

The outcome variables used were buildup rate and peak amplitude (for details on how these were generated see section 3.2.4). In total, five independent predictor variables were used as proxies for non-directional trial difficulty. Two trial-difficulty binning rules were used for Congruence (the ideal integrator probability, and trial difficulty calculated from coefficients of Model 3.9), and three rules for Value (the trial difficulty – proportion; trial difficulty – between trade-off; and trial difficulty derived from coefficients of Model 3.9). The ideal integrator probability, based on $p_{Gt}$ (Equation 4), was calculated as the probability of a correct response[22] by the ideal integrator (Equation 14) and grouped by median split for each participant into two groups (low probability – hard trial, and high probability – easy trial). The trial difficulty by 'model', for both Congruence and Value conditions, used coefficients ($\theta_0$ to $\theta_9$) from Model (3.9), and values of predictor variables and their interactions (denoted as $x_{nit}$[23]) in the logistic equation to derive the probability that an actual participant makes a correct response on a given trial (Equation 15). Note that these probabilities are calculated individually for each participant given their individual fixed effects. These probabilities were also grouped by a median split into two groups. The trial difficulty by proportion was given by three proportions (Equation 7) using combined attribute ranges (for more detail, see section 2.2.2). Finally, the trial difficulty by between trade-off (Equation 13) was grouped by a median split for each participant into two groups.

[22] The probability of correct response is different to the probabilities of responding congruent (Congruence condition) and of responding right-hand-side semi-circle has higher value (Value condition). They are derived from equations 14 and 15.

[23] $x_{nit}$ is a simplification and represents dummy variable ($x_{2it}$ as dummy variable for Congruence or Value condition), directional trial difficulty ($x_{1it}$), the level of within attribute trade-off ($x_{4it}$), the level of between attribute trade-off ($x_{6it}$) and interactions between those predictor variables (e.g., $x_{9it} = x_{2it} * x_{1it} * x_{4it} * x_{6it}$) for given participant ($i$) on a given trial ($t$).

$$ip_{Gt\,corr} = |0.5 - p_{Gt}| + 0.5 \qquad 14$$

*Probability ideal integrator makes correct response on a given trial in Congruence condition ($ip_{Gt\,corr}$); Probability ideal integrator responds the trial is congruent ($p_{Gt}$).*

$$p_{it\,corr} = \left|0.5 - \frac{1}{1 + \exp(-(\theta_{0i} + \theta_{1i} * x_{1it} + \theta_{2i} * x_{2it} + \cdots + \theta_{9i} * x_{9it}))}\right| + 0.5 \qquad 15$$

*Probability the actual participant (i) makes a correct response on a given trial derived from estimates of model 3.9 adjusted by fixed effects for a given participant ($p_{it\,corr}$); Model coefficients for a given participant ($\theta_{0i}$ - $\theta_{9i}$); Level of predictor variables on a given trial for a given participant representing: dummy variable for condition, directional trial difficulty, within-product attribute trade-off, between-product attribute trade-off and interactions of these predictor variables on a given trial for a given participant ($x_{1it}$ - $x_{9it}$).*

None of the analyses of buildup rate or peak amplitude revealed significant differences between groups of trial difficulties for either stimulus or response locked CPP in the Congruence (Figure 3.8) or Value conditions (Figure 3.9). For the results of t-tests and anovas conducted, see Table 3.5. To ascertain that the lack of significance was not the result of relatively small sample size and the low statistical power resulting from epoch averaging to participant level, single trial analyses were conducted with a series of mixed-effects linear regressions. Both continuous and factor (categorical) predictor variables of non-directional trial difficulties were used. Each model was checked for violation of assumptions and if necessary, correctional steps were undertaken. The conducted models (not reported here) confirmed the lack of statistical effect of the trial difficulty on the buildup rate or the peak amplitude of CPP.

Table 3.5: T-test models on EEG Exp. 2 – Congruence & Value
Outcomes of statistical tests (t-tests and Anovas) investigating the effects of the non-directional trial difficulties on the buildup rate and peak amplitude of CPP waveforms by condition (Congruence, Value). The 1st column shows condition and whether buildup rate or peak amplitude was tested. The 2nd column shows the outcome variable used: The ideal integrator probability, trial difficulty calculated from coefficients of Model 3.9 (difficulty model) and trial difficulty by proportion. The 3rd and 4th columns shows the outcomes of the tests for stimulus-aligned and response-aligned CPP wave forms respectively.

| Condition, test | Predictor variable | Stimulus-aligned | Response-aligned |
|---|---|---|---|
| Congruence buildup rate | ideal integrator prob. | t(19) = 0.91, *p* = .37 | t(19) = -1.17, *p* = .29 |
| | difficulty model | t(19) = 0.31, *p* = .76 | t(19) = 0.34, *p* = .74 |
| Congruence peak ampl. | ideal integrator prob. | t(19) = 0.23, *p* = .82 | t(19) = -1.08, *p* = .29 |
| | difficulty model | t(19) = 1.01, *p* = .33 | t(19) = 0.38, *p* = .71 |
| Value buildup rate | difficulty proportion | F(2,57) = 0.07, *p* = .93 | F(2,57) = 1.5, *p* = .23 |
| | between trade-off | t(19) = -0.97, *p* = .34 | t(19) = -1.98, *p* = .06 |
| | difficulty model | t(19) = 0.09, *p* = .93 | t(19) = 1.46, *p* = .16 |
| Value peak ampl. | difficulty proportion | F(2,57) = 0.01, *p* = .99 | F(2,57) = 0.16, *p* = .85 |
| | between trade-off | t(19) = 0.11, *p* = .92 | t(19) = 0.74, *p* = .47 |
| | difficulty model | t(19) = -0.40, *p* = .69 | t(19) = -0.16, *p* = .88 |

A visual inspection of the CPP plots (Figure 3.8 and Figure 3.9), however, revealed a number of distinctions between them and the CPP waveforms that had previously been reported (e.g., O'Connell et al., 2012; Kelly & O'Connell, 2014). Firstly, a stimulus-aligned CPP displayed a sudden and rapid onset of buildup, peaking relatively early on in a trial. Secondly, a response-aligned CPP showed a gradual decrease in activity, followed by a small-but-short increase, peaking at the response. To further investigate this, it was decided to pool all the trials together across participants and plot CPP waveforms by response time bands of 400 ms from 750 to 2750 ms in Congruence condition, and 750 to 2350 ms in Value condition (Figure 3.10), excluding extremely fast and slow trials. It is revealed that the current CPP waveform differs from those reported previously and its amplitude decrease appears to be modulated by response time. The peak amplitude of the fast trials is smaller in comparison to slow trials. This pattern is visible in the Congruence and Value condition for both the Stimulus- and Response-aligned CPP. The rate of buildup does not seem to vary by response time but the decrease in activity observed from peak towards response is accelerated in faster trials. For a possible explanation of this unusual pattern, see below.

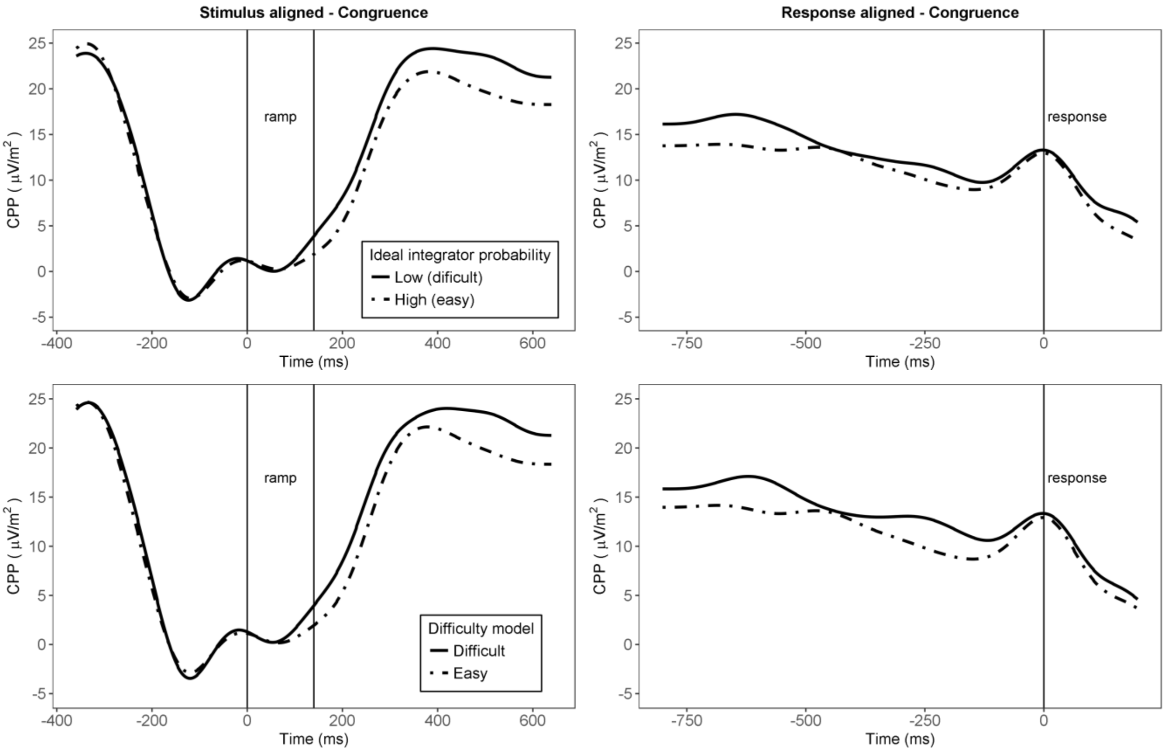


*Figure 3.8 CPP waveforms - Congruence*

*CPP is grouped by the probability of correct response by ideal integrator (top row), and by non-directional trial difficulty calculated from coefficients of best fitting model (bottom row). The left column shows stimulus-locked CPP, and the right column shows response-locked CPP. The difficult trials are represented with a solid line, while the easy trials with a dash-dotted line. The stimulus-locked graphs show a steep buildup at the beginning of the trial, peaking around 350 ms, followed by a gradual decrease in activity. The peak amplitude appears to be higher for difficult trials, but this is not significant, while the rate of buildup appears to be the same for all trials. The response-locked graphs shows a gradual decrease in CPP activity towards response, and the pattern of the activity appears to be similar between easy and difficult trials.*

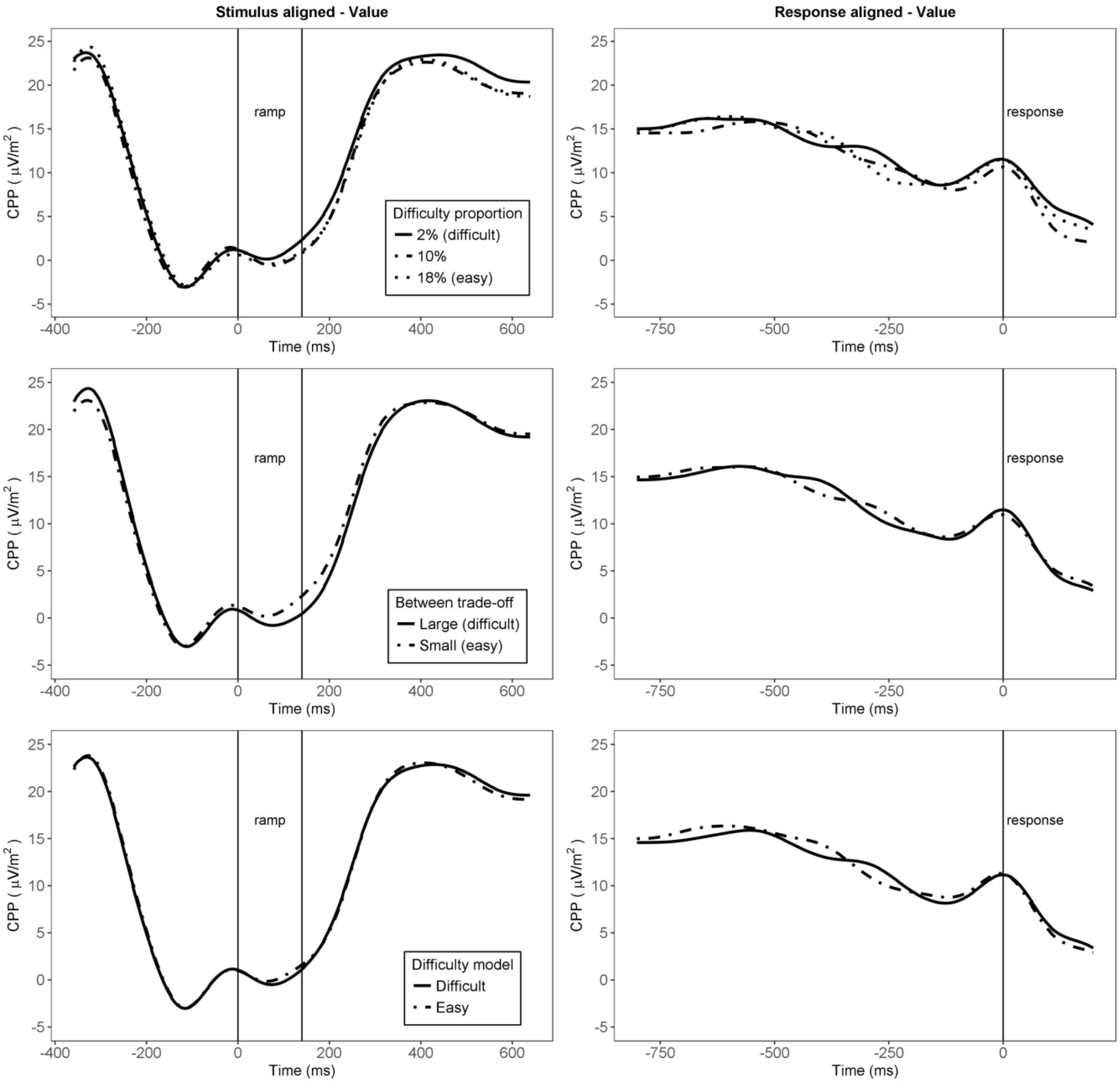


*Figure 3.9 CPP waveforms - Value*

*CPP is grouped by trial difficulty as given by the proportion determined by difference of combined attribute ranges between left and right stimulus (top row), and by the size of between-product attribute trade-off (middle row), and by the trial difficulty calculated from coefficients of the best-fitting model (bottom row). The left column shows stimulus-locked CPP, and the right column shows response-locked CPP. The difficult trials are represented with a solid line while the easy trials are represented with a dash-dotted line (and dotted line; top row - trial difficulty as proportion). As with the Congruence task graph, (*Figure 3.8*) the stimulus-locked graphs show a steep buildup at the beginning of the trial, peaking around 400 ms, followed by a gradual decrease in activity. There is no difference between the peak amplitude and rate of buildup by trial difficulty. The response-locked graphs shows a gradual decrease in CPP activity towards response, and the pattern of the activity appears to be similar between easy and difficult trials.*

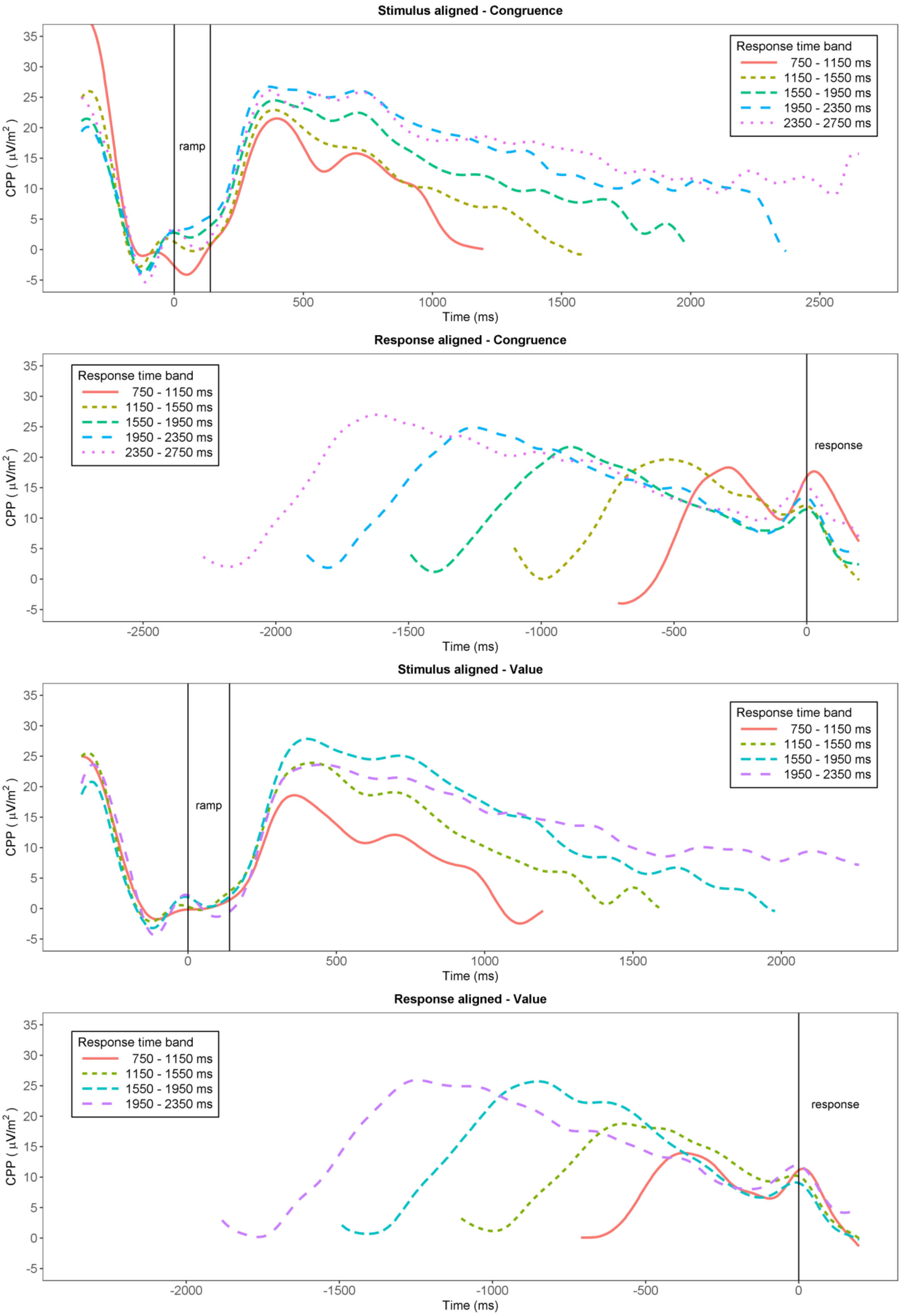


*Figure 3.10 CPP waveforms vs. response time – Congruence & Value.*
*CPP waveforms grouped by response time for Congruence and Value conditions. From top to bottom: Stimulus-aligned Congruence, Response-aligned Congruence, Stimulus-aligned*

*Value, and Response-aligned Value. The peak amplitude of faster trials is smaller compared to slower trials. This pattern is visible in both the Response- and Stimulus-aligned graphs. The slope of the buildup rate does not seem to vary. In contrast, the decrease in activity after the initial buildup visible in Stimulus-aligned graphs appears to be positively correlated with response time. The faster trials have a faster decrease in activity.*

## 3.4 Discussion

A comparison of the behavioural results from the two experiments reveals that the data from Experiment 2 were a little noisier as suggested by various analyses of the individual psychometric functions from all four stages (Colour, Motion, Congruence and Value) of the experiment. Despite the increase in the number of trials and change to the presented range of Colours, the fits of the individual psychometric functions did not improve for the Colour and Motion conditions. However, the increase in the number of trials revealed consistent patterns that were not so clear from Experiment 1. The distribution of JNDs of judgement of motion appeared to be bimodal, suggesting that, either two different strategies to judge the direction of motion were used by the participants, or the sample of participants did not represent a population distribution of motion JNDs. Provided that participants used the same strategy throughout the experiment, this bimodality poses no problem to the Congruence-Value task. The participant's ability to discriminate motion direction in each of the conditions (Motion, Congruence and Value conditions) would not change, and the estimated personalized motion JND used to set the motion range would be valid.

The reported bias towards the right response in the Motion task could be explained by research of perceptual *assimilation* in motion (Ramachandran, 1987). This *motion capture effect* represents a bias whereby one moving stimulus biases a perceived direction of motion of another stimulus with which it shares a border (Murakami & Shimojo, 1996). Due to the nature of the direction of motion, being from left to right, in the Congruence-Value task, only the right product could bias the perceived motion of the left product, which probably caused the observed bias. In all, the choice of the attributes used in these experiments had some effect on the level of noise in data of the Congruence and Value conditions. The noise in data could also be attributed to the attentional requirements of EEG, such as keeping still, minimizing blinking, etc. However, the good fits of psychometric functions in the Congruence condition posit that this noise is of a second order and has little-or-no effect on the behavioural findings.

The findings from Experiment 2 replicated all the main findings from Experiment 1 (for a detailed discussion of the findings from Experiment 1, see section 2.4). The large decrease in the ability to trade incommensurable attributes as found by Lunn and colleagues (2016) originates in the Mapping stage. Moreover, this decrease is strongly moderated by the between-product attribute trade-off. It is harder to compare a product that is good on Colour and bad on Motion with a product that is bad on Colour and good on Motion, but it is easier to compare products where the distance between magnitudes of corresponding attributes is not large[24]. Furthermore, participants were biased against those products with extreme attributes (e.g., good on Colour and bad on Motion), which might be a compensating strategy of the cognitive system that undervalues products that are perceived less precisely. This finding echoes findings from choice experiments that have revealed that consumers are less likely to opt for products with extreme attribute magnitudes (Simonson & Tversky, 1992).

However, there are some differences between the findings of the two experiments. A lack of the significant average bias in Experiment 2 in both conditions can probably be attributed to the choice of model used. The fixed-effect model used in Experiment 2 has less statistical power than the mixed-effects model because it estimates thresholds for each participant. Hence, the estimate is based on a smaller number of trials, which increases its standard error. However, the average bias (0.18 iJND Congruence, 0.13 iJND Value) if calculated from the estimates of Model (3.9), reveals a reduction in bias when compared to Experiment 1. The direction of the bias is still towards the right-hand response, though. There was also a small difference in the average precision in the Congruence and Value conditions in comparison to Experiment 1; A small decrease (0.06 iJND) in the Congruence condition; and a small increase (0.14 iJND) in the Value condition. However, these differences are small and have no real effect on the overall pattern. In general, it can be concluded that Experiment 2 replicated the findings of Experiment 1 well.

The aim of the EEG analyses was to explore the potential similarities and/or differences between the CPP waveforms of the Congruence task representing the Assessment stage, and

[24] The effect of the between-product attribute trade-off is present after controlling for trial difficulty. This means that the probability of a correct response in a trial with a trial difficulty of 1 iJND and a large between-product attribute trade-off is lower than the probability of a correct response in a trial of 1 iJND difficulty and a small between-product attribute trade-off.

of the Value task representing a multi-attribute judgement involving a trade-off (assessment + Mapping stage), as well as the previously-reported CPP waveforms in PDM tasks hypothesized to represent evidence accumulation during decision making in general (O'Connell et al., 2012; Kelly & O'Connell, 2013; Twomey et al., 2016). None of the analyses conducted found a significant trial difficulty modulation of the buildup rate or the peak amplitude in any condition in the response- or stimulus-aligned CPP waveforms. This was unexpected, especially in the Congruence condition, which represents the Assessment stage requiring judgment of two attributes. Moreover, a similarity between the CPP waveforms of the Congruence and Value conditions is apparent, but they are quite different to those reported by Kelly and O'Connell (2013), for example. The initial decrease in activity before the onset of the ramp can be attributed to visual-evoked potentials elicited by the stimulus onset. However, the recorded CPP signal peaks early on in a trial, which is followed by a slow-and-steady decrease towards about 100 ms before response. The final blip, whose peak is aligned with the response, most likely results from motor response preparation. Hence, the crucial difference is that instead of the anticipated buildup towards response, a decrease in activity towards response, clearly visible in Figure 3.10, was found.

The difference in the recorded CPP signal points towards the possibility that even during the Assessment stage (the early part of decision making involving multi-attribute trade-off) the accumulation of evidence is not represented by a single decision process, but by a series of discrete decisions (e.g., which product is greener, which has better motion, whether the trial is congruent). If these decisions are temporally misaligned and completed at different time points in a trial, then the resulting pattern of decrease in activity as time wears on within a trial will be observed. This suggests that such multi-attribute decision making are performed sequentially rather than simultaneously, which is consistent with theories of limited-attentional resources (e.g., Broadbent, 1958; Eriksen & St James, 1986; Pashler, 1994). This further implies the need to keep the outcomes of each cognitive process in short-term memory, which has been suggested to represent the capacity limit during PDM involving complex images (e.g., Todd & Marois, 2004). If one assumes that trade-off of incommensurable attributes is performed through multiple comparisons of attributes within a choice set and retrieved samples from memory, as suggested by Type 3 theories (e.g., Tversky, 1969; Stewart et al., 2006), the substantial reduction in precision during the Value task could have resulted from such limited short term memory capacity.

When the CPP signal is plotted by response time (Figure 3.10), it appears that the maximum peak amplitude (and perhaps the rate of signal decrease) is modulated by it. The fast trials have a smaller peak amplitude and faster rate of signal decrease than slow trials. It is unclear why this might be so, when no such pattern is produced by any of the trial difficulty variables. However, it underscores that both experimental tasks produce a more complex CPP pattern than those found during PDM, suggesting that the CPP signal might be affected by a number of different cognitive processes during decision making. It has been shown that CPP shares many characteristics of the classic P300 component (O'Connell et al., 2012), which has led to the suggestion that P300 and CPP are in fact the same signal. However, various studies have assigned many different cognitive roles to P300. For example, P300 has been associated with available processing capacity (Kok, 2001); attention-allocation effects during memory tasks (Curran, 2004); inhibition of extraneous brain activation (Soltani & Knight, 2000); and many others (for a detailed review, see Polich, 2007). In fact, the role of P300 in cognition is not clearly understood. Hence, it is possible that CPP/P300 represent much more than just the decision variable. The recorded CPP in the current study could represent multiple cognitive processes, or perhaps the transfer of information to consciousness.

Figure 3.1 supports the explanation that recorded CPP in this experiment might represent multiple cognitive processes. It shows a bilateral frontal component during the CPP time-window, which might be relevant to attentional modulation during decision making. During the Congruence and the Value task participants might be shifting their attention back and forth between two products and/or two attributes. This constant attentional shifting might represent a covariate to the decision variable in the recorded CPP waveform and hence might better explain the variance in performance. However, a difficult trial ought to require more attentional shifts as participants would be less certain about colour and/or motion differences and hence it should be correlated with trial difficulty. This appears not to be so as CPP waveforms are not modulated by trial difficulty but are modulated by response time (Figure 3.10).

To summarize, the EEG findings from the current experiment do not provide evidence about the cause of the cognitive limits during the Mapping stage. However, the findings show that the CPP signal appears to represent multiple signals that cannot be easily separated from the EEG data, or alternatively it represents a different cognitive process or processes to that of evidence accumulation found during PDM. The findings cast doubt on the notion that evidence-accumulation models in their current form can be extended easily into the more complex domain of EDM.

# CHAPTER 4: Conclusion

## 4.1 Summary of findings

The aim of this thesis was to experimentally separate and assess the distinctive components of multi-attribute decision making involving trade-off. These decision making components are: the Assessment and Mapping stages. This thesis confirms that trade-off of incommensurable attributes is imprecise and subject to biases. These include: bias towards products with balanced attributes, or against products with extreme attributes. This loss of accuracy originates mostly from the Mapping stage, with the possible exception of a small reduction in precision and a small overall pro-right response bias originating from the Assessment stage. However, the scale of imprecision resulting from mapping incommensurable attributes onto each other is substantial, and is further exacerbated by between-product attribute trade-off.

To put it in perspective, the findings from two experiments shows that participants' precision reduces on average by 40–45% compared to the ideal integration, which is based on the participant's own performance on one-dimensional judgement tasks using the same attributes. Participants find it difficult to compare how much better a product is on one attribute versus how much worse it is on the other attribute. Moreover, when a large between-attribute trade-off is present, the precision reduction is over 70%. Hence, the cognitive ability of comparing incommensurable attributes reduces the further apart from each other these attributes are, as measured in absolute distance of normalized attribute ranges. This is in contrast to the ability to decide which product has a better attribute, which participants can do with relative ease even for two attributes.

The second aim of this thesis was to experimentally-separate the distinctive components of multi-attribute decision making involving trade-off to allow the isolation of the underlying neural signals representing the decision variable during the Assessment and Mapping stages. Previous research hypothesized that the decision variable is represented by CPP (O'Connell et al., 2012), so the aim was to capture CPP during the Congruence and Value tasks. The current study did not produce a key component of the CPP signal (the accumulation of evidence peaking at response) during both experimental conditions, but instead discovered a steep increase early on in the trial, followed by a gradual decrease in activity towards response. This pattern was remarkably similar between the Congruence and Value conditions, highlighting the existence of substantial similarities between the two tasks. Furthermore, the trial difficulty had no significant effect on the CPP pattern.

Two possible explanations were suggested. Firstly, the experiment failed to separate the actual underlying CPPs because the accumulation of evidence during the Congruence and Value tasks is not represented by one CPP, but instead by a series of independent, temporally-overlapping CPPs each corresponding to a different decision within the task. Moreover, as these decisions are temporally separated, the suggestion that judgements of the quality of attributes during the Assessment stage are performed sequentially, and not simultaneously, was made. The second explanation for this pattern is that the recorded CPP represents some additional cognitive processes that are involved during complex decisions (Is this trial congruent? Which product is more valuable?), but are not present during simple perceptual judgements. This finding highlights that current evidence accumulation theories cannot be easily extended to account for more complex EDM.

## 4.2 Generalizing these results to everyday trade-offs

There are a number of potential reasons why decisions involving a trade-off might be performed with better accuracy in the 'real' world. When consumers are trading-off incommensurable attributes, they decide how much of one attribute equals the other one. In other words, consumers decide about the weighing of the attributes because they have subjective tastes. Hence, it is possible that ability to trade-off attributes improves under real life scenarios. However, in the current study the cognitive ability of trading incommensurable attributes was studied under ideal conditions. While participants did not decide about weighing of the attributes, the weights were determined by their own ability to discriminate motion and colour. It was not determined by subjective tastes, but by the performance of their own cognitive system. Moreover, participants received immediate and 100% accurate feedback after each decision, which does not really happen in the real world. Feedback in real world is often delayed and imprecise.

Another limitation of the current study is that it uses purely visual attributes. Moreover, Colour and Motion were not the ideal attributes, as shown by the nonlinearity in colour perception and/or the right hand bias during motion judgement. However, the experiments were designed so that any such effects would have a minimal impact on the Congruence and Value tasks. Such effects would have been captured in the individual analyses of the Colour and Motion conditions, and negated by random selection of the actual colours and motions presented during the Congruence and Value tasks.

A related issue is the possibility that consumers are able to perform a trade-off more accurately with attributes that are numeric and/or categorical, or those that are correlated or perceived with multiple senses. Research by Lunn and colleagues (2016) found a comparable accuracy between perceptual, numeric and categorical attributes with at least three categories. However, they also found improved accuracy when categorical attributes with two categories, or perfectly-correlated perceptual attributes were used. Nevertheless, the improvements were only modest and did not approach the accuracy of ideal integration.

Finally, an argument can be made that the trade-off in the case of important decisions is resolved more accurately. It is possible that when the participants were making decisions during the Congruence-Value task, they did not try hard enough, but it is unlikely as they were incentivized and appeared to be competitive. On the other hand, people could also be better in decisions that they are experienced at making. It is unlikely that the participants would ever trade-off colour-versus-motion in real life. However, many real-world decisions are to be made only a few times during peoples' lives. For example, decisions regarding mortgages, pensions, health insurance cover, or even electricity plans, are not made that often. However, if experience were to improve the accuracy of trade-offs, it would be expected that significant learning effects would have been found in the current study, which was not the case.

## 4.3 Relevance to decision making theories

Experiment 2 found a lack of buildup rate towards response in the CPP signal in both conditions, suggesting that the underlying independent parts of decision making were not perfectly isolated, or additional cognitive processes were involved. Hence, it is unclear whether decision making involving trade-off of incommensurable attributes, which forms the basis for much of EDM, is guided by evidence accumulation implicated in PDM (Usher

& McClelland, 2001; Brown & Heathcote, 2008; Ratcliff & McKoon, 2008). However, the current findings highlight the difficulty in trying to study the basic components of more complex decisions, which might explain why deterministic-static theories have dominated the field of EDM over dynamic, stochastic theories (Busemeyer & Townsend, 1993).

There are, however, a number of implications of the current findings for the models of EDM. The basic tenet of Type 1 theories which assume calculation of internal value is that each option from a choice is independent of other available options. This implies that behaviour is approximated by the optimization of utility functions defined over an unconstrained number of attributes (Von Neumann & Morgenstern, 1944). This contrasts with the current findings of persistent biases, as well as the decreased accuracy during the Mapping stage. A number of Type 1 theories incorporated a stochastic element into their models. For example, *Random utility models* (McFadden, 2005) introduced a valuation error, and the theory of *Rational inattention* (Sims, 2003) models the information-processing constraint explicitly. However, all of these theories still assume that behaviour converges to approximately that of neoclassical predictions. The consistent biases identified here pose a problem as they point to systematic deviations during decision making that are impervious to feedback and learning. Furthermore, the size of the error assumed by these models is substantially smaller than the decrease in precision revealed here. Moreover, Type 1 theories do not account for the effects of between-attribute trade-off, either.

In contrast to Type 1 theories, the current findings do not contradict the existence of the comparative processes suggested by Types 2 and 3 theories in EDM. Type 2 theories (e.g., Tversky & Simonson, 1993; González-Vallejo, 2002) suggest that internal utility is affected by additional comparative process, while Type 3 theories (e.g., Stewart et al., 2006) suggest no utility calculation at all. In fact, a possible explanation of between-attribute trade-off effects on precision in the Mapping stage of multi-attribute decision making can be explained by a comparative process similar to that suggested by Lockhead (2004). For example, the cognitive system could be comparing attribute magnitudes against stored memory examples or prototypes. An efficient system with a limited capacity ought to place more prototypes around the peak of internal distribution of attribute magnitudes, or alternatively, place prototypes near or at magnitudes of recent encounters. Interestingly, the latter suggestion is consistent with sequential effects in the large body of literature on absolute judgements (Laming, 1984). Either way, this leads to increased precision at the centre of the attribute range as there are more prototypes, but to a decreased precision at the tails representing infrequent attribute examples. In other words, such a cognitive system maximizes discriminability where it matters most by trading it off against the discriminability of rare attribute instances. This explanation is valid from an evolutionary perspective. An organism that is more accurate 80% of the time is advantaged against those that are less accurate 100% of the time.

Interestingly, the current study suggests that the accuracy during the Mapping stage translates to discriminability for about 7.5 distinct products. This is very close to Miller's magical number 7±2, which has been implicated in many psychological concepts, such as working memory capacity, absolute judgement, attention span, etc. (Miller, 1956). A coincidence, some might say.

## 4.4 Future direction

The logical follow-up to the current study would incorporate different attributes in the Congruence-Value task to ascertain that the current findings are not the result of using colour and motion discrimination only. Furthermore, categorical and or numeric attributes could be included as well. Numbers could be presented via the means of the moving dot patterns, for example. Such a dot pattern would be made of dots of different colour within each product, minimizing any potential influence of sensory processing on CPP. The main objective for follow-up studies, however, should be to investigate the distinctive components of multi-attribute decision making involving trade-off. Ideally, a clear accumulation of evidence within the CPP signals associated with different parts of decision making can be isolated. This could potentially be achieved via an experimental or analytical route.

An experimental approach would seek to develop a Congruence-Value task that temporally separates individual decisions (e.g., which product is better on Motion and which on Colour) to the extent of capturing independent CPP signals. Moreover, such a task would require that the sequence of the decisions, as they are processed by the cognitive system, is known to the experimenter. Pre-trial triggers signalling response variations could be used. Participants would respond to one attribute first, followed by a response about the congruence of the trial, for example. Alternatively, trials that require response to one attribute only could be randomly presented within the task. The attribute is always the same one within a conditional run and participants would be informed about it. Such trials would be signalled by an auditory trigger after the trial onset but would not be analysed. They would serve as reinforcement for the participant to always evaluate that attribute first. Both of the approaches would hopefully isolate the initial part of the decision making, allowing for comparison of CPP signals between trials where Colour or Motion is assessed first.

The analytical approach could attempt to separate the individual decisions from the EEG signal via blind source separation (BSS) techniques such as Independent Component Analysis, Principal Component Analysis or Maximum Noise Fraction. In particular, these techniques have been useful in extracting the P300 source information from the background noise (Cashero & Anderson, 2011). These techniques, however, present only a small subset of possible approaches. The BSS literature is diverse, including a multitude of different methods whose application might be useful to the current task. For example, Nonnegative Matrix Factorization has been used to identify intra-subject and inter-subject variations in EEG data (Lee, Kim, Cichocki, & Choi, 2007), and a Common Spatial Patterns algorithm has been used to distinguish different classes of EEG signals (Yong, Ward, & Birch, 2008). In addition, a Bayesian statistical approach to BSS could also be explored. However, a main challenge to the analytical approach lies in matching identified signal components with distinctive decisions (e.g., which product is better on Motion and which on Colour) during the task. For this reason a combination of the analytical and experimental approach might be the best option.

To fully address the question of whether people will perform more accurately when making decisions in contexts that are important to them, participants' motivation could be manipulated during the Value stage of the Congruence-Value task. For example, participants could be presented with an unexpected block of trials at the end of the Value stage. They would be encouraged to try hard. They would also be informed that the following trials have no time limit and that if the participant improves their performance in this last block of trials, compared to their previous performance in the Value task, they will win a shopping voucher of a certain value. This manipulation gets around a potential problem whereby the participant considers his performance as being poor in comparison to other participants and hence believes that she has no chance of outperforming the other participants and winning a shopping voucher. This is true because the participants are no longer competing against each other but against their own previous performance.

## 4.5 Policy implications

In recent years more and more policy interventions are being informed by the findings of behavioural economics research. However, the majority of this research focuses on systematic biases people make or heuristics people use with the aim of using such biases and heuristics to increase desirable decision making. The current study uncovered consistent biases, but the biggest impact on decision making involving multi-attribute trade-off comes from the reduction in precision. On the other hand, there have been calls in support of mandatory simplification of products (services) and/or product descriptions (Sunstein, 2011). Given the reduced precision resulting from mapping just two incommensurable attributes, product simplification might not be sufficient to reduce this mapping error, especially when large between-attribute trade-offs are involved. This is especially relevant to products in markets for financial services (e.g., insurance, savings products and mortgages) or contracts for services (energy, internet, mobile services), where large multi-attribute trade-offs need to be resolved. The implication of the current study is that consumers are likely to struggle in such markets.

The use of policy interventions promoting consumer advice or support through promotion, accreditation or provision of 'choice engines' that assist in the trade-off of incommensurable attributes is one possibility to alleviate the effects of between-attribute trade-off. Choice engines such as price comparisons sites, loan and pensions calculators, or user ratings effectively circumvent the need to map incommensurable attributes as they provide users with what is effectively a single-attribute decision. Similarly, the current findings also support the use of 'meta attributes' such as APR on credit products, or total cost over the term of service contracts, as they also reduce decisions to single-attribute comparisons.

Even though there are a number of limitations as discussed above, the evidence presented in this thesis suggests that many of the errors in multi-attribute decision making are the result of the ability of the cognitive system to map incommensurable attributes onto each other. Consequently, there is a large scope for regulatory policy to enhance consumer welfare.

Additionally, it also has the potential to steer the development of EDM theories towards aspects of decision making such as deliberation, attention, conflict and cognitive limitations, as these are largely not addressed in current EDM theories.

## References


Allais, P. M. (1953). Le comportement de l'homme rationnel devant le risque: Critique des postulats et axiomes de l'ecole americaine. *Econometrica*, *21*(4), 503–546.

Ashby, F. G., Alfonso-Reese, L. A, Turken, A. U., & Waldron, E. M. (1998). A neuropsychological theory of multiple systems in category learning. *Psychological Review*, *105*(3), 442–481.

Ashby, F. G., & Maddox, W. T. (1992). Complex decision rules in categorization: Contrasting novice and experienced performance. *Journal of Experimental Psychology: Human Perception and Performance*, *18*(1), 50–71.

Ashby, F. G., & Maddox, W. T. (2005). Human category learning. *Annual Review of Psychology*, *56*(1), 149–178.

Ashby, F. G., Waldron, E. J., Lee, W. W., & Berkman, A. (2001). Suboptimality in human categorization and identification. *Journal of Experimental Psychology. General*, *130*(1), 77–96.

Ashby, F. G., & Waldron, E. M. (1999). On the nature of implicit categorization. *Psychonomic Bulletin & Review*, *6*(3), 363–378.

Atkinson, A. C. (1981). Two graphical displays for outlying and influential observations in regression. *Biometrika*, *68*(1), 13–20.

Barlow, H. (1961). Possible principles underlying the transformation of sensory messages. In W. A. Rosenblith (Ed.), *Sensory communication* (pp. 217–234). MIT Press.

Binder, J. R., Liebenthal, E., Possing, E. T., Medler, D. A, & Ward, B. D. (2004). Neural correlates of sensory and decision processes in auditory object identification. *Nature Neuroscience*, *7*(3), 295–301.

Blavatskyy, P. R. (2007). A stochastic expected utility theory. *Journal of Risk and Uncertainty*, *34*(3), 259–286.

Britten, K. H., Newsome, W. T., Shadlen, M. N., Celebrini, S., & Movshon, J. A. (1996). A relationship between behavioral choice and the visual responses of neurons in macaque MT. *Visual Neuroscience*, *13*(1), 87–100.

Broadbent, D. E. (1958). *Perception and communication*. London: Pergamon.

Brown, R., Durbin, J., & Evans, J. (1975). Techniques for testing the constancy of regression relationships over time. *Journal of the Royal Statistical Society*, *37*(2), 149–192.

Brown, S. D., & Heathcote, A. (2008). The simplest complete model of choice response time: linear ballistic accumulation. *Cognitive Psychology*, *57*(3), 153–78.

Brown, W. R. J., & MacAdam, D. L. (1949). Visual sensitivities to combined chromaticity and luminance differences. *Journal of the Optical Society of America*, *39*(10), 808–834.

Busemeyer, J. R., Byun, E., Delosh, E. L., & McDaniel, M. A. (1997). Learning functional relations based on experience with input-output pairs by humans and artificial neural networks. In K. Lamberts & D. R. Shanks (Eds.), *Knowledge, concepts and categories* (pp. 408–437). The MIT Press.

Busemeyer, J. R., & Townsend, J. T. (1993). Decision field theory: A dynamic-cognitive approach to decision making in an uncertain environment. *Psychological Review*, *100*(3), 432–459.

Carroll, J. (1963). *Functional learning: The learning of continuous functional mappings relating stimulus and response continua.* NJ: Educational Testing Service Princeton.

Cashero, Z., & Anderson, C. (2011). Comparison of EEG blind source separation techniques to improve the classification of P300 trials. In *Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBS* (pp. 7183–7186).

Chernev, A. (2005). Context effects without a context: Attribute balance as a reason for choice. *Journal of Consumer Research*, *32*(2), 213–223.

Cooke, A. D. J., & Mellers, B. A. (1998). Multiattribute judgment: Attribute spacing influences single attributes. *Journal of Experimental Psychology: Human Perception and Performance*, *24*(2), 496–504.

Cowan, N. (2001). The magical number 4 in short-term memory: A reconsideration of mental storage capacity. *The Behavioral and Brain Sciences*, *24*(1), 87-114.

Curran, T. (2004). Effects of attention and confidence on the hypothesized ERP correlates of recollection and familiarity. *Neuropsychologia*, *42*(8), 1088–1106.

de Lange, F. P., Rahnev, D. A., Donner, T. H., & Lau, H. (2013). Prestimulus oscillatory activity over motor cortex reflects perceptual expectations. *Journal of Neuroscience*, *33*(4), 1400–1410.

Delorme, A., & Makeig, S. (2004). EEGLAB: An open source toolbox for analysis of single-trial EEG dynamics including independent component analysis. *Journal of Neuroscience Methods*, *134*(1), 9–21.

Delosh, E. L., Busemeyer, J. R., & Mcdaniel, M. A. (1997). Extrapolation: The sine qua non for abstraction in function learning. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *23*(4), 968–986.

Donner, T. H., Siegel, M., Fries, P., & Engel, A. K. (2009). Buildup of choice-predictive activity in human motor cortex during perceptual decision making. *Current Biology, 19*(18), 1581–1585.

Eriksen, C. W., & St James, J. D. (1986). Visual attention within and around the field of focal attention: a zoom lens model. *Perception & Psychophysics*, *40*(4), 225–240.

Fehr, E., & Schmidt, K. (1999). A theory of fairness, competition and cooperation. *Quarterly Journal of Economics, 114*(3), 817–868.

Gold, J. I., & Shadlen, M. N. (2007). The neural basis of decision making. *Annual Review of Neuroscience*, *30*, 535–574.

Goldstein, D. G., & Gigerenzer, G. (2002). Models of Ecological Rationality: The Recognition Heuristic. *Psychological Review*, *109*(1), 75–90.

González-Vallejo, C. (2002). Making trade-offs: A probabilistic and context-sensitive model of choice behavior. *Psychological Review*, *109*(1), 137–155.

Gravetter, F., & Lockhead, G. R. (1973). Criterial range as a frame of reference for stimulus judgment. *Psychological Review*, *80*(3), 203–216.

Hammond, K. R., & Summers, D. A. (1972). Cognitive control. *Psychological Review*, *79*(1), 58–67.

Heekeren, H. R., Marrett, S., Bandettini, P. A, & Ungerleider, L. G. (2004). A general mechanism for perceptual decision-making in the human brain. *Nature*, *431*(7010), 859–862.

Heuer, H. W., & Britten, K. H. (2004). Optic flow signals in extrastriate area MST: Comparison of perceptual and neuronal sensitivity. *Journal of Neurophysiology*, *91*(3), 1314–1326.

Hillyard, S., Squires, K., Bauer, J., & Lindsay, P. (1971). Evoked potential correlates of auditory signal detection. *Science*, *172*(990), 1357–1360.

Ho, T. C., Brown, S., & Serences, J. T. (2009). Domain general mechanisms of perceptual decision making in human cortex. *The Journal of Neuroscience, 29*(27), 8675–8687.

Hsee, C. K., Hsee, C. K., Rottenstreich, Y., Rottenstreich, Y., Xiao, Z., & Xiao, Z. (2005). When is more better? *Society*, *14*(5), 234–238.

Hsee, C. K., & Rottenstreich, Y. (2004). Music, pandas, and muggers: On the affective psychology of value. *Journal of Experimental Psychology*, *133*(1), 23–30.

Huk, A. C., & Shadlen, M. N. (2005). Neural activity in macaque parietal cortex reflects temporal integration of visual motion signals during perceptual decision making. *The Journal of Neuroscience*, *25*(45), 10420–10436.

Ishihara, S. (1917). *Tests for color-blindness*. Tokyo: Hongo Harukicho.

Johnson, D. M. (1939). *Confidence and speed in the two-category judgment*. New York: Columbia University.

Kahneman, D., & Tversky, A. (1979). Kahneman & Tversky (1979). Prospect Theory: An analysis of decision under risk. *Econometrica*, *47*(2), 263–292.

Kayser, J., & Tenke, C. E. (2006). Principal components analysis of Laplacian waveforms as a generic method for identifying ERP generator patterns: II. Adequacy of low-density estimates. *Clinical Neurophysiology*, *117*(2), 369–380.

Kelly, S., & O'Connell, R. (2014). The neural processes underlying perceptual decision making in humans: Recent progress and future directions. *Journal of Physiology-Paris*, *109*(1–3), 27–37.

Kelly, S. P., & O'Connell, R. G. (2013). Internal and external influences on the rate of sensory evidence accumulation in the human brain. *J Neurosci.*, *33*(50), 19434–19441.

Klayman, J. (1988). On the how and why (not) of learning from outcomes. In *Human judgment: The SJT view*. *Advances in psychology*, *54*. (pp. 115–162).

Koh, K. (1993). Induction of combination rules in two-dimensional function learning. *Memory & Cognition*, *21*(5), 573–590.

Koh, K., & Meyer, D. E. (1991). Function learning: Induction of continuous stimulus-response relations. *Journal of Experimental Psychology. Learning, Memory, and Cognition*, *17*(5), 811–836.

Kok, A. (2001). On the utility of P3 amplitude as a measure of processing capacity. *Psychophysiology*, *38*(3), 557–577.

Laming, D. (1984). The relativity of "absolute" judgements. *British Journal of Mathematical and Statistical Psychology*, *37*(2), 152–183.

Laming, D. R. J. (1997). *The measurement of sensation*. Oxford University Press.

Lau, B., & Glimcher, P. W. (2008). Value representations in the primate striatum during matching behavior. *Neuron*, *58*(3), 451–63.

Lee, H., Kim, Y. D., Cichocki, A., & Choi, S. (2007). Nonnegative tensor factorization for continuous EEG classification. *International Journal of Neural Systems*, *17*(4), 305–317.

Liu, T., & Pleskac, T. J. (2011). Neural correlates of evidence accumulation in a perceptual decision task. *Journal of Neurophysiology*, *106*(5), 2383–2398.

Lockhead, G. R. (2004). Absolute judgments are relative: A reinterpretation of some psychophysical ideas. *Review of General Psychology*, *8*(4), 265–272.

Lunn, P., Bohacek, M., Somerville, J., Ní Choisdealbha, Á., & McGowan, F. (2016). *Price*

*Lab: An investigation of consumers' capabilities with complex products*. Dublin.

Maddox, W. T., & Ashby, F. G. (1993). Comparing decision bound and exemplar models of categorization. *Perception & Psychophysics*, *53*(1), 49–70.

Marr, D. (1982). *Vision: A computational investigation into the human representation and processing of visual information.* New York: Freeman.

Matthews, W. J., & Stewart, N. (2009). Psychophysics and the judgment of price : Judging complex objects on a non-physical dimension elicits sequential effects like those in perceptual tasks. *Judgement and Decision Making*, *4*(1), 64–81.

McDaniel, M. A., Dimperio, E., Griego, J. A., & Busemeyer, J. R. (2009). Predicting transfer performance: A comparison of competing function learning models. *Journal of Experimental Psychology. Learning, Memory, and Cognition*, *35*(1), 173–195.

McFadden, D. (2005). Revealed stochastic preference: A synthesis. *Economic Theory, 26*(2), 245–264.

Meyvis, T., & Janiszewski, C. (2002). Consumers' beliefs about product benefits: The effect of obviously irrelevant product information. *Journal of Consumer Research, 28*(4), 618–635.

Miller, G. (1956). The magical number seven, plus or minus two: some limits on our capacity for processing information. *Psychological Review*, *101*(2), 343–352.

Milosavljevic, M., Malmaud, J., & Huth, A. (2010). The Drift Diffusion Model can account for the accuracy and reaction time of value-based choices under high and low time pressure. *Judgment and Decision Making 5*(6), 437–449.

Moscatelli, A., Mezzetti, M., & Lacquaniti, F. (2012). Modeling psychophysical data at the population-level: The generalized linear mixed model. *Journal of Vision*, *12*(11), 26.

Murakami, I., & Shimojo, S. (1996). Assimilatin-type and contrast-type bias of motion induced by the surrond in a random-dot display: Evidence for ceter-surround antagonism. *Vision Research*, *36*(22), 3629–3639.

Nosofsky, R. M. (1986). Attention ,similarity, and the identification-categorization relationship. *Journal of Experimental Psychology*, *115*(1), 39–57.

O'Connell, R. G., Dockree, P. M., & Kelly, S. P. (2012). A supramodal accumulation-to-bound signal that determines perceptual decisions in humans. *Nature Neuroscience*, *15*(12).

Orban, G. A., Vandenbussche, E., & Vogels, R. (1984). Human orientation discrimination tested with long stimuli. *Vision Research*, *24*(2), 121–128.

Padoa-Schioppa, C., & Assad, J. A. (2006). Neurons in the orbitofrontal cortex encode economic value. *Nature*, *441*(7090), 223–226.

Padoa-Schioppa, C., & Assad, J. A. (2008). The representation of economic value in the orbitofrontal cortex is invariant for changes of menu. *Nature Neuroscience*, *11*(1), 95–102.

Parducci, A. (1965). Category judgment: A range-frequency model. *Psychological Review*, *72*(6), 407–418.

Pashler, H. (1994). Dual-task interference in simple tasks: Data and theory. *Psychological Bulletin*, *116*(2), 220–244.

Pleger, B., Ruff, C. C., Blankenburg, F., Bestmann, S., Wiech, K., Stephan, K. E., … Dolan, R. J. (2006). Neural coding of tactile decisions in the human prefrontal cortex. *The Journal of Neuroscience*, *26*(48), 12596–12601.

Polich, J. (2007). Updating P300: An integrative theory of P3a and P3b. *Clinical Neurophysiology*, *118*(10), 2128–2148.

Pollack, I. (1954). Information of elementary multidimensional auditory displays. *The Journal of the Acoustical Society of America*, *26*(1), 155–158.

Ramachandran, V. S. (1987). Interaction between colour and motion in human vision. *Nature*, *328*(6131), 645–647.

Ratcliff, R. (1978). A theory of memory retrieval. *Psychological Review*, *85*(2), 59–108.

Ratcliff, R., & McKoon, G. (2008). The diffusion decision model: Theory and data for two-choice decision tasks. *Neural Computation*, *20*(4), 873–922.

Riskey, D. R., Parducci, A., & Beauchamp, G. K. (1979). Effects of context in judgments of sweetness and pleasantness. *Perception & Psychophysics*, *26*(3), 171–176.

Ritter, W., Simson, R., & Vaughan, H. G. (1972). Association cortex potentials and reaction time in auditory discrimination. *Electroencephalography and Clinical Neurophysiology*, *33*(6), 547–555.

Roe, R., Busemeyer, J., & Townsend, J. (2001). Multialternative decision field theory: A dynamic connectionst model of decision making. *Psychological Review*, *108*(2), 370–92.

Roitman, J. D., & Shadlen, M. N. (2002). Response of neurons in the lateral intraparietal area during a combined visual discrimination reaction time task. *The Journal of Neuroscience : The Official Journal of the Society for Neuroscience*, *22*(21), 9475–9489.

Romo, R., Hernández, A., Zainos, A., & Salinas, E. (1998). Somatosensory discrimination based on cortical microstimulation. *Nature*, *392*(6674), 387–390.

Royston, P. (1992). Approximating the Shapiro-Wilk W-test for non-normality. *Statistics and Computing*, *2*(3), 117–119.

Rubichi, S., & Nicoleti, R. (2006). The Simon effect and handedness: Evidence for a dominant-hand attentional bias in spatial coding. *Perception & Psychophysics*, *68*(7), 1059–1069.

Salinas, E., Hernandez, A., Zainos, A., & Romo, R. (2000). Periodicity and firing rate as candidate neural codes for the frequency of vibrotactile stimuli. *The Journal of Neuroscience : The Official Journal of the Society for Neuroscience*, *20*(14), 5503–5515.

Salzman, C. D., Britten, K. H., & Newsome, W. T. (1990). Cortical microstimulation influences perceptual judgements of motion direction. *Nature*, *346*(6280), 174–177.

Samejima, K., Ueda, Y., Doya, K., & Kimura, M. (2005). Representation of action-specific reward values in the striatum. *Science*, *310*(5752), 1337–1340.

Schkade, D. A., & Kahneman, D. (1998). Does living in california make people happy? A focusing illusion in judgments of life satisfaction. *Psychological Science*, *9*(5), 340–346.

Serences, J. T., & Boynton, G. M. (2007). The representation of behavioral choice for motion in human visual cortex. *The Journal of Neuroscience*, *27*(47), 12893–12899.

Simonson, I. (1989). Choice based on reasons: The case of attraction and compromise effects. *Journal of Consumer Research*, *16*(2), 158–174.

Simonson, I., & Tversky, A. (1992). Choice in context: Tradeoff contrast and extremeness aversion. *Journal of Marketing Research*, *29*(3), 281–295.

Sims, C. A. (2003). Implications of rational inattention. *Journal of Monetary Economics*, *50*(3), 665–690.

Smith, J. D., & Minda, J. P. (1998). Prototypes in the mist: The early epochs of category learning. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *24*(6), 1411–1436.

Soltani, M., & Knight, R. T. (2000). Neural origins of the P300. *Critical Reviews in Neurobiology*, *14*(3–4), 199–224.

Stevens, S. S. (1957). On the psychophysical law. *Psychological Review*, *64*(3), 153–181.

Stewart, N., Chater, N., & Brown, G. D. A. (2006). Decision by sampling. *Cognitive Psychology*, *53*(1), 1–26.

Stewart, N., Chater, N., Stott, H. P., & Reimers, S. (2003). Prospect relativity: How choice options influence decision under risk. *Journal of Experimental Psychology. General*, *132*(1), 23–46.

Summerfield, C., & Tsetsos, K. (2012). Building bridges between perceptual and economic decision-making: Neural and computational mechanisms. *Frontiers in Neuroscience*, *6*(70), 1–20.

Sunstein, C. R. (2011). Empirically informed regulation. *University of Chicago Law Review*, *78(4)*, 1349–1429.

Sutton, S., Braren, M., Zubin, J., & John, E. R. (1965). Evoked-potential correlates of stimulus uncertainty. *Science*, *150*(700), 1187–1188.

Teghtsoonian, M., & Teghtsoonian, R. (1971). How repeatable are Stevens's power law exponents for individual subjects? *Perception & Psychophysics*, *10*(3), 147–149.

Thurstone, L. L. (1927). A law of comparative judgment. *Psychological Review*, *34*(1), 273–286.

Todd, J. J., & Marois, R. (2004). Capacity limit of visual short-term memory in human posterior parietal cortex. *Nature*, *428*(6984), 751–754.

Townsend, J. T., & Ashby, F. G. (1983). *Stochastic modeling of elementary psychological processes.* New York : Cambridge University Press.

Trueblood, J. S., Brown, S. D., Heathcote, A., & Busemeyer, J. R. (2013). Not just for consumers: Context effects are fundamental to decision making. *Psychological Science*, *24*(6), 901–908.

Tversky, A. (1969). Intransitivity of preferences. *Psychological Review*, *76*(1), 31–48.

Tversky, A., & Kahneman, D. (1974). Judgment under uncertainty: Heuristics and biases. *Science*, *185*(4157), 1124–1131.

Tversky, A., & Kahneman, D. (1992). Advances in prospect theory: Cumulative representation of uncertainty. *Journal of Risk and Uncertainty*, *5*(4), 297–323.

Tversky, A., & Simonson, I. (1993). Context-dependent preferences. *Management Science*, *39*(10), 1179–1189.

Tversky, A., Slovic, P., & Kahneman, D. (1990). The causes of preference reversal. *The American Economic Review*, *80*(1), 204–217.

Twomey, D. M., Kelly, S. P., & O'Connell, R. G. (2016). Abstract and effector-selective decision signals exhibit qualitatively distinct dynamics before delayed perceptual reports. *Journal of Neuroscience*, *36*(28), 7346–7352.

Ungemach, C., Stewart, N., & Reimers, S. (2011). How incidental values from the environment affect decisions about money, risk, and delay. *Psychological Science*, *22*(2), 253–260.

Usher, M., & McClelland, J. L. (2001). The time course of perceptual choice: The leaky, competing accumulator model. *Psychological Review*, *108*(3), 550–592.

Verrillo, R. T. (1983). Stability of line-length estimates using the method of absolute magnitude estimation. *Perception & Psychophysics*, *33*(3), 261–265.

Vlaev, I., Chater, N., Stewart, N., & Brown, G. D. A. (2011). Does the brain calculate value? *Trends in Cognitive Sciences*, *15*(11), 546–54.

Von Neumann, J., & Morgenstern, O. (1944). *Theory of games and economic behavior*. Princeton: Princeton University Press.

Wagenmakers, E. (2007). An EZ-diffusion model for response time and accuracy. *Psychonomic Bulletin & Review*, *14*(1), 3–22.

Wald, A. (1947). *Sequential analysis*. New York: Wiley.

Wallach, H. (1948). Brightness constancy and the nature of achromatic colors. *Journal of Experimental Psychology*, *38*(3), 310–324.

Wang, X. (2002). Probabilistic decision making by slow reverberation in cortical circuits. *Neuron*, *36*(5), 955–968.

Weaver, K., Garcia, S. M., & Schwarz, N. (2012). The presenter's paradox. *Journal of Consumer Research*, *39*(3), 445–460.

Welch, B. L. (1951). On the comparison of several mean values: An alternative approach. *Biometrika*, *38*(3/4), 330–336.

Yong, X., Ward, R. K., & Birch, G. E. (2008). Robust common spatial patterns for EEG signal preprocessing. In *Conference proceedings: Annual International Conference of the IEEE Engineering in Medicine and Biology Society. IEEE Engineering in Medicine and Biology Society. Conference* (pp. 2087–2090).

# Appendix

**<u>Consent form:</u>**

TRINITY COLLEGE
Institute of Neuroscience
TCIN *from molecules to mind*

**Consent Form**

*''Investigating dynamics of perceptual and economic based decision-making''*

I, the undersigned, give my informed consent to participate in the study ''Investigating dynamics of perceptual and economic based decision-making'' conducted in the Trinity College Institute of Neuroscience, Trinity College Dublin.

Participant ID: ______________________________

Full Name: ______________________________

Signed: ______________________________

Email: ______________________________

Date: ______________________________

Researcher: Marek Bohacek

**Demographics questionnaire:**

TRINITY COLLEGE
Institute of Neuroscience
TCIN *from molecules to mind*

**Participant ID:** ________

Please do not write your name on this form. It will be stored separately from any other information that you complete during this study. The information will allow us to provide an accurate description of the sample.

For the following items, please select the *one* response that is most descriptive of you or fill in the blank as appropriate.

| | | | | | |
|---|---|---|---|---|---|
| Gender: | female ☐ | male ☐ | | | |
| Age: | 18-21 ☐ | 22-25 ☐ | 26-30 ☐ | 31-35 ☐ | over 35 ☐ |
| Handedness: | Right handed ☐ | Left handed ☐ | | | |

Many thanks again for your participation in this experiment.

**Information sheet:**

TRINITY COLLEGE
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## Information Sheet

*''Investigating dynamics of perceptual and economic based decision-making"*

**Research Team**: Dr. Redmond O'Connell & Mr. Marek Bohacek

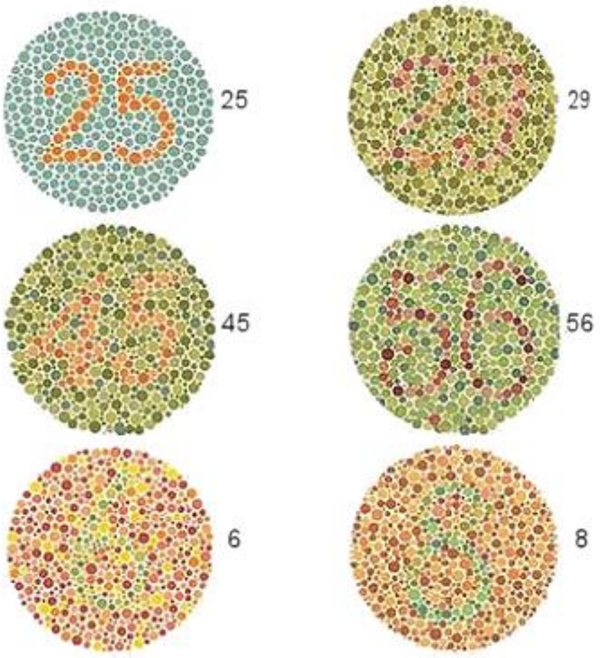
**What is the project?**

We would like to invite you to take part in a study that investigates the dynamics of perceptual and economic based decision-making and the neural processes that underlie them. While perceptual decision making has been investigated with rigorous psychophysical methods allowing assessment of accuracy of the decisions, research on the economic decision making has mostly focused on biases and, or, heuristics people use. This is partly due to the subjective nature of the economic based decision making. The present study aims to explore this gap in the literature by using psychophysical approach to study economic based decision making, hence allowing for direct comparison between the two. This is an important question to address, not only for the insights it will offer about how the brain works, but it can also provide us with a far better understanding of how consumers decide about which product to buy and about their strengths and weaknesses associated with the decision process, which has potential implications to policy. The study involves four tasks over two separate sessions (2 tasks in each session) using computerised test of perceptual and economic decision-making. All tasks require you to monitor two semicircles joined along their vertical axes, each containing dots moving in different direction and of different colour. In session 1, your job is to judge either which semicircle has greener dots (task 1) or dots of greater upward motion (task 2). In session 2 your job is to combine the information about the colour and the motion, and decide which semicircular aperture has a greater (greener; more upward motion) combination of the two (task 3) or to judge both colour and motion and decide whether one of the semicircular aperture is better on both the colour and motion (task 4). You will receive feedback about your performance at the end of each trial. Each testing session will take approximately an hour to complete. The best performer from 20 participants will win a 50 Euro shopping voucher (One4all voucher).

**Inclusion criteria**

There are no risks associated with any of the procedures in neurologically healthy individuals. However in order to take part in the study you must meet the following criteria:

1 No personal or family history of epilepsy
2 No personal or family history of unexplained fainting
3 No sensitivity to flickering light
4 No personal history of neurological or psychiatric illness or brain injury
5 No personal history of colour vision deficiency
6 Being able to see indicated numbers (not other numbers!) in the colour dot circles:




**What are my rights if I join the study?**

Participation in the study is entirely voluntary and if you agree to participate you have the following rights:

1 The personal information collected from you during the study will be kept strictly confidential and will not be made available to any other people.

2 All other data collected from you during the study will be anonymous (containing unique experiment ID only) and will not contain any personal information.

3 We will aim to publish our results in scientific journals but any information we have will be completely anonymous and presented as a group.

4 As participation is completely voluntary, you are free to withdraw from the study at any time. You are also free to withdraw your data at the conclusion of your participation should you so wish.

5 Under the Freedom of Information Act you can have access to any information we store about you, if requested.

**Contact Details**

If you have any further questions about this study please do not hesitate to contact a member of the research team:

**Dr. Redmond O'Connell**
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**Debriefing form:**

TRINITY COLLEGE
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## Debriefing Form

*''Investigating dynamics of perceptual and economic based decision-making"*

Dear Participant,

Thank you for taking part in this study investigating dynamics of perceptual and economic based decision-making and the neural processes that underlie them. A considerable body of research has investigated economic based decision-making but most of it has focused on biases that people consistently display and or heuristics that they deploy. However, very little is understood about the accuracy with which people make those decisions which is down to subjectivity of our tastes as it is difficult to assess quality of a subjective choice. In contrary, accuracy of perceptual based decision making has been studied in great detail but most of it has focused on basic decisions employing uni-dimensional stimuli, which is in contrary to most economic based decisions where information from multiple sources has to be integrated. An everyday example of such a decision is when a person is comparing two products each having multiple attributes that one cares about, in order to decide which of the two products is a better buy. For those reasons, the task used in this experiment employed psychophysical methods used in study of perceptual decisions combined with multidimensional stimuli (colour + motion). The aim is to examine how decisions such as economic based ones requiring integration of information (the second part of the experiment) compare to more simple perceptual ones (the first part of the experiment) while removing the subjectivity out of the decision. This is an important question to address as it will provide insight into the workings of brain as well as better understanding about the type of economic based decisions consumers struggle with, which has direct implications to policy.

Using a recently developed EEG paradigm (O'Connell et al., 2012) we are able to isolate electrical signals that reflect the three key information-processing stages involved in making a perceptual and an economic based decisions. Those stages include the encoding sensory evidence, forming a decision and preparing a motor response. In this study we examine how these stages differ across the two parts of the task, that is, between perceptual and economic decisions. The aim is to isolate the key component of the information integration, as information integration is only required during economic decision making.

If you have any questions about the study please contact a member of the research team. We would like to remind you that your data will remain confidential and that you are free to withdraw from the study at any point in time.

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## References

O'Connell, R. G., Dockree, P. M., & Kelly, S. P. (2012). A supramodal accumulation-to-bound signal that determines perceptual decisions in humans. *Nature Neuroscience, 15*(12), 1729 – 1735.