

A biomechanical analysis of cyclist collisions in Ireland

by

Kevin Gildea

BAI, MAI

Dissertation

Presented to the University of Dublin, Trinity College

in fulfillment of the requirements for the Degree of

Doctor of Philosophy

University of Dublin, Trinity College

March 2023

Declaration

I, the undersigned, declare that this work has not previously been submitted as an exercise for a degree at this, or any other University, and that unless otherwise stated, is my own work.

I, the undersigned, 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.

I consent / do not consent to the examiner retaining a copy of the thesis beyond the examining period, should they so wish (EU GDPR May 2018).

Kevin Gildea

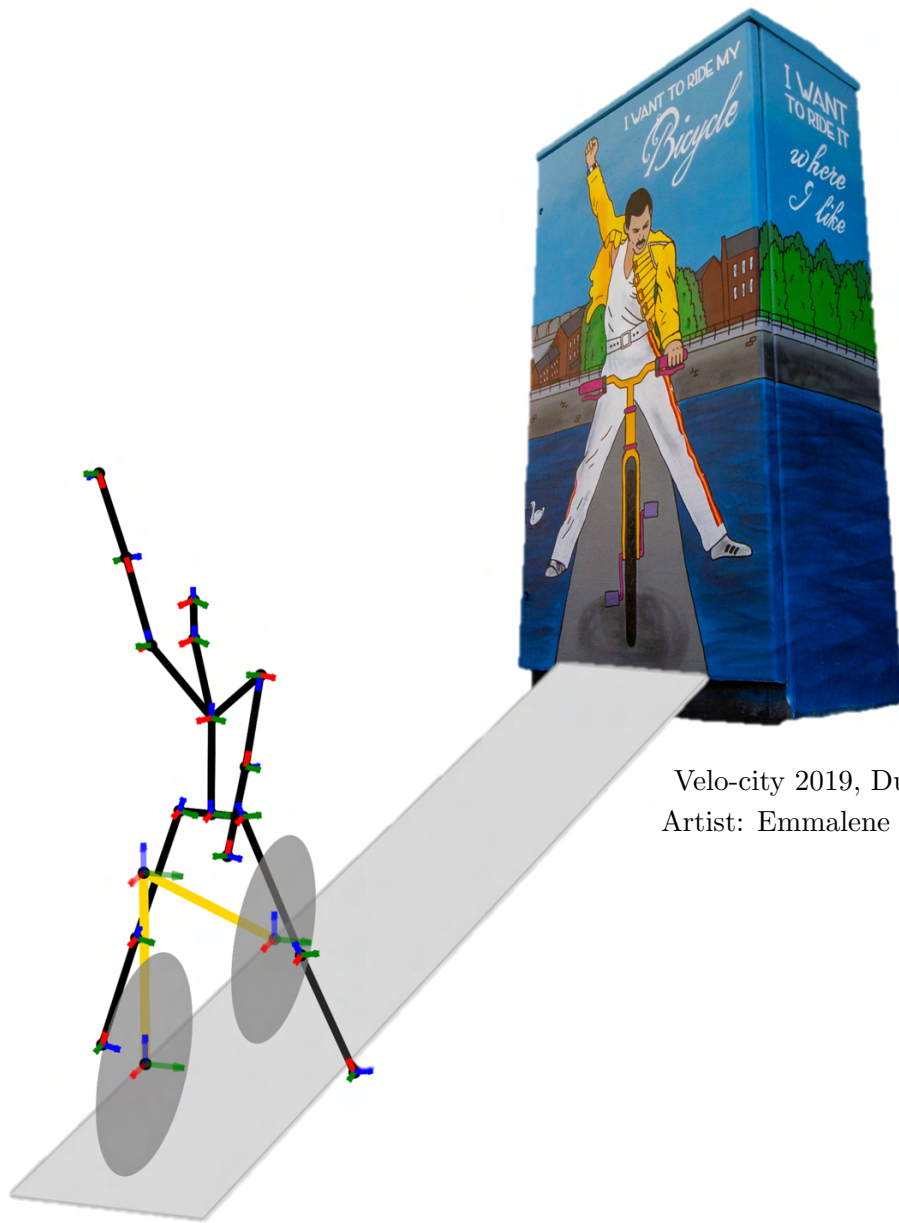
March 14, 2023

Permission to Lend and/or Copy

I, the undersigned, agree that Trinity College Library may lend or copy this thesis upon request.

Kevin Gildea

March 14, 2023



Velo-city 2019, Dublin
Artist: Emmalene Blake

“The first real grip I ever got on things
 Was when I learned the art of pedaling
 (By hand) a bike turned upside down, and drove
 Its back wheel preternaturally fast.”

Seamus Heaney – Wheels Within Wheels

“And the sun set merciless
 And every merciful
 Register inside us yearned
 To run the film back,
 For you to step into the road
 Wheeling your bright-rimmed bike,
 Safe and sound as usual,
 Across, then down the lane,
 The twisted spokes all straightened out,
 The awful skid-marks gone
 But no.”

Seamus Heaney - The Summer of Lost Rachel

Abstract

As both a mode of transport and recreational activity, cycling has well-known health, environmental, and economic benefits. For these reasons, it has been encouraged in many countries, including the Republic of Ireland. However, with increasing popularity, there have been concurrent increases in road traffic-related cyclist injuries. This project aims to characterise cyclist collisions, which are known to be underreported in police statistics, and develop tools to inform engineering interventions.

For data collection, a survey addressing collisions was distributed to cyclists across the country in 2018. Police investigation files were also analysed for a sample of fatal and serious cyclist collisions in Ireland to supplement the analysis with further details specific to these more severe cases. Logistic regression modelling was used to clarify biasing factors for police reporting for collisions, and taxonomy schemes were developed for cyclist-motorised vehicle and single cyclist collisions to ascertain the distribution of pre-crash manoeuvres, and resulting impact configurations.

Findings from chapter 3 indicate that the largest proportion of collisions was between cyclists and motorised vehicles (56%), followed by single cyclist collisions (29%), collisions with other cyclists (8%), and pedestrians (7%). The odds of police reporting for collisions with motorised vehicles was 20 times greater than single cyclist collisions, 10 times greater than cyclist-cyclist collisions, and 4 times greater than collisions with pedestrians. The odds of police reporting for serious injury collisions was 7 times greater than minor injury collisions. Furthermore, findings from chapter 4 highlights the relative importance of collisions resulting from the cyclist and vehicle travelling in the same direction, specifically, nearside-

hook, vehicle lane changing, and overtaking manoeuvres are emphasised. Furthermore, cases involving the cyclist being struck from the side by vehicle fronts comprise a smaller share than in previous studies. Specifically, side to side impacts, impacts between the front of the cyclist/bicycle and the side of the vehicle, and impacts with open(ing) doors emerge as important impact configurations with the inclusion of self-reported cases. For single cyclist collisions, the importance of loss of traction of the tires due to slippery road conditions and interactions with tram tracks and kerbs are emphasised. In chapter 5 a number of common scenarios have been identified for fatal and serious cases from police investigation files. In particular, this study highlights the prevalence of left/nearside-turning Heavy Goods Vehicles (HGVs) at junctions in urban environments, and overtaking manoeuvres from bonnet-type vehicles in rural environments. Furthermore, findings indicate that single cyclist collisions are common. Future safety interventions should aim to address these collision types.

Single cyclist collisions are common and underreported in official statistics (chapters 3, and 4). Internationally in urban environments, light rail tram tracks are a frequent factor in these cases, however, they have not yet been the subject of engineering analysis. The prevalence of traffic camera footage in urban environments presents an opportunity for detailed site-specific safety insights. Therefore in chapter 6 a video-based analysis is presented with an investigation into the frequency and risk of unsuccessful crossings on tram tracks in wet road conditions at 9 locations around Dublin city centre. A predictive model for crossing success is also devised as a function of crossing angle for use in a Surrogate Measure of Safety (SMoS) framework. Modelling results show that crossing angle is a strong predictor of crossing success, and that cyclist velocity is not. Findings indicate that infrastructural planners should design for cyclist crossing angles of 30° or greater. The prevalence of external factors which limit crossing angles for cyclists are highlighted. In particular, kerbs are a common factor, along with passing/approaching vehicles or other cyclists. Furthermore, a new SMoS for cyclist interactions with tram tracks is introduced, and its utility is demonstrated through an open-source application (SafeCross).

Findings from chapters 3, and 4 indicate that single cyclist falls are common. Furthermore, self-reported injury patterns in chapter 4 suggest that protective movements of falling

cyclists may influence kinematics and dynamics. However, previous computational modelling attempts have not considered kinematic or dynamic components of protective response in single cyclist falls. Novel computer vision/deep learning-based 3D human pose estimation methods localise human joints from images and videos. Pose representation is normally limited to 3D joint positional/translational degrees of freedom (3DOFs), however, an additional three rotational DOFs (6DOFs) are required for many potential biomechanical applications. Positional DOFs are insufficient to analytically solve for joint rotational DOFs in a 3D human skeletal model.

Therefore, in chapter 7 a temporal inverse kinematics (IK) optimisation technique is proposed to infer joint orientations throughout a biomechanically informed, and subject-specific kinematic chain. For this, link directions from a position-based 3D pose estimate are prescribed. Sequential least squares quadratic programming is used to solve a minimisation problem that involves both frame-based pose terms, and a temporal term. With this, in chapter 8 a novel pipeline is presented for reconstruction of falls from monocular footage. The IK algorithm is adapted for use with the MADYMO (MAtheMatical DYnamic MOdels) ellipsoid computational human body model, to initialise a model using 3D human kinematics obtained using a deep learning-based 3D human pose estimator. The method is applied to a case study of a sideways falling cyclist after an unsuccessful crossing of railway tracks. Findings from this study indicate that initialised pose and velocity significantly influence resulting kinematics, and that the limbs are used to prevent falls, or break falls by absorbing impact energy and protecting the head. This approach can be applied to a variety of impact biomechanics tasks not limited to cyclist falls.

Acknowledgments

Road safety concerns are felt most profoundly by those who have been directly affected, i.e., the victims of road traffic collisions, and their families. Therefore, first and foremost, this thesis is dedicated to the many victims of road traffic collisions in Ireland and abroad - I hope this work contributes in some way towards road safety improvements.

Many thanks to the Irish Road Safety Authority, which funded this research as part of the RSA-Helena Winters scholarship for studies in road safety. I would like to express my sincere gratitude to Aoife, Velma, and Sharon of the research department for their invaluable advice and guidance throughout the project.

I would like to extend my sincere thanks to the Garda National Roads Policing Bureau and Dublin City Council for data provision, and for facilitating this work. Their assistance has been invaluable, and I greatly appreciate their contribution.

I would like to give special recognition to my supervisor Ciaran Simms for his help and advice through all the ups and downs. The time and effort you put into teaching and student mentorship are phenomenal, and it has been a pleasure to work with you on this project over the past few years.

I pay tribute to my fellow postgrads on the 5th floor of the Parsons who fought alongside me in the trenches - you've been a source of reassurance, and I've had a great time with you all. I would also like to thank Eeyore for your company and entertainment during the work-from-home era.

Sincere thanks to my loving and supportive family. In particular, I thank my parents, David and Patricia, for their support and guidance over the years. Your hard work and conscientiousness have been an inspiration to me, and none of this would have been possible without you.

Finally, I would also like to dedicate this thesis to Deirdre. Your unwavering support and encouragement have been a vital source of strength for me throughout this journey, and I consider myself extremely fortunate to have you by my side.

KEVIN GILDEA

University of Dublin, Trinity College

March 2023

List of Publications

This thesis is based on the following peer-reviewed publications:

- KinePose: A temporally optimized inverse kinematics technique for 6DOF human pose estimation with biomechanical constraints,
K. Gildea, C. Mercadal-Baudart, R. Blythman, A. Smolic, C. Simms,
Irish Machine Vision & Image Processing Conference (IMVIP) (2022)
- Video-based assessment of cyclist-tram track interactions in wet road conditions,
K. Gildea, C. Mercadal-Baudart, B. Caulfield, C. Simms,
International Cycling Safety Conference (ICSC) (2022)
- Towards computational modelling of active response in cyclist falls from in-the-wild footage,
K. Gildea, C. Simms,
Congress of the European Society of Biomechanics (ESB) (2022)
- Temporally optimized inverse kinematics for 6DOF human pose estimation,
K. Gildea, C. Mercadal-Baudart, R. Blythman, C. Simms,
Congress of the European Society of Biomechanics (ESB) (2022)
- Characteristics of fatal and serious cyclist collisions in Ireland: Analysis of police investigation files,
K. Gildea, A. Kervick, C. Simms,
International Research Council on Biomechanics of Injury Europe (IRCOBI Europe) (2022)
- Configurations of underreported cyclist-motorised vehicle and single cyclist collisions: Analysis of a self-reported survey,
K. Gildea, D. Hall, C. Simms,
Accident Analysis & Prevention (2021)
- Characteristics of cyclist collisions in Ireland: Analysis of a self-reported survey,
K. Gildea, C. Simms,
Accident Analysis & Prevention (2021)

Other relevant publications:

- An investigation into the effects of European vehicle type testing regulations on cyclist injury occurrence,
G. Li, **K. Gildea**, M. Wisch, O. Zander, C. Simms,
International Research Council on Biomechanics of Injury Asia (IRCOBI Asia) (2020)
- Cycling related major trauma in Ireland,
J. Foley, M. Cronin, L. Brent, T. Lawrence, C. Simms, **K. Gildea**, J. Ryan, C. Deasy, J. Cronin,
Injury (2019)

Contents

Abstract	vi
Acknowledgments	ix
List of Publications	xi
List of Tables	xxi
List of Figures	xxv
List of Abbreviations	xxxiii
Chapter 1 Introduction	1
1.1 Background	1
1.2 Thesis approach, & layout	3
Chapter 2 Literature review	6
2.1 National cycling policy	7
2.2 Vision Zero & the Safe System approach	8
2.3 Safety trends	11
2.4 Road traffic collision data sources	14

2.4.1	Traditional data sources, & underreporting	14
2.4.2	Self-reporting	15
2.4.3	Police investigation files	16
2.4.4	Surrogate measures of safety, & video-based approaches	16
2.5	Computational models for traumatic injury biomechanics	20
2.6	Cyclist collisions with motorised vehicles	24
2.6.1	Common pre-crash scenarios, & impact configurations	24
2.6.2	Impacts with bonnet-type vehicles	27
2.6.3	Heavy goods vehicles	40
2.7	Single cyclist collisions	43
2.7.1	Scale of the problem	43
2.7.2	Direct causes	44
2.7.3	Fall kinematics, & dynamics	46
2.8	Human motion capture, & pose estimation	52
2.9	Conclusions	57
Chapter 3	Study A: Collision characteristics, & underreporting biases	58
3.1	Introduction	59
3.2	Study aims	60
3.3	Methods	61
3.3.1	Survey design & dissemination	61
3.3.2	Data cleaning	62
3.3.3	Statistical analysis	62
3.3.4	Data descriptions & summary of methodological approach	64
3.4	Results	65

3.4.1	Collision characteristics	65
3.4.2	Injury patterns	70
3.4.3	Underreporting & data source comparisons	72
3.5	Discussion	75
3.5.1	Underreporting biases	75
3.5.2	Comparisons of collision characteristics	76
3.5.3	Descriptive comparisons to Irish police statistics	78
3.5.4	Limitations	79
3.6	Conclusions	81

Chapter 4 Study B: Collision configurations, with the inclusion of underreported cases

83

4.1	Introduction	84
4.2	Study aims	85
4.3	Methods	86
4.3.1	Survey design & cleaning	86
4.3.2	Collision taxonomy	86
4.3.3	Injury outcomes	89
4.4	Results	90
4.4.1	Configurations of cyclist collisions with motorised vehicles	90
4.4.2	Configurations of single cyclist collisions	93
4.4.3	Injury patterns	99
4.5	Discussion	101
4.5.1	Representative cyclist impact scenarios	101
4.5.2	Collision configurations	103

4.5.3	Recommendations for monitoring cyclist safety	103
4.5.4	Limitations	103
4.6	Conclusions	105
Chapter 5	Study C: Collision configurations for fatal & serious injuries	107
5.1	Introduction	108
5.2	Study aims	108
5.3	Methods	108
5.4	Results	110
5.4.1	Collision partners	110
5.4.2	Directions of travel	111
5.4.3	Collisions with bonnet-type vehicles	111
5.4.4	Collisions with heavy goods vehicles	114
5.5	Discussion	116
5.6	Conclusions	116
Chapter 6	Study D: Video-based assessment, predictive modelling, & SMoS for cyclist-tram track interactions	118
6.1	Introduction	119
6.2	Study aims	119
6.3	Methods	120
6.3.1	Data collection	120
6.3.2	Track description and effective groove gap width	121
6.3.3	Frequency & risk analysis	122
6.3.4	Fall type taxonomy	122
6.3.5	Crossing angles & trajectories	122

6.3.6	Statistical analysis & predictive modelling of crossing success	124
6.3.7	Domain-specific cyclist detection	125
6.4	Results	126
6.4.1	Data summary	126
6.4.2	Site study: Camera 1	127
6.4.3	Site study: Camera 7	128
6.4.4	Multivariable testing & predictive modelling for crossing success . . .	129
6.4.5	Application of predictive models for SMOs	133
6.4.6	Further training for domain-specific cyclist detection	134
6.4.7	Automatic vs. manual tracking	136
6.5	Discussion	137
6.6	Conclusions	141

Chapter 7	Study E: KinePose: a novel inverse kinematics algorithm for au-	
	tomatic configuration of biomechanical models from video	143
7.1	Introduction	144
7.2	Study aims	144
7.3	Methods	145
7.3.1	Forward kinematics	146
7.3.2	Kinematic indeterminacy	148
7.3.3	Inverse kinematics optimisation	153
7.4	Results	161
7.4.1	General accuracy	161
7.4.2	Overcoming twist angle ambiguity	162
7.5	Discussion	163

7.6	Conclusions	165
-----	-----------------------	-----

Chapter 8 Study F: Towards computational modelling of cyclist falls with the inclusion of protective response 167

8.1	Introduction	168
8.2	Study aims	169
8.3	Methods	171
8.3.1	Data	171
8.3.2	Coding kinematic forms	171
8.3.3	Case study for reconstruction	171
8.3.4	Human pose estimation	172
8.3.5	Inverse kinematics & initialisation	174
8.3.6	Computational modelling	176
8.3.7	Effect of initialisation	176
8.4	Results	178
8.4.1	Kinematic forms	178
8.4.2	Case study	178
8.4.3	Effect of initialisation	179
8.5	Discussion	182
8.6	Conclusions	184

Chapter 9 Discussion 186

9.1	Targeting & treating risk	187
9.2	Priorities for cyclist-motorised vehicle collisions	189
9.2.1	Longitudinal/same directions of travel	191
9.2.2	Lateral/crossing & oncoming directions of travel	196

9.2.3	Impact configurations	196
9.3	Priorities for single cyclist collisions	199
9.3.1	Loss of traction	199
9.3.2	Infrastructural collision partners	200
9.3.3	Avoidance manoeuvres	201
9.4	Potentials of AI-based approaches	203
9.4.1	Surrogate measures of safety	203
9.4.2	Computational modelling	204
9.5	Summary list of priorities	206
Chapter 10 Conclusions		207
Appendix A		210
A.1	Nomenclature & definitions	211
A.2	Survey flowchart	212
A.3	Locations of survey respondents	213
A.4	Modelling results	214
Appendix B		215
B.1	Taxonomy for collisions with bonnet-type vehicles	216
B.2	Taxonomy for single cyclist collisions	219
Appendix C		222
C.1	Single cyclist collisions	223
Appendix D		224
D.1	Rail profile	225
D.2	Unsuccessful crossings	226

D.3 Predictive modelling results	228
Appendix E	230
E.1 Boundary cases for twist angle ambiguity	231
E.2 Convergence to local minimum	234
Bibliography	235

List of Tables

2.1	Comparing the traditional road safety approach and a Safe System. Adapted from International Transport Forum (ITF) (2016) [5].	10
2.2	Description of top 5 ranked use cases for collisions between bonnet-type vehicles and cyclists in urban areas (right-hand traffic environment). Adapted from Wisch et al. (2017) [75].	26
2.3	AIS 3+ injury source vs. cyclist body region (Cyclists percentages in orange, pedestrian percentages in green). Significant differences are denoted by an asterisk ($p < 0.05$). Adapted from Fredriksson et al. (2012) [90].	36
2.4	Proportions of single cyclist collision casualties among road casualties admitted to hospital for various countries/locations, including modal shares. Adapted from Schepers et al. (2015) [116].	44
2.5	Studies that have examined the characteristics or crash types of single cyclist collisions. Adapted from Utriainen et al. (2022) [136].	45
3.1	Road factors for collisions with and without the involvement of motorised vehicles.	67
3.2	Environmental factors for collisions with and without the involvement of motorised vehicles.	68

3.3	Human factors for collisions with and without the involvement of motorised vehicles.	69
3.4	Underreporting of collisions to the police.	73
4.1	Impact configurations and injury outcomes (for categories with 10 cases or more) of collisions with bonnet-type vehicles by vehicle/cyclist directions of travel, ranked by frequency.	91
4.2	Impact configurations and injury outcomes (for categories with 10 cases or more) of collisions with bonnet-type vehicles for the eight most common collision scenarios, ranked by frequency.	95
4.3	Direct causes for single cyclist collisions, the resulting fall types, and resulting injury outcomes.	96
4.4	Most prevalent factors for single cyclist collisions, and the resulting fall types, including the injury outcomes, ranked by frequency.	97
4.5	A comparison of the occurrence of selected serious injuries in the four most common impact configurations in collisions with bonnet-type vehicles, and the three defined fall types in single cyclist collisions.	100
4.6	Representative cases for cyclist-motorised vehicle collisions and single cyclist collisions.	102
5.1	Pre-crash directions of travel for serious and fatal collisions.	111
5.2	Pre-crash manoeuvres for cyclist collisions involving bonnet-type vehicles. . .	112
5.3	Impact configurations for cyclist collisions involving bonnet-type vehicles. . .	112
5.4	Environmental details for common scenarios of cyclist collisions with bonnet-type vehicles.	113
5.5	Pre-crash manoeuvres for cyclist collisions with HGVs.	114

5.6	Impact configurations for cyclist collisions with HGVs.	114
5.7	Environmental details for common scenarios of cyclist collisions with HGVs. .	115
6.1	Summary description of the study data, and UC risk estimates.	126
6.2	Predicted numbers of UCs for models (b) and (c), where $N_C=1,000$, and $M=100$, with randomly generated angles (θ) within a stated range.	134
6.3	Comparison of crossing trajectories for a sample of cases at camera 1.	136
7.1	Accuracy of IK Algorithms 1 and 2. MPJAS ₁₄ per frame for three levels of motion speed (fps: Optimisation frames per second, E: 14-joint Mean Per Joint Angular Separation (rad/joint)).	161
7.2	MPJAS ₁₄ per frame for motion sequences with 1) only bent limbs, or 2) phases of extended limbs.	161
8.1	Frequency of ground-impact to various body regions for fall type 1, type 2, and overall.	178
9.1	Representative cases for cyclist-motorised vehicle collisions in Ireland.	190
A.1	Nomenclature and definitions.	211
A.2	Pooled results of 30 imputations for the binary logistic regression on Police reporting.	214
B.1	Traffic environment and pre-crash scenario coding scheme used in cyclist- motorised vehicle collisions with bonnet-type vehicles.	217
B.2	Coding of general impact configurations.	218
B.3	Coding of direct causes for single cyclist collisions.	219
B.4	Pre-crash scenario coding scheme used in single cyclist collisions.	220

C.1 Direct causes for single cyclist collisions (including those involving secondary impact with a vehicle). 223

D.1 All UCs noted in this study. 226

D.2 Results for regression model (a). 228

D.3 Results for regression model (b). 228

D.4 Results for regression model (c). 228

List of Figures

1.1	Thesis structure.	5
2.1	Progress in reducing road deaths in Europe between 2010-2018. Adapted from Stipdonk et al. (2020) [21].	12
2.2	Trend in cyclist injuries in Ireland, 2007-2018. Adapted from Road Safety Authority (2020) [22].	12
2.3	Share of cyclist injuries in Ireland, 2007-2018. Adapted from Road Safety Authority (2020) [22].	13
2.4	Hydén’s safety pyramid [51]. Adapted from Johnsson et al. (2018) [53]. . . .	17
2.5	T-Analyst software for road user trajectory tracking. Figure from Johnsson et al. (2021) [62].	18
2.6	MADYMO ellipsoid MB models, left: 3-year-old child, 6-year-old child, small female, mid-size male, and large male, right: joints available for repositioning the models. Figure adapted from the MADYMO manual on human models [65].	20
2.7	THUMS FE models, from left to right; 3-year-old child, 6-year-old child, 10-year-old, small female, mid-size male, and large male.	22

2.8	Combined approaches to computational modelling, left: MADYMO facet pedestrian model from the MADYMO manual on human models [65], right: coupled MB-FE model from Wang et al. (2022) [73].	23
2.9	10 type-test scenarios devised in PROSPECT for assessment of cyclist-vehicle impacts (right-hand traffic environment). Adapted from Esquer et al. (2018) [78].	25
2.10	Pedestrian and Cyclist fatality risk curves by vehicle impact velocity. Adapted from Nie et al. (2015) [96].	29
2.11	Head injury risk by vehicle impact velocity for pedestrians, and cyclists. Adapted from Peng et al. (2012) [92].	29
2.12	Cyclist lower limb fracture risk by vehicle impact velocity. Adapted from Nie et al. (2014) [98].	30
2.13	(a) and (b): A comparison of cyclist and pedestrian behaviour in Type 2 collisions with vehicles for different bonnet leading edge heights at 80ms. (c): A plot of the corresponding head trajectories up until first contact with the vehicle. (d): Comparison of vertical and horizontal head displacements in similarly modelled collisions with bonnet-type vehicles. (a), (b) and (c) from Maki et al. (2003) [89], and (d) from Peng et al. (2012) [92].	32
2.14	Three cycling postures described by Peng et al. (2012) [92]. Where $\alpha > 12^\circ$, $\alpha = 5-12^\circ$ and $\alpha < 5^\circ$ correspond to CP1, CP2 and CP3, respectively. Adapted from Peng et al. (2012) [92].	33
2.15	(a), (b), and (c): Three cycling postures used by Fanta et al. (2013) [94] for mountain, road, and trekking bicycles, respectively. (d) HIC values calculated for each of the cycling postures by vehicle speed. Adapted from Fanta et al. (2013) [94].	33

2.16 Kinematics of lower extremities for three positions of pedal stroke. Adapted from Mizuno et al. (2016) [100].	34
2.17 Kinematic response of cyclists in front and rear-impacts with a low hood-height vehicle. Adapted from Maki et al. (2001) [101].	35
2.18 Comparison of head impact locations for cyclists and pedestrians in collisions with (a): bonnet-type vehicles, and (b): minivans. Adapted from Maki et al. (2003) [89].	36
2.19 Pedestrian impact testing according to EC 78/2009. Figure from Schmitt et al. (2016) [108].	39
2.20 Possible positions of cyclists that may be visible to drivers through direct/indirect vision. Figure from a report by Transport for London (2016) [113].	41
2.21 Example kinematic form for a sideways fall. Adapted from Hsiao et al. (1997) [144].	47
2.22 Computational modelling of fictive cyclist falls. Adapted from Wang et al. (2022) [73].	49
2.23 Computational modelling of fictive electric scooter falls by Posirisuk et al. (2022) [155].	49
2.24 FE computational modelling of of a fall. Adapted from Sahandifar et al. (2022) [157].	51
2.25 Simulated fall from height, with motion capture data informed initial conditions. Adapted from Milanowicz et al. (2017) [158].	51
2.26 Schematic overview of the GAST-Net framework. Figure from Liu et al. (2020) [171].	54
2.27 Classification of pedestrian pre-crash pose using a statistical human body model (SMPL). Adapted from Schachner et al. (2020) [180].	55

2.28	The Pose2Sim framework. Figure from Pagnon et al. (2021) [185].	56
3.1	The methodological approach used in this study.	64
3.2	Injury patterns for injured cyclists, overall and for each collision type.	71
3.3	Reporting of injurious collisions to the police and hospital attendance, represented as a proportional area Euler Diagram (generated using the approach by Micallef et al. (2014) [199]).	74
4.1	Taxonomy flowchart for collisions with bonnet-type vehicles.	88
4.2	Taxonomy flowchart for single cyclist collisions.	90
4.3	Injury patterns for injured cyclists, for the four most common impact configurations in collisions with bonnet-type vehicles, and the three defined fall types in single cyclist collisions.	99
5.1	Breakdown of collision types, and collision partners (for all cases involving a motorised vehicle) for serious and fatal cyclist cases.	110
6.1	Study locations in Dublin city centre.	120
6.2	Effective track groove gap width (EW) by crossing angle (θ) for various track types. Some of the curves overlap.	121
6.3	The three defined categories for unsuccessful crossings (UCs).	122
6.4	Ground plane calibration for Westmoreland St./College St. (Camera 7).	123
6.5	Trajectory analysis of cyclist interactions with a track at Abbey St./Beresford St. (Camera 1).	127
6.6	Cat. 3 fall at Abbey St./Beresford St. (Camera 1).	127
6.7	Trajectory analysis of cyclist interactions with the inside track at Westmoreland St./College St. (Camera 7).	128

6.8	Crossing angles and velocities (vector magnitudes).	129
6.9	SC probability risk curve by crossing angle with 95% confidence levels for model (b).	130
6.10	SC probabilities for various crossing angles from model (b).	131
6.11	Approximate SC probability risk curves for various track types, vs. crossing angle, calculated as a function of effective track width from model (c).	132
6.12	SC probabilities for various crossing angles from model (c) (Groove gap = 42.36mm).	133
6.13	Accuracy results for YOLOv5x after further training on various dataset sizes.	134
6.14	Visualisation of model improvements between YOLOv5x and YOLOv5xDCC for a sample of unseen images.	135
6.15	Comparison of crossing trajectories for a sample of cases at camera 1.	136
6.16	SafeCross tool for prediction of unsuccessful crossing numbers in wet road conditions given 1) a representative random sample of crossing angles, 2) a cyclist traffic count, and 3) the track gap width.	140
7.1	KinePose applied to an example cases, with 3D poses from Liu et al. (2020) [171] (multicolor keypoints and gray dashed lines).	145
7.2	The Euler axis-angle solution space (EAS) for mapping/retargeting incongru- ent vectors.	151
7.3	Solution space for mapping/retargeting a kinematic chain to an incongruent hierarchical set of 3D positions.	152
7.4	Kinematic chain parameters and bounds used in IK optimisation.	155
7.5	Global and local vectors used to formulate the pose loss terms.	156
7.6	Overview of the proposed IK approach (patch length $M=5$).	159

7.7	MPJAS ₁ by joint and algorithm, for motion sequences with phases of bent and extended limbs.	162
7.8	MPJAS ₁ by joint and algorithm, for motion sequences with bent limbs only. .	163
8.1	Pipeline for reconstruction of cyclist falls from monocular camera footage. . .	170
8.2	Two general kinematic form types common in sideways falls.	172
8.3	Automatic vs. manual 2D pose estimates.	173
8.4	Definition of global motion for the cyclist.	175
8.5	KinePose output given an input sequence of 3D poses.	177
8.6	Four initialisation cases for comparison in computational modelling.	177
8.7	Acceleration time histories with 3ms peak accelerations for the pipeline case with DOFs and <i>d</i> DOFs.	179
8.8	Qualitative comparison of kinematics in the ground impact phase for the pipeline case with DOFs and <i>d</i> DOFs.	180
8.9	Overlaid visualisations, and comparisons of simulation results (3ms peak accelerations) for the four initialisations.	181
A.1	Flowchart of the survey questionnaire including numbers of respondents entering, exiting, and excluded (R: Respondent, C: Collision).	212
A.2	Survey respondent numbers by county (N = 2,509), compared to census data for commuting cyclists in the Republic of Ireland in 2016 (N = 82,123) (in parentheses: ‘()’), and Cycling Ireland’s membership in 2017 (N = 21,470) (in square brackets: ‘[]’).	213
B.1	Impact location map used in coding impacts with bonnet-type vehicles for both door closed and door open situations.	216
B.2	Impact location map used for cyclists/bicycles.	216

D.1	Profile of the 59R2 (Ri59N) grooved rail.	225
D.2	Receiver Operating Characteristic (ROC) curve for model (b).	229
E.1	$MPJAS_1$ errors for limb joints in a 15-frame motion sequence involving an initial phase of bent limbs (blue), followed by a phase extended limbs (orange) (mean values over 10 IK runs).	232
E.2	$MPJAS_1$ errors for limb joints in a 15-frame motion sequence involving an initial phase of extended limbs (orange), followed by a phase bent limbs (blue) (mean values over 10 IK runs).	233
E.3	Optional tool for manual setting of the initial guess for model parameters in frame 1.	234

List of Abbreviations

3D	3-Dimensional.
6DOF	Degrees Of Freedom for position and orientation.
ADAS	Advanced Driver Assistance Systems.
AEB	Autonomous Emergency Braking.
AES	Autonomous Emergency Steering.
AGS	An Garda Síochána.
AI	Artificial Intelligence.
AIS	Abbreviated Injury Scale.
AP	Average Precision.
APROSYS	European Integrated Project on Advanced Protection Systems.
AsPeCSS	Assessment methodologies for forward looking Integrated Pedestrian and further extension to Cyclist Safety Systems.
BLIS	Blind Spot Information System.
BSD	Blind Spot Detection.

CATS	Cyclist-AEB Testing System.
CCC	Cyclist-Cyclist Collision.
CNN	Convolutional Neural Network.
CPC	Cyclist-Pedestrian Collision.
CV	Computer Vision.
DH	Denavit-Hartenberg.
DMURS	Design Manual for Urban Roads & Streets.
DOF	Degree Of Freedom.
DR	Deceleration Rate.
DVS	Direct Vision Standard.
EAS	Euler Axis-Angle Solution Space.
EOMs	Equations Of Motion.
EPA	Environmental Protection Agency.
ETSC	European Transport Safety Council.
EW	Effective Width of the groove gap.
FCW	Forward Collision Warning.
FE	Finite Element.
FK	Forward Kinematics.
GHBMC	Global Human Body Models Consortium.
GHG	GreenHouse Gas.
GIDAS	German In-Depth Accident Study.
HBM	Human Body Model.
HGV	Heavy Goods Vehicle.

HIC	Head Injury Criterion.
IK	Inverse Kinematics.
IoU	Intersection over Union.
IPCC	Intergovernmental Panel on Climate Change.
ISA	Intelligent Speed Assist.
ITF	International Transport Forum.
MADYMO	MAthematical DYnamic MOdels.
MAIS	Maximum Abbreviated Injury Scale.
MAR	Missing At Random.
MB	MultiBody.
MCAR	Missing Completely At Random.
MNAR	Missing Not At Random.
MOIS	Moving Off Information System.
MPJAS	Mean Per Joint Angular Separation.
MPJPE	Mean Per Joint Position Error.
MS COCO	Microsoft Common Objects in Context.
MVC	Cyclist-Motorised Vehicle Collision.
NCAP	New Car Assessment Program.
OR	Odds Ratio.
PET	Post-Encroachment Time.
PROSPECT	PROactive Safety for PEdestrians and Cy- clisTs.
PTW	Powered Two-Wheeler.

RISC	Road Incidence Statistics Capture.
ROC	Receiver Operating Characteristic.
ROM	Range Of Motion.
RSA	Irish Road Safety Authority.
SC	Successful Crossing of tram tracks.
SCC	Single Cyclist Collision.
SMoS	Surrogate Measure of Safety.
SMPL	Skinned Multi-Person Linear model.
SSM	Surrogate Safety Measure.
STRADA	Swedish TRaffic Accident Data Acquisition.
STRUDL	Surveillance TRacking Using Deep Learning.
SUV	Sports Utility Vehicle.
THUMS	Total HUman Model for Safety.
TTC	Time To Collision.
UC	Unsuccessful Crossing of tram tracks.
V CAD	Volvo Cars Accident Database.
VIF	Variance Inflation Factor.
VRU	Vulnerable Road User.
WAD	Wrap Around Distance.
YOLO	You Only Look Once.

Chapter 1

Introduction

1.1 Background

Internationally, roughly 1.35 million people died as a result of road traffic collisions in 2016 [1]. They are the eighth leading cause of death for all age groups, and are currently the leading cause of death for children and young adults (aged 5–29 years) (ibid.). Injuries due to collisions are a significant public health problem; they impose a large economic burden on both individuals themselves and states through healthcare costs and loss of productivity. In Ireland, based on police-reported data and national estimates of injury and fatality costs in 2013, minor injury collisions were estimated to have cost the state 161 million, serious injury collisions 148 million, and fatal collisions 497 million euros [2]. However, as detailed in section 2.4.1, there is a well-established phenomenon of police underreporting for all injurious collisions internationally, which leads to an underestimation of the economic burden of non-fatal injuries, and certain collision types. Out of all road users, underreporting rates have been shown to be the highest among cyclist collisions, and so their economic burden is likely the most underestimated.

With increasing concerns over climate change, sustainable and active transport options are being promoted throughout Europe (detailed in section 2.1), alongside efforts to reduce collisions among vulnerable road users (VRUs), e.g., cyclists and pedestrians. While overall fatality and injury numbers have been on the decline in Ireland and throughout Europe, cyclist fatality numbers have remained consistent, and cyclist injury numbers have been increasing in Ireland, reflecting increases in popularity (detailed in section 2.2).

As described in section 2.7.1, cyclist-motorised vehicle collisions comprise the largest share among fatalities, however, among serious injuries and lower severity cases single cyclist collisions dominate. Historically, drastic improvements in road safety have been achieved through targeted decreases in fatality rates (detailed in section 2.3), by focusing on collision/injury prevention strategies for cyclist-motorised vehicle collisions.

Vision Zero is an international road safety project that aims to eliminate all road deaths and serious injuries [3], which now forms the basis of Ireland's road safety strategy [4]. The Safe System approach to road safety is a complementary strategy that seeks to minimise the risk of road traffic collisions by designing and managing roads, vehicles, and speeds in a holistic and integrated way [5]. Since reductions in serious and lower severity collisions are now targeted under this paradigm, and called for by international transport organisations, e.g., the International Transport Forum [6], efforts towards reducing the occurrence and severity of single cyclist collisions should now also be prioritised.

1.2 Thesis approach, & layout

This thesis takes an engineering perspective toward reducing the occurrence and severity of cyclist collisions. Engineering interventions should be grounded in data, however, as detailed in section 2.4.1, underreporting of cyclist collisions to the police, and limited detail in traditional data sources hampers the identification of common collision and impact configurations for collision/injury prevention strategies. Therefore, the broad aims of this thesis are twofold:

1. To characterise the most common cyclist collision configurations in Ireland.
2. To develop engineering tools for collision/injury prevention strategies in the context of the Safe System approach.

The flowchart shown in Figure 1.1 illustrates the structure of the thesis, which is comprised of two main stages: 1) data analysis, and 2) engineering analysis. Each stage includes three individual studies. The first element of work involves a nationally distributed self-reporting collision survey (chapter 3, Study A: Collision characteristics, & underreporting biases, and chapter 4, Study B: Collision configurations, with the inclusion of underreported cases). Furthermore, in order to identify common collision and impact configurations for fatal and more severe cases, police investigation files are examined in chapter 5 (Study C: Collision configurations for fatal & serious injuries).

Findings from chapters 3, 4, and 5 indicate that single cyclist collisions comprise a significant share of cases. Furthermore, as detailed in sections 2.6, and 2.7, while cyclist-vehicle collisions have been well-investigated internationally, collision/injury prevention strategies for single cyclist collisions have not. Therefore, the engineering analyses in chapters 6, 7, and 8 focus on single cyclist collisions/falls.

Since findings from chapters 3, and 4 highlight that falls on light rail tram tracks comprise a large share of single cyclist collisions, the analysis in chapter 6 is focused on these

cases (Study D: Video-based assessment, predictive modelling, & SMoS for cyclist-tram track interactions). Using calibrated traffic camera footage from various locations across Dublin city centre, the relationship between crossing trajectories and fall likelihood is investigated. Furthermore, a Surrogate Measure of Safety (SMoS) (described in section 2.4.4) pipeline is created for site-specific safety assessments.

As detailed in section 2.7.3, human kinematics and dynamics in single cyclist falls have not been well investigated, and self protective response has not been considered in computational modelling. With increasing availability of camera footage in urban environments, the potential use of real-world 'in-the-wild' footage of falls is investigated as a source for informing computational modelling. The output from a monocular position-based 3D human pose estimator is insufficient for the task of initialising the pose/motion of a biomechanical model, e.g., the MADYMO ellipsoid human body model. Further mathematical processing is required to infer model-specific joint orientations. Therefore, in chapter 7 an inverse kinematics optimisation procedure is developed (Study E: KinePose: a novel inverse kinematics algorithm for automatic configuration of biomechanical models from video). Finally, in chapter 8 (Study F: Towards computational modelling of cyclist falls with the inclusion of protective response), a computational modelling pipeline is developed for the reconstruction of falls from in-the-wild monocular video footage.

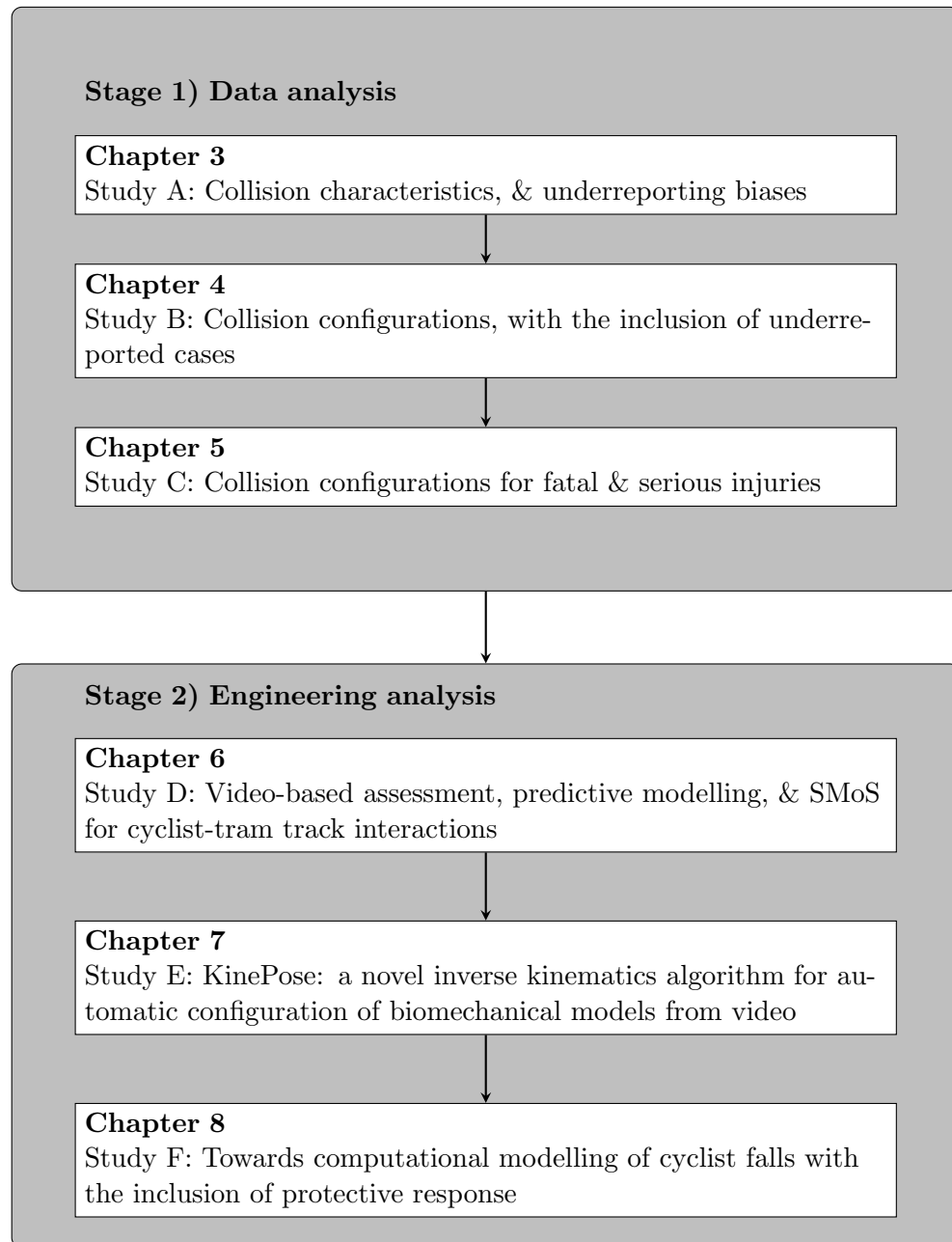


Figure 1.1: Thesis structure.

Chapter 2

Literature review

This chapter contains a review of both national and international policy and academic literature relating to cyclist safety, with a focus on common collision configurations and injury biomechanics. In section 2.1, national policy relating to cycling uptake and safety is reviewed, and section 2.2 the Safe System approach to road safety is detailed in the context of European/Irish road safety strategies. In section 2.3, cyclist safety trends are presented. In section 2.4, common collision data sources are described in the context of underreporting and levels of collision detail, and surrogate safety measures are introduced. In section 2.5, computational human body models for traumatic injury biomechanics are introduced, and in sections 2.6, and 2.7, common collision configurations and injury biomechanics for cyclist collisions with motorised vehicles and single cyclist collisions/falls are described. Finally, in section 2.8, human motion capture and pose estimation methods are detailed in the context of the potential application of initialising computational human body models for traumatic injury biomechanics applications.

2.1 National cycling policy

There are numerous personal and public benefits associated with cycling uptake. People who cycle regularly are less likely to develop cardiovascular disease, cancer, type II diabetes, or have a stroke [7]. Furthermore, in the past two decades levels of overweight and obesity in Ireland have doubled [8]. The facilitation and encouragement of active transport modes such as walking, and cycling is recommended as one of a number of societal interventions to reduce this burden [9].

In June 2018, Ireland was ranked 27th out of the 28 European Union member states for action on climate change [10], resulting from failure to meet Greenhouse Gas (GHG) emissions targets. Nationally, we aim to halve our emissions by 2030, and achieve net zero by 2050 [11], however, findings from the Intergovernmental Panel on Climate Change (IPCC), and the Environmental Protection Agency (EPA) highlight that our emissions reductions are not meeting our targets¹. Notwithstanding reductions in travel due to covid restrictions, the transport sector was responsible for 17.7% of Ireland's GHG emissions in 2021 and was the 2nd largest contributor after the Agriculture sector (37.5%).

The passenger car is the most popular form of transport in Ireland, accounting for 59.7% of commuting trips in urban environments and 76.4% of trips in rural environments [12], and contributes to 54% of road transport emissions¹. All modes of transport require an amount of energy to manufacture, operate, maintain, and dispose of over their life-cycles. The same is the case for the infrastructure that each mode requires for their use. Increased cycling modal share in urban environments is considered the most effective measure towards achieving net-zero emissions [13], i.e., life-cycle emissions from cycling are 30 times lower for each trip than driving a fossil fuel car, and 10 times lower than driving an electric car.

¹<https://www.epa.ie/our-services/monitoring-assessment/climate-change/ghg/transport/>

Due to these numerous benefits, an increase in cycling modal share is targeted by the government of Ireland [11]. The challenge to policymakers in this regard is to effectively increase the attractiveness of and incentivise cycling while at the same time disincentivise the use of private cars. Cycling has been promoted in Ireland according to the national cycle policy framework [14], by a combination of planning/infrastructure changes, educational/promotional campaigns, and financial incentives. A key factor affecting the uptake of cycling is safety, i.e., the perceived risks of cycling have been shown to deter the uptake of in Dublin [15]. In 2013, the Design Manual for Urban Roads and Streets (DMURS) was published [16] setting out guidelines in urban design aiming to prioritise sustainable and active modes of transport such as walking and cycling. DMURS sets out safety standards for cycle-friendly environment, though compliance has received criticism from cycling advocacy organisations², and work is underway to improve oversight [17].

In any case, as more people turn to cycling as a sustainable mode of transportation, it is crucial that road safety measures keep up with this shift. Thus, with increases in cycling there is an increased responsibility on road safety stakeholders to ensure a safe cycling environment.

2.2 Vision Zero & the Safe System approach

Vision Zero is a road safety strategy that aims to eliminate all traffic-related fatalities and serious injuries [3]. The strategy is grounded in the belief that no level of traffic-related fatalities or serious injuries is acceptable, and recognises that traffic-related deaths and injuries are not inevitable, but rather are the result of design choices and human error. The Vision Zero strategy was first adopted in Sweden in 1997, and it was later adopted by other countries in Europe, such as Norway, Denmark, and the Netherlands. The European Union also endorsed the Vision Zero approach in 2010, as part of its Road Safety Policy Framework for the period

²<https://cyclingforall.ie/>

2011-2020 [18], and again for the period of 2021-2030 [19]. Many other countries around the world have recently adopted the Vision Zero strategy, and it is now reflected in Ireland's road safety strategy [4].

According to the International Transport Forum, road safety management approaches generally fall into two common categories: 1) traditional approaches which are reactive, and focus on the personal responsibilities of road users, or 2) a proactive approach which places responsibility primarily with system designers, i.e., a Safe System approach [5] (see Table 2.1). The Safe System approach can be seen as a means to achieve the goals of Vision Zero. The approach seeks to reduce the severity of crashes and the likelihood of fatalities and serious injuries by designing road systems that take into account human error and limit the impact of crashes. The Safe System approach stands on four pillars (ibid.):

1. People make mistakes that can lead to road crashes.
2. The human body has a limited physical ability to tolerate crash forces before harm occurs.
3. A shared responsibility exists amongst those who design, build, manage and use roads and vehicles and provide post-crash care to prevent crashes resulting in serious injury or death.
4. All parts of the system must be strengthened to multiply their effects; and if one part fails, road users are still protected.

The Safe System approach acknowledges that people make mistakes, and that VRUs, i.e., pedestrians, cyclists, motorcyclists, scooter riders, children, the elderly, etc., require added protection. Increased focus is therefore placed on improving the road environment for VRUs [19, 4].

Table 2.1: Comparing the traditional road safety approach and a Safe System. Adapted from International Transport Forum (ITF) (2016) [5].

	Traditional	Safe System
What is the problem?	- Try to prevent all crashes.	- Prevent crashes from resulting in fatal and serious casualties.
What is the appropriate goal?	- Reduce the number of fatalities and serious injuries.	- Zero fatalities and serious injuries.
What are the major planning approaches?	- Reactive to incidents. - Incremental approach to reduce the problem.	- Proactively target and treat risk. - Systematic approach to build a safe road system.
What causes the problem?	- Non-compliant road users.	- People make mistakes and people are physically fragile/vulnerable in crashes. - Varying quality and design of infrastructure and operating speeds provides inconsistent guidance to users about what is safe use behaviour.
Who is ultimately responsible?	- Individual road users.	- Shared responsibility by individuals with system designers.
How does the system work?	- Is composed of isolated interventions.	- Different elements of a Safe System combine to produce a summary effect greater than the sum of the individual treatments, so that if one part of the system fails others parts provide protection.

2.3 Safety trends

Ireland has previously received two European Transport Safety Council (ETSC) ‘PIN’ awards in recognition of progress in improving national road safety, including achieving reductions in fatal collision numbers [20]. However, these reductions are typically limited to road users in motorised vehicles, and cyclist deaths have actually increased in Ireland by 8% on average since 2010 compared to a 5% annual decrease in motorised road user deaths [21]. In 2010 there were 5 cyclist fatalities, while in 2018 this number had risen to 9 fatalities, though low numbers make it difficult to discern a trend. Nonetheless, throughout Europe between 2010 and 2018 fatality reductions have been achieved across all road users apart from cyclists (Figure 2.1), whose fatality numbers have remained consistent. Specifically, cyclist fatality numbers have remained unchanged since 2010, while reductions have been achieved for all other road users, i.e., -19% for pedestrians, -20% for powered two-wheeler (PTW) users, and -24% for motorised vehicle occupants.

Furthermore, both the frequency and the share of cyclist casualties in Ireland (fatalities and injuries) have increased in recent years (Figures 2.2, and 2.3). The share of cyclist injuries has increased from 4% in 2007 to 14% in 2018 [22], mirroring a decrease in injuries to motorised vehicle occupants, and an increase in cycling numbers. There has also been a slight increase in the injury share for pedestrians, from 11% to 14% over the same period (*ibid.*). Evidently, increased efforts should be made to reduce the occurrence of injuries to cyclists.

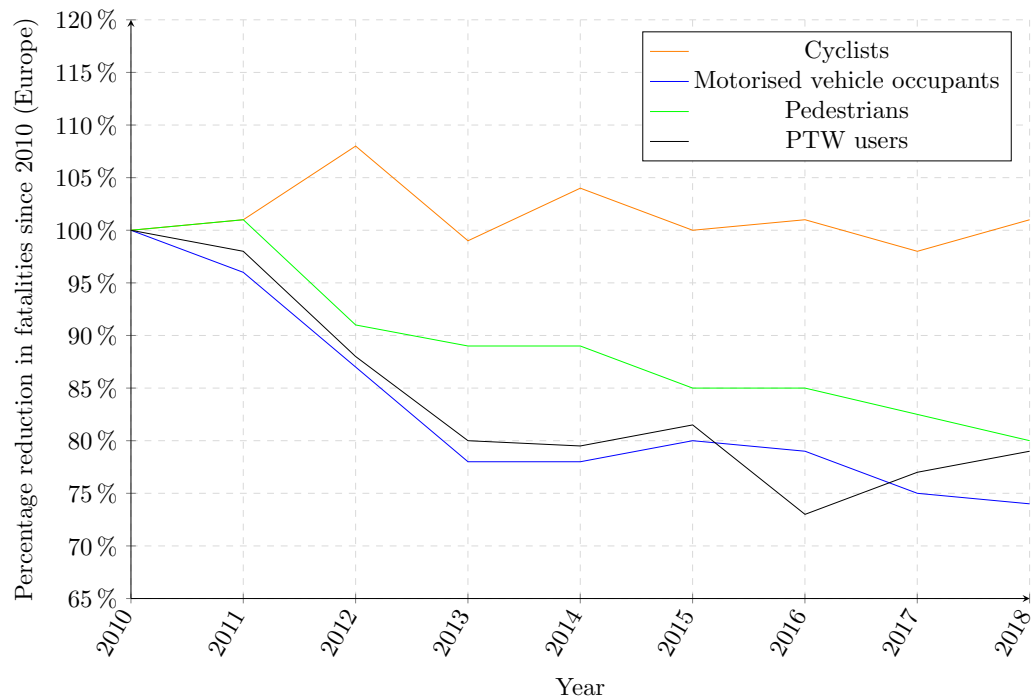


Figure 2.1: Progress in reducing road deaths in Europe between 2010-2018. Adapted from Stipdonk et al. (2020) [21].

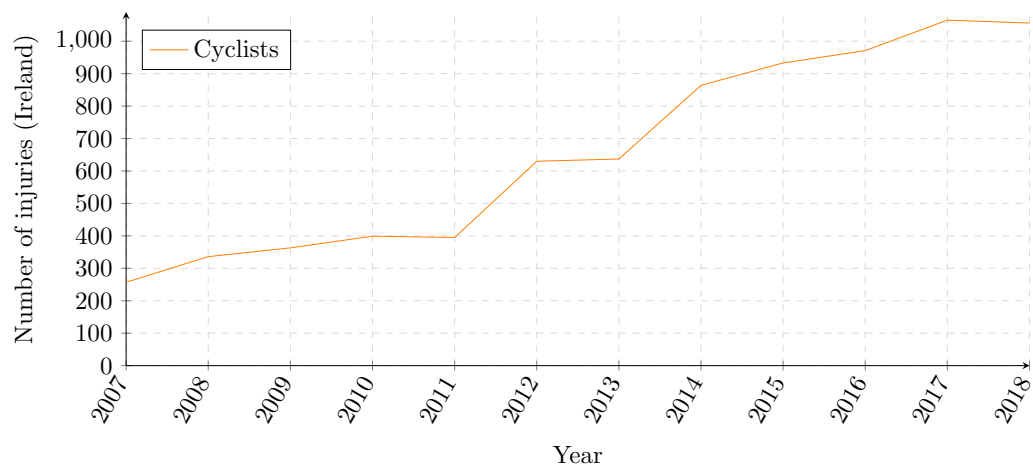


Figure 2.2: Trend in cyclist injuries in Ireland, 2007-2018. Adapted from Road Safety Authority (2020) [22].

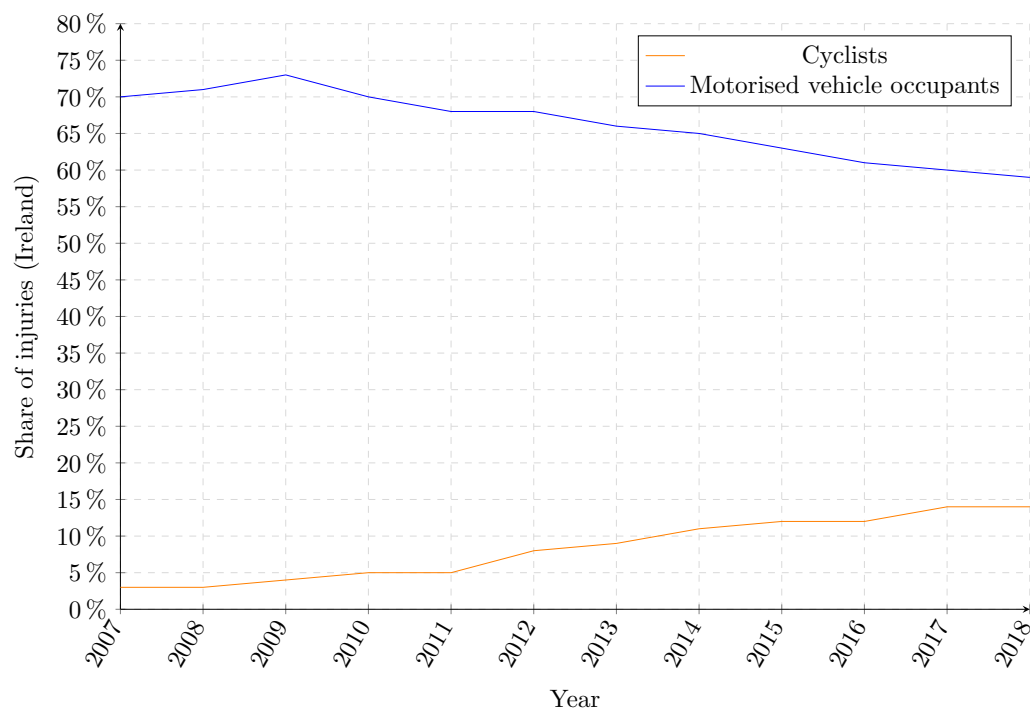


Figure 2.3: Share of cyclist injuries in Ireland, 2007-2018. Adapted from Road Safety Authority (2020) [22].

2.4 Road traffic collision data sources

2.4.1 Traditional data sources, & underreporting

In Ireland, much of the analysis performed on police-reported data has focused on frequencies of cyclist collisions for various collision factors (e.g., environmental, road, human, and vehicle factors) [23, 24, 25]. One study has taken a multivariable statistical approach, highlighting relationships between collision factors (e.g., speed limits, cyclist age, and lighting conditions) and injury severity [26]. These kinds of analyses are very useful for facilitating the identification of patterns and trends in collision occurrences, enabling officials to develop targeted strategies for reducing collision rates. It also enables targeted interventions such as education campaigns, enforcement efforts, and infrastructure improvements for specific high-risk groups. However, although police data is the most complete source for road traffic collisions in Ireland, limited detail is available for an engineering analysis (e.g., information on injuries to individual body regions, collision configuration, helmet, and bicycle light use are not available to researchers). As detailed in section 2.6, knowledge of pre-crash manoeuvres and impact configurations is an essential precursor to treating road safety risks. Furthermore, it is well documented that cycling collisions are underreported in police data both internationally [27, 6, 28, 29, 30, 31] and in Ireland [32, 33, 26]. Less severe cyclist collisions have lower odds of being reported to the police [34, 6, 35, 30]. Since injurious collisions are much more frequent than fatal ones, their underrepresentation is a significant shortcoming in the assessment of the national burden of cycling injuries. The effects of less severe collisions are also non-trivial, for example, Hours et al. (2013) [36] found that close to half of those who experience a minor injury in a collision (MAIS1 or MAIS2) still experience regular pain after a year. Due to their non-inclusion in police or hospital statistics, non-injurious collisions are not commonly investigated, however, recent studies have demonstrated how near misses have

negative effects on perceived safety and cycling participation [37, 38], which in turn may have adverse effects on cyclist safety via the ‘safety in numbers’ effect [39]. This is an effect observed in cycling, which suggests that as the number of cyclists on the road increases, the overall safety of cycling also increases (*ibid.*).

The vast majority of cyclist collisions in Irish police statistics are with motorised vehicles, and fewer than 10% are single cyclist collisions [23, 24]. However, internationally it is known that collisions where a motorised vehicle is not involved as a collision partner, i.e., single cyclist, cyclist-pedestrian or cyclist-cyclist collisions have lower odds of being reported to the police [6, 29, 30]. The biased nature of cyclist collision reporting has clear implications for policymakers, and road safety researchers, who generally rely on police data to determine road safety priorities.

2.4.2 Self-reporting

As detailed in section 2.4.1, a major challenge with understanding the overall burden of cycling collisions in Ireland and internationally relates to a substantial proportion of missing data. One approach used to address this is to combine existing injury datasets, for example, collisions in hospital and police data are systematically linked in Sweden, i.e., STRADA (Swedish Traffic Accident Data Acquisition). However, since all existing datasets lack completeness, a common approach has been to use self-reported surveys to gain a greater understanding of cycling collisions not appearing in police, hospital, or insurance data (e.g., Madsen et al. (2018) [28], and Shinar et al. (2018) [30]). As part of the European Horizon 2020 InDeV project³ (In-Depth understanding of accident causation for Vulnerable road users), Madsen et al. (2018) [28] found that roughly $\frac{3}{4}$ of self-reported collisions were not reported to the police nor an insurance institution by the cyclist, and did not result in a hospital/GP visit; indicating

³ <https://cordis.europa.eu/project/id/635895/>

their low likelihood of appearing in police, insurance, or hospital statistics. The self-reported nature of these surveys presents challenges, but they are a valuable mechanism for the assessment of otherwise unobserved cases and unrecorded information. Internationally, they have been used to identify rates and biasing factors for underreporting [30], establish collision factors for various cyclist cohorts (e.g., age groups, or bicycle types), as well as categorise general collision mechanisms for underreported collision types (e.g., infrastructural design, slipping, lane departure, loss of balance, and risky behaviour) [40, 41, 42, 43, 44, 45, 46] (elaborated on in section 2.7).

2.4.3 Police investigation files

In Ireland, the Road Safety Authority (RSA) manages the national road traffic collision database. For this, the RSA receives an electronic copy of incidents from An Garda Síochána (AGS) on a daily basis through the Road Incidence Statistics Capture (RISC) system. Since this data is provided in electronic form with specific variable fields, certain collision details are not included. Whereas, hardcopy police investigation files contain detailed information on the collision scene, vehicles involved, road users, manoeuvres, impact configurations, and other contextual information that can help provide a more complete understanding of collision causes. Previous examinations of these files have provided valuable insights into the factors that contribute to fatal collisions [47, 48, 49, 50].

2.4.4 Surrogate measures of safety, & video-based approaches

As evident from section 2.3, the occurrence of less severe collisions is significantly greater than that of collisions resulting in serious injury or death. Likewise, incidents of non-collision conflict events happen much more frequently than collisions. Hydén’s safety pyramid (Figure 2.4) illustrates this, and emphasises the potential of making use of details from these cases

to prevent the occurrence of more serious road traffic collisions [51]. Relying on the implied correlative relationship between these conflict events and future casualties, Surrogate Measures of Safety (SMoS) aim to quantify their severity. According to Laureshyn (2010) [52], the severity of a conflict event can be defined in two ways: either as the risk of a collision occurring, or as the risk of a collision resulting in injuries. This is also referred to as the traffic conflict technique, or Surrogate Safety Measures (SSM). This technique often involves observing traffic behavior and identifying situations where two or more road users are on conflicting paths, such as a vehicle making a turn in front of an oncoming cyclist. These measures do not rely on historical collision data, allowing for rapid proactive assessment of potential road safety risks. Therefore, this approach is well aligned with the proactive element of Safe System approach (see section 2.2).

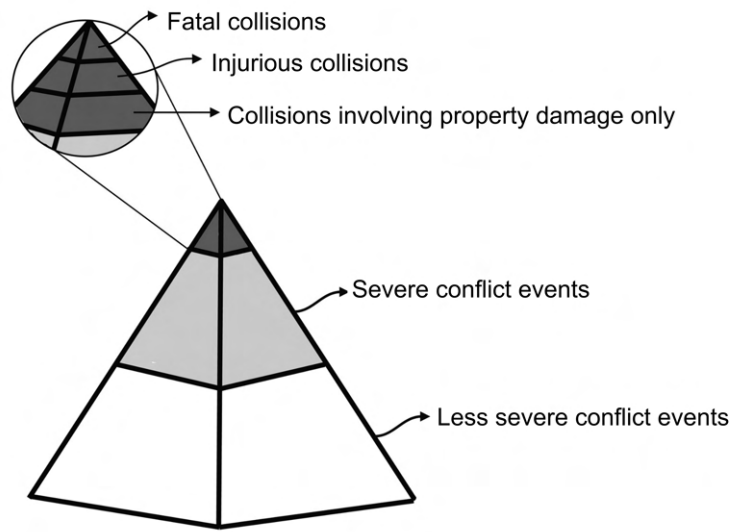


Figure 2.4: Hydén's safety pyramid [51]. Adapted from Johnsson et al. (2018) [53].

Given the prevalence of traffic cameras in urban environments, video-based approaches have obvious potential for capturing detailed observations of cyclist safety issues. Video footage is often used for the analysis of collisions [54, 55], as well as near-miss incidents or

SMoS. A variety of SMoS metrics exist, e.g., Time To Collision (TTC) [56], Post-Encroachment Time (PET) [57], or bicycle Deceleration Rate (DR) [58]. Generally, these metrics are based on vehicle trajectories (direction, velocity, or acceleration), and sometimes mass (Extended Delta-V) [59], which are used as proxies for collision risk.

Various analysis services (e.g., Transoft solutions⁴, Viscando⁵), and open-source softwares exist for SMoS analysis with traffic camera footage, e.g., T-analyst⁶, Traffic Intelligence project⁷, and Surveillance TRacking Using Deep Learning (STRUDL)⁸. After collection of traffic camera footage, a common first step is camera calibration to determine the relationship between pixel coordinates and the ground-plane, after which road user tracking is performed. Tracking may be manual (e.g., T-analyst [60]) (see Figure 2.5), or automatic (e.g., STRUDL [61]), i.e., using deep neural networks.



Figure 2.5: T-Analyst software for road user trajectory tracking. Figure from Johnsson et al. (2021) [62].

⁴<https://safety.transoftsolutions.com/>

⁵<https://viscando.com/applications/traffic/>

⁶ <https://bitbucket.org/TrafficAndRoads/tanalyst/wiki/Home/>

⁷<https://bitbucket.org/Nicolas/trafficintelligence/wiki/Home/>

⁸<https://github.com/ahrnbon/strudl/>

A recent International Transport Forum round table highlighted the potential utility of using Computer Vision (CV) and Artificial Intelligence (AI) to acquire relevant information for crash risk in a proactive site-assessment framework [63]. However, while a proactive approach is ideally preferred internationally, due to methodological constraints most road safety analysts are confined to performing reactive analyses of historical collision data. Therefore, it is expected that these technologies will play an increasingly important role in the future of transportation safety.

As discussed by Johnsson et al. (2018) [53], due to underreporting, traffic conflict analysis may be particularly important for addressing collisions involving VRUs. However, few SMoS studies focus on VRUs, i.e., pedestrians and cyclists (*ibid.*), and fewer again consider SMoS for single cyclist falls. Though SMoS metrics have been developed and used since the 1970s, validation remains a challenge (*ibid.*), and validation studies are rare. A common approach for validation involves the correlation of observed critical SMoS situations to historical collision data (*ibid.*). Theoretically, this may allow for the prediction of expected collision numbers, however, the problem of underreporting imposes uncertainty. Furthermore, since single cyclist falls are particularly underreported [30], SMoS metrics are less likely to be effectively validated in this way for these cases. Therefore, probabilistic risk modelling with the inclusion of crash footage may be the most robust approach, i.e., using an observational study design for a location/interaction of interest and obtaining footage for both successful (non-crash) and unsuccessful (crash) cases. If the latter are not readily available, recent promising approaches have used extreme value theory for probabilistic risk modelling, e.g., Ali et al. (2023) [64].

2.5 Computational models for traumatic injury biomechanics

The use of Human Body Models (HBMs) enables detailed analysis of injury mechanisms and what-if investigations into the potential of injury reduction strategies. A variety of multibody (MB) and finite element (FE) models and solvers exist for modelling the human body in traumatic injury biomechanics, e.g., MADYMO (MATHematical DYNAMIC MOdels)⁹, PC-Crash¹⁰, THUMS (Total HUMAN Model for Safety)¹¹, GHBMC (Global Human Body Models Consortium)¹², and VIVA+¹³.

The MADYMO pedestrian ellipsoid models, shown in Figure 2.6, consist of 52 rigid bodies linked by kinematic joints. The bodies are ellipsoid in shape and are used to represent the outer surface of the human body. The kinematic joints are used to constrain relative motion between bodies, with DOFs and ranges of motion (ROMs) which are representative of the human body.

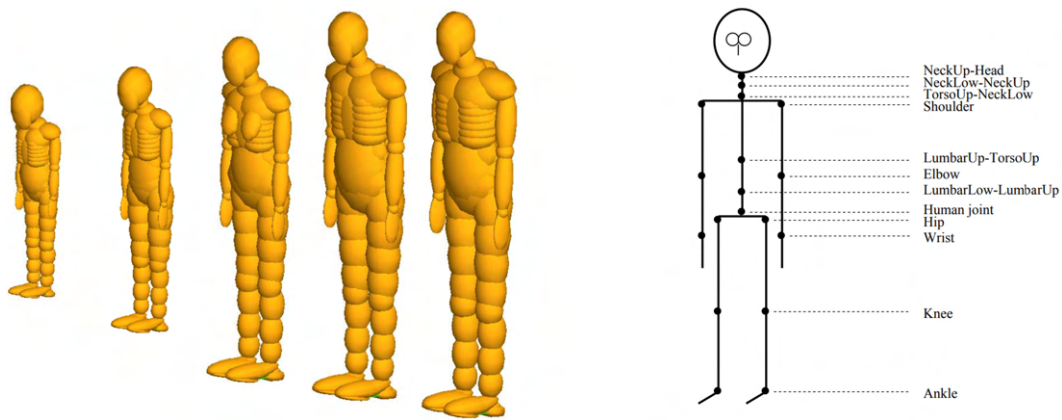


Figure 2.6: MADYMO ellipsoid MB models, left: 3-year-old child, 6-year-old child, small female, mid-size male, and large male, right: joints available for repositioning the models. Figure adapted from the MADYMO manual on human models [65].

⁹ <https://www.tassinternational.com/madymo/>

¹⁰ <https://www.pc-crash.com/>

¹¹ <https://www.toyota.co.jp/thums/>

¹² <http://www.ghbmc.com/>

¹³ <https://vivaplus.readthedocs.io/>

In generalised form, the equations of motion (EOMs) for forward dynamics form a system of non-linear second-order differential equations [66, 67] (Equation 2.1).

$$\ddot{\underline{q}} = \underline{h}(\underline{q}, \dot{\underline{q}}, t), \quad (2.1)$$

where $\underline{h}$ defines the EOMs; $\underline{q}$ is a column matrix with the generalised coordinates, the joint positional degrees of freedom; $\dot{\underline{q}}$ and $\ddot{\underline{q}}$ are the joint velocity degrees of freedom and their first time derivatives. The column matrix $\underline{q}$ contains m elements, corresponding to the m degrees of freedom of the model.

In multibody simulations in MADYMO, the EOMs are generally numerically solved using a modified Euler integration method with a fixed time step (t_s). Initial values for positions $\underline{q}_0$ and velocities $\dot{\underline{q}}_0$ are first defined. These must be set for a number of reorientable joints in the MADYMO ellipsoid models (see Figure 2.6). The velocity variables are then solved for at the next time point ($t_{n+1} = t_n + t_s$) using Equation 2.2, which gives the position variables using Equation 2.3.

$$\dot{\underline{q}}_{n+1} = \dot{\underline{q}}_n + t_s \ddot{\underline{q}}_n, \quad (2.2)$$

$$\underline{q}_{n+1} = \underline{q}_n + t_s \dot{\underline{q}}_{n+1}, \quad (2.3)$$

Reconstruction fidelity in computational modelling refers to the accuracy of a model in replicating or reconstructing the behaviour or characteristics of the real-world system being studied. It can be assessed by comparing the output of the model to experimental or observational data, e.g., Tierney et al. (2019) [68], and Shang et al. (2021) [69]. Reconstruction fidelity is reliant on many factors, including initial positions and motion ($\underline{q}_0$, and $\dot{\underline{q}}_0$), i.e., the EOMs are numerically solved as an 'initial value problem'. The effect of initial positions and

velocities are demonstrated in section 2.6.2.

A wide variety of injury metrics have been developed which allow predictions of injury severity by body region according to the Abbreviated Injury Scale (AIS) using MB modelling outputs, i.e., kinematic and dynamic responses to external forces [70]. However, injuries to bones, joints, and soft tissues cannot be directly estimated from MB models. In MB modelling, surfaces, internal structures, and contacts are modeled in a simplified manner. Surface topology is represented using groupings of ellipsoids, and contacts between bodies/objects are represented by force-penetration relationships, and various contact characteristics (i.e., stiffness, damping, hysteresis). In FE modelling, surfaces, and internal structures are defined using finite elements (i.e., discrete shapes), connected by nodes (e.g., THUMS: Figure 2.7). Their biomechanical properties are derived through postmortem human testing. Traumatic injury biomechanics analysis using FE models is performed using solver software, e.g., LS-Dyna¹⁴. As with the MADYMO solver, these software solve the EOMs as an initial value problem.

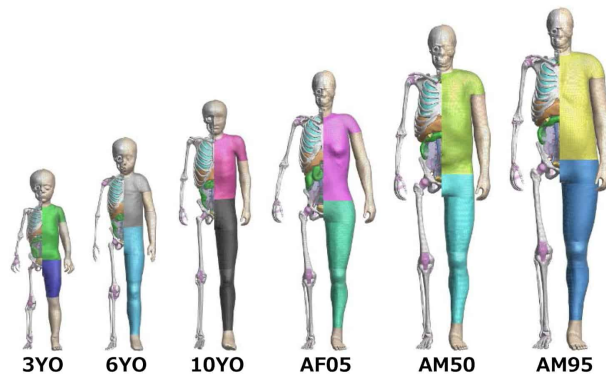


Figure 2.7: THUMS FE models, from left to right; 3-year-old child, 6-year-old child, 10-year-old, small female, mid-size male, and large male.

While allowing for more biofidelic impact deformations, the added complexity of FE models comes with a larger computational cost, and therefore, FE models are unsuited to large

¹⁴ <https://www.lstc.com/products/ls-dyna/>

parametric studies. Furthermore, compared to MB models, FE models are difficult to reposition or set with initial body segment velocities. Specification of initial model pose ($\underline{q}_0$) often requires complicated and time-consuming marionette/string-pulling simulation techniques and mesh smoothing in post-processing [71].

Due to the difficulty balancing efficiency and accuracy between FE and MB models, combined approaches have also been developed. For example, MADYMO contains a 'facet' model with an FE surface of massless contact elements (Figure 2.8). The surfaces are FE elements, allowing for a better geometric surface representation compared to ellipsoids, and the underlying model itself is MB, allowing for computational efficiency and easy specification of initial conditions ($\underline{q}_0$, and $\dot{\underline{q}}_0$). Similarly, a coupled MB-FE model has been created using the 50th percentile adult male THUMS head-neck complex model attached to the MADYMO ellipsoid model body [72, 73] (see Figure 2.8). Again, this approach allows for easy specification of initial conditions and lower computational cost, as well as more detailed head/brain injury estimates.

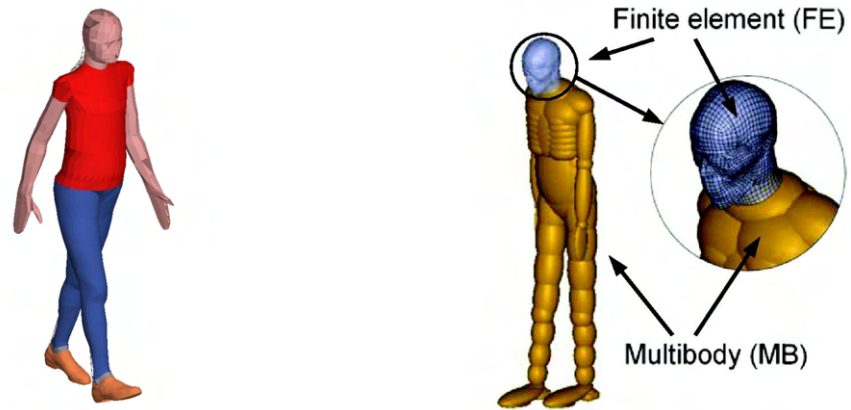


Figure 2.8: Combined approaches to computational modelling, left: MADYMO facet pedestrian model from the MADYMO manual on human models [65], right: coupled MB-FE model from Wang et al. (2022) [73].

2.6 Cyclist collisions with motorised vehicles

2.6.1 Common pre-crash scenarios, & impact configurations

Pre-crash cyclist/driver manoeuvre scenarios have often been used to prioritise infrastructural interventions to reduce conflicts, and recently they have been identified to direct type-testing protocols for vehicle active safety features, or advanced driver assistance systems (ADAS) for vulnerable road users in Europe. There have been a number of European projects dedicated to this task, i.e., PROactive Safety for PEdestrians and CyclisTs (PROSPECT)¹⁵, Cyclist-AEB Testing System (CATS), and Assessment methodologies for forward-looking Integrated Pedestrian and further extension to Cyclist Safety Systems (AsPeCSS)¹⁶. PROSPECT findings from the German in-depth accident study (GIDAS) indicated that generally, due to their severity-weighted frequency, a variety of crossing scenarios, and dooring scenarios should be addressed [74, 75] (Table 2.2). Longitudinal/turning collisions were not highlighted in German data, however, PROSPECT used findings from CATS as guidance which had identified these as being important among other European countries (particularly for fatalities) [76].

Furthermore, 10 type-test scenarios were devised in PROSPECT for 3 demonstrator ADAS systems capable of warning/braking/steering to avoid collisions with cyclists, i.e., Autonomous Emergency Braking (AEB), Autonomous Emergency Steering (AES), Forward Collision Warning (FCW), and Blind Spot Detection (BSD) [77, 78] (Figure 2.9). These supplement AEB and FCW type-testing procedures which were developed in AsPeCSS and CATS for 1) cyclist crossing in front of vehicles, and 2) vehicle approaching cyclist from the rear [79, 80, 81].

¹⁵ <https://cordis.europa.eu/project/id/634149/>

¹⁶ <https://cordis.europa.eu/project/id/285106/>

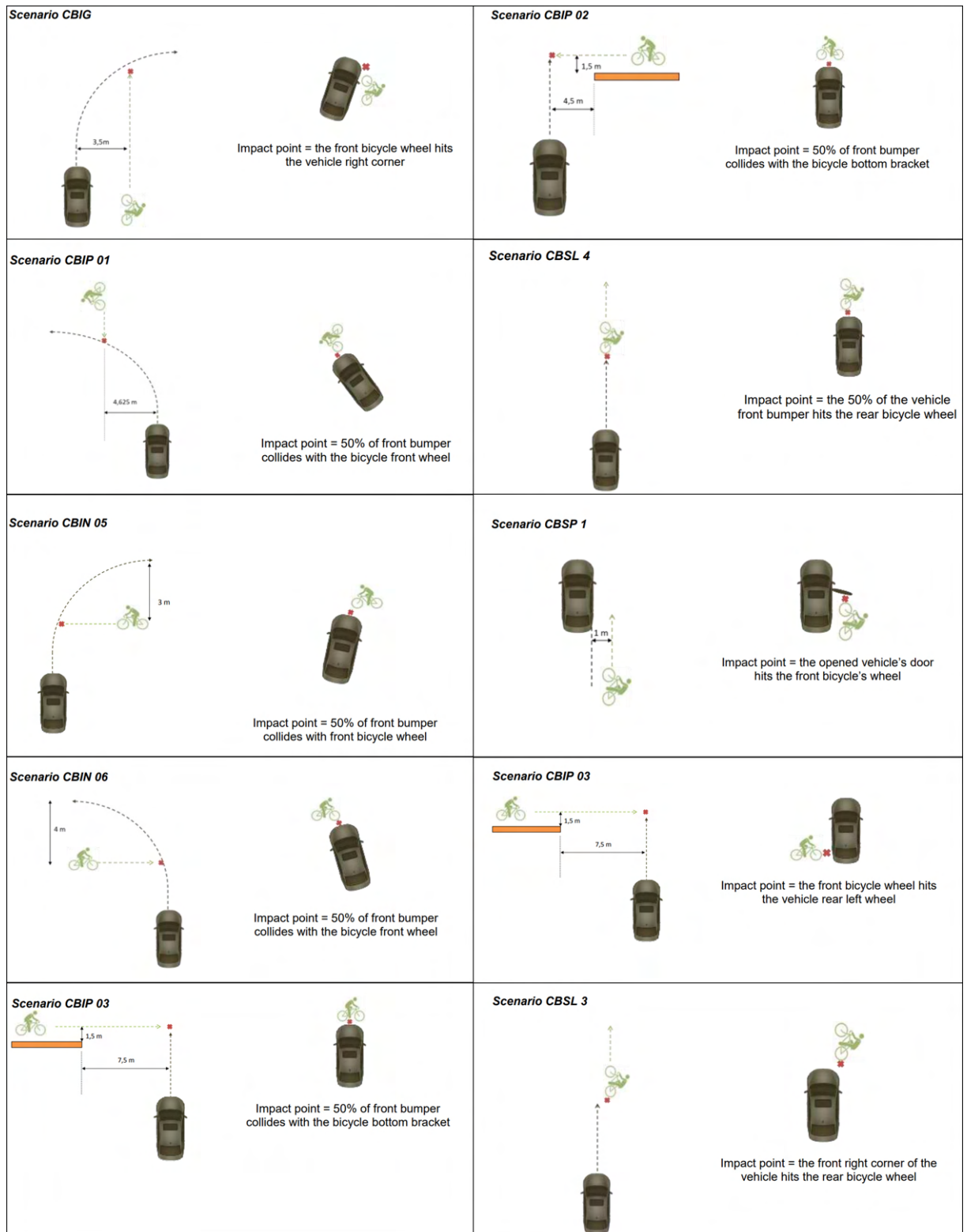


Figure 2.9: 10 type-test scenarios devised in PROSPECT for assessment of cyclist-vehicle impacts (right-hand traffic environment). Adapted from Esquer et al. (2018) [78].

Table 2.2: Description of top 5 ranked use cases for collisions between bonnet-type vehicles and cyclists in urban areas (right-hand traffic environment). Adapted from Wisch et al. (2017) [75].

Ranking	Description of crash situation
1	A passenger car travels on a minor road approaching a 3-arm (50%) or 4-arm junction (14%) intending to turn right. The driver does not give priority (as indicated by a stop or yield sign) to the cyclist crossing from the right, riding on the sidewalk/cycle lane.
2	A passenger car is going straight. A cyclist crossed the road from the sidewalk/cycle on the right directly in front of the car.
3	A passenger car travels on the main road approaching a 3- (31%) or 4-arm junction (31%) intending to go straight. A cyclist approached from the right side intending to cross the junction, not giving priority (as indicated by a yield sign) to the car.
4	Cyclist overtook a vehicle, while door opening on driver's side.
5	A passenger car travels on a minor road approaching a 3- (49%) or 4-arm junction (7%) intending to turn right. The driver does not give priority (as indicated by a stop or yield sign) to the cyclist crossing from the left, riding on the sidewalk/cycle lane.

The findings from these projects were used to inform New Car Assessment Program (NCAP) [82] and European regulated type-testing ((EU) 2019/2144), and the development of ADAS in the automotive industry. However, an acknowledged limitation in PROSPECT and other studies investigating cyclist collisions with motorised vehicles using police, hospital, or insurance data is that underreporting may bias findings [83, 84, 75, 85]. The nature and scale of lower-severity cyclist-motorised vehicle collisions are poorly understood. Since, as detailed in section 2.4.1, lower severity collisions are less likely to be included in official data sources [30], current priorities for infrastructural interventions, and vehicle type-testing may be biased towards collision types more prone to result in severe injuries/fatalities. Furthermore, safety priorities for pre-crash scenarios and impact configurations are known to vary substantially by cycling environment [74, 76, 75], and are only relevant to certain countries with data collection systems that allow for a detailed level of analysis. For many countries, the collision details included in official data sources are often limited, for example in Ireland, police data for vehicle driver manoeuvres in cyclist collisions are not always available [23], and the vehicle regions involved in impact are not currently recorded.

2.6.2 Impacts with bonnet-type vehicles

There has been extensive analysis of traumatic injury biomechanics for cyclist collisions with motorised vehicles (e.g., Simms et al. (2009) [86]). Collisions with bonnet-type vehicles (Sedans, Hatchbacks, SUVs, or Vans) are the most frequent cause of injuries and fatalities, though heavy goods vehicles (HGVs) account for disproportionate shares of fatalities/serious injuries [6] (discussed in section 2.6.3). Early studies found that over 80% of serious/fatal cyclist collisions involving bonnet-type vehicles were with the vehicle front (e.g., Otte et al. (1980) [87], and Huijbers et al. (1984) [88]), leading to the regulated type-testing of vehicle fronts in Europe ((EC) 78/2009), as well as consumer testing (e.g., Euro NCAP).

Accordingly, efforts have focused on reducing the aggressiveness of vehicle fronts, e.g., Maki et al. (2003) [89], Fredriksson et al. (2012) [90], Otte et al. (2012) [91], Peng et al. (2012) [92], VanSchijndel et al. (2012) [93], Fanta et al. (2013) [94], Katsuhara et al. (2014) [95], Nie et al. (2015) [96], and Lv et al. (2018) [97].

Vehicle velocity

Out of all collision factors, vehicle impact velocity has perhaps the most evident effect on injury outcomes for vulnerable road users [96, 98, 92, 99]. For example, Nie et al. (2015) [96] analysed 67 cyclist collisions and 371 pedestrian collisions, finding that a similar relationship exists between fatality risk and vehicle impact velocity for both cyclists and pedestrians (Figure 2.10). Peng et al. (2012) [92] showed that there is a significant correlation between head injury risk and impact velocity, specifically for the risk of occurrence of AIS 2+ and AIS 3+ head injuries for both cyclists and pedestrians (Figure 2.11). Injury risk was higher for pedestrians than for cyclists, for example, a 50% AIS 2+ head injury risk was at 53.7km/h for cyclists, compared to 38.9km/h for pedestrians, and a 50% AIS 3+ head injury risk was at 58.9km/h for cyclists, compared to 54.4km/h for pedestrians. Nie et al. (2014) [98] modelled the risk of leg fracture by impact velocity, finding a significant correlation. For example, a 50% fracture risk was at 36.7km/h (Figure 2.12).

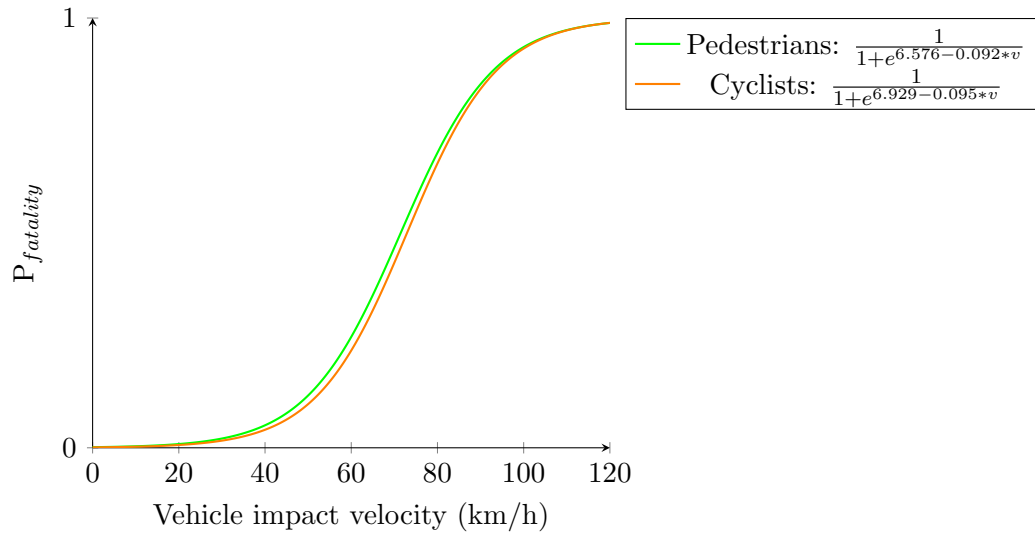


Figure 2.10: Pedestrian and Cyclist fatality risk curves by vehicle impact velocity. Adapted from Nie et al. (2015) [96].

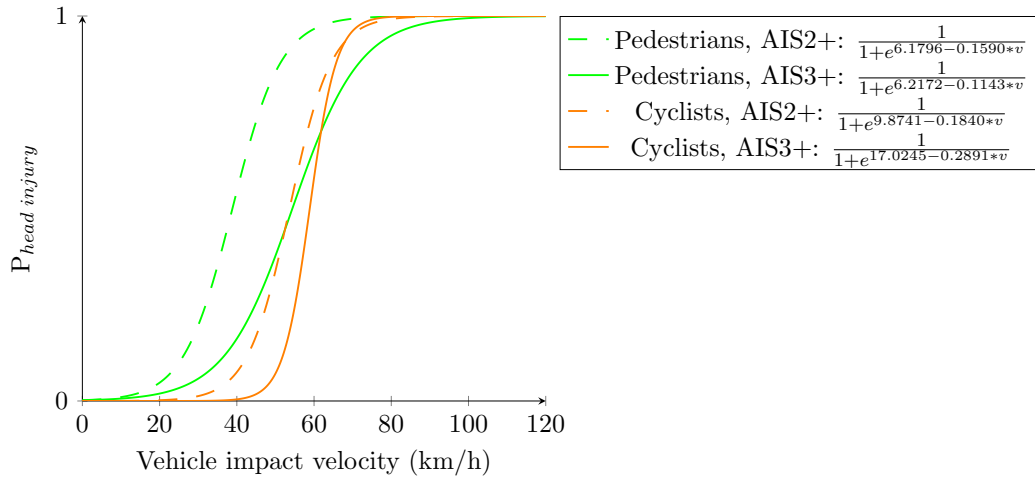


Figure 2.11: Head injury risk by vehicle impact velocity for pedestrians, and cyclists. Adapted from Peng et al. (2012) [92].

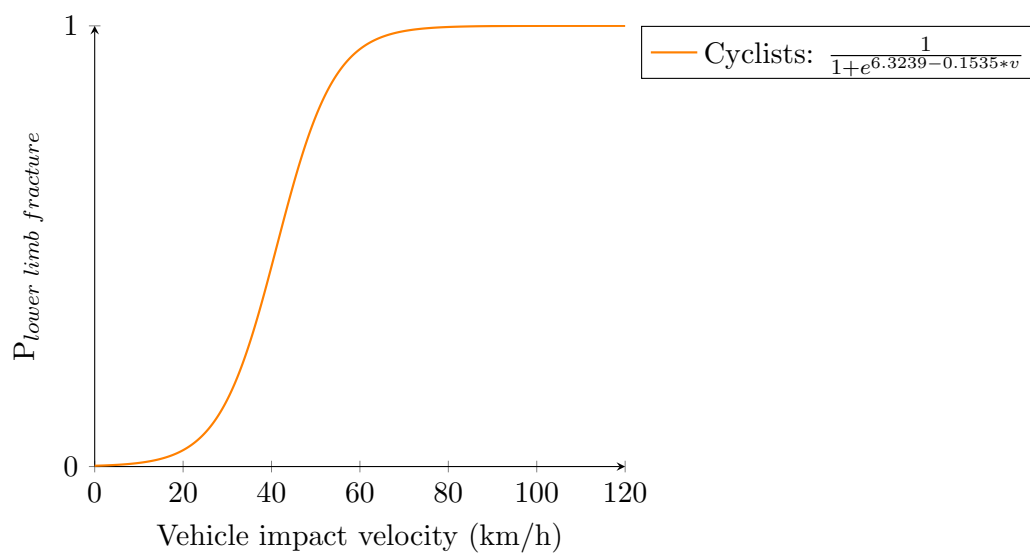


Figure 2.12: Cyclist lower limb fracture risk by vehicle impact velocity. Adapted from Nie et al. (2014) [98].

Impact configurations, & initial conditions

Insights gained from computational modeling studies can inform the design of safer vehicles and prompt updates to safety standards for protecting VRUs in specific scenarios. Since side impacts, i.e., involving the front of the vehicle impacting with the side of the cyclist, have been shown to constitute the majority of serious and fatal cyclist collisions, many computational modelling studies have focused on these cases [89, 92, 98, 100]. A number of comparative analyses have been performed on cyclist and pedestrian kinematics and injuries in collisions with vehicles [89, 91, 92], and others have focused on outcomes for cyclists [98, 100]. In the context of vehicle type-testing, common locations of head impact on the vehicle are important to note, or the distance along the vehicle that head impacts may be expected. For this, the wrap-around distance (WAD) is often used, i.e., the traced distance from the impact location of the head along the vehicle front to the ground (Figure 2.13 (a)). Height-adjusted WAD is also used, i.e., the WAD divided by the sitting height of the cyclist. Maki et al. (2003) [89] used MB computational modelling (MADYMO) to gain an understanding of the effects of various collision parameters on impact kinematics and head injury outcomes. Figure 2.13 (a),(b), and (c) show the effect of differences in bonnet leading edge heights on head trajectories for large sedans and Sports Utility Vehicles (SUVs). Pronounced sliding was observed in modelled cyclist collisions with large sedans compared to those with SUVs, demonstrating that lower bonnet leading edge heights have the effect of increasing the head trajectory and WAD of cyclists by a larger degree than for pedestrians. Similar conclusions were reached by Peng et al. (2012) [92] (Figure 2.13 (d)). Maki et al. (2003) [89] found that when involved in a side-impact collision with a bonnet-type vehicle, cyclists experience height-adjusted WAD (WAD/Height) 1.2 times greater than pedestrians do, between roughly 1.25 and 1.6. These findings are consistent with subsequent examples from the literature [98, 92]. Maki et al. (2003) [89] further investigated the effects of cyclist velocity and offset positioning

at the front of the vehicle, finding that both have effects on the occurrence of head injuries.

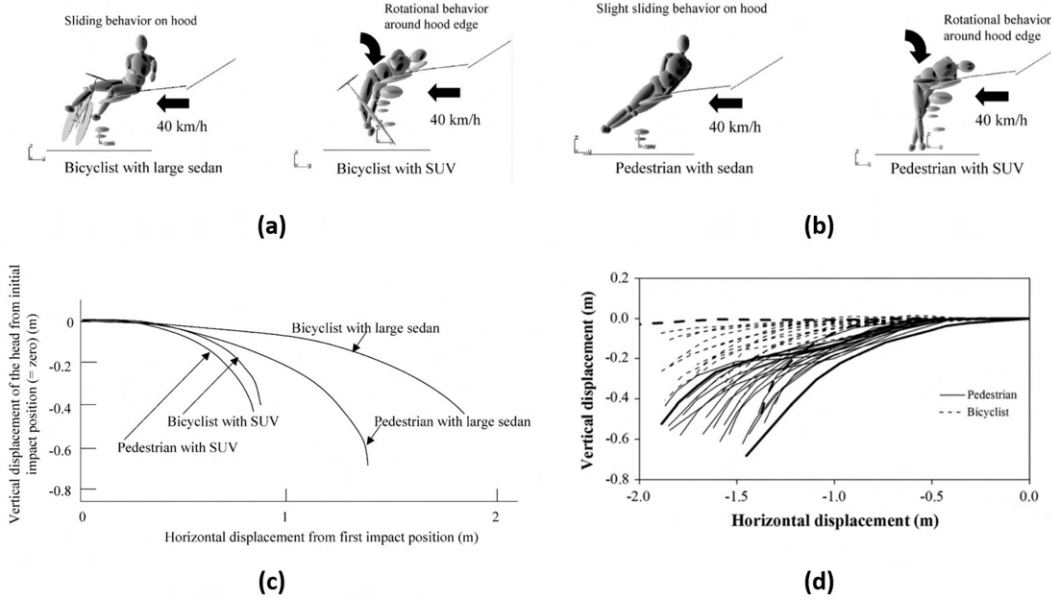


Figure 2.13: (a) and (b): A comparison of cyclist and pedestrian behaviour in Type 2 collisions with vehicles for different bonnet leading edge heights at 80ms. (c): A plot of the corresponding head trajectories up until first contact with the vehicle. (d): Comparison of vertical and horizontal head displacements in similarly modelled collisions with bonnet-type vehicles. (a), (b) and (c) from Maki et al. (2003) [89], and (d) from Peng et al. (2012) [92].

Cyclists exhibit a variety of postures while cycling, depending on their anthropometry as well as the kind of bicycle they are using. This has been investigated in computational modelling studies, for example, Peng et al. (2012) [92] defined three cycling postures (CP) based on the back angle of the cyclist while cycling (α). As shown in Figure 2.14, angles greater than 12° , between $5\text{--}12^\circ$ and $0\text{--}5^\circ$ were classified as CP1, CP2, and CP3, respectively.

Fanta et al. (2013) [94] found differences in the Head Injury Criterion (HIC) depending on the seating positions of cyclists on mountain bicycles, road bicycles, and trekking/commuter bicycles. The highest HIC scores were observed for cases with higher seating positions, i.e., trekking/commuter bicycles produced the highest, followed by mountain bicycles, and road bicycles the lowest (Figure 2.15).

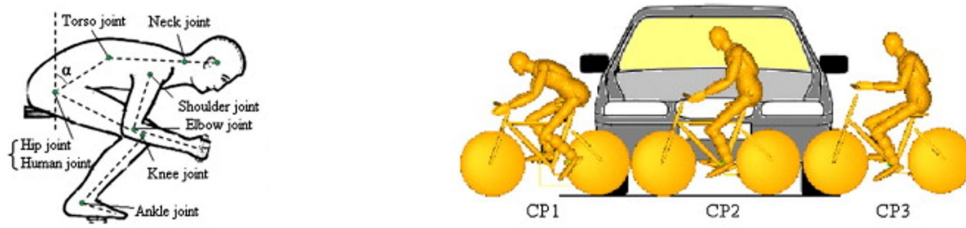


Figure 2.14: Three cycling postures described by Peng et al. (2012) [92]. Where $\alpha > 12^\circ$, $\alpha = 5-12^\circ$ and $\alpha < 5^\circ$ correspond to CP1, CP2 and CP3, respectively. Adapted from Peng et al. (2012) [92].

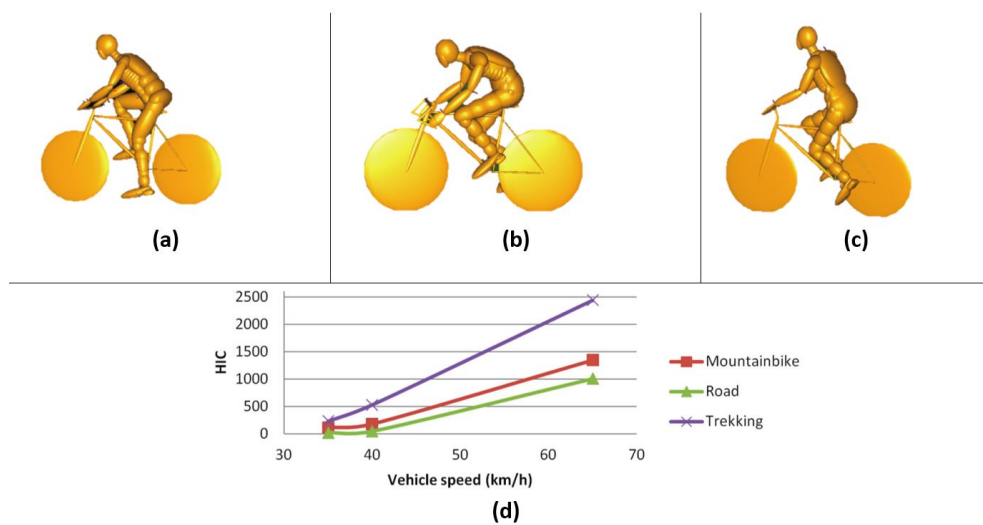


Figure 2.15: (a), (b), and (c): Three cycling postures used by Fanta et al. (2013) [94] for mountain, road, and trekking bicycles, respectively. (d) HIC values calculated for each of the cycling postures by vehicle speed. Adapted from Fanta et al. (2013) [94].

Mizuno et al. (2016) [100] found that the position of cyclist lower extremities, or the phase of pedal stroke affected kinematics and injury outcomes. Three pedal phases were defined; ‘foot up’ where the inside foot of the cyclist was at the highest point of the pedal stroke (Figure 2.16 (a)), ‘foot front’ where the inside and outside feet were horizontal (Figure 2.16 (b)), and ‘foot down’ where the inside foot was at the lowest point of the pedal stroke (Figure 2.16 (c)). Two Impact conditions were computationally modelled using the THUMS FE model, one where the cyclist velocity was 20km/h and another where the cyclist velocity

was 0km/h, both with a vehicle velocity of 40km/h. For both conditions, the WAD of cyclists in the foot-up position was the highest, followed by the foot-front position, this was attributed to the effect of the pelvis sliding on the bonnet.

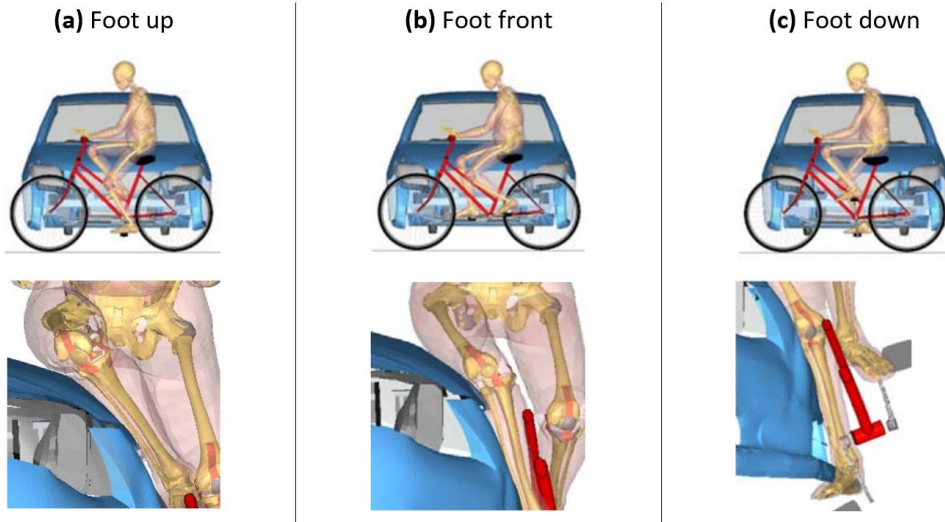


Figure 2.16: Kinematics of lower extremities for three positions of pedal stroke. Adapted from Mizuno et al. (2016) [100].

Maki et al. (2001) [101] investigated both front and rear-impacts in Japanese data between the years of 1994 to 1996. The study formed part of the same project reported on in Maki et al. (2003) [89], and Maki et al. (2000) [102] which both focused on side-impacts. It was found that similar to side-impacts, for both rear and front impacts cyclist kinematics differ depending on hood height. In front-impacts with vehicle hood heights at levels below the knee height of the cyclist resulted in greatly reduced head impact velocities to roughly 20% of the initial relative velocity of the cyclist's head, see Car A in Figure 2.17 (c). This was attributed to a sliding contact between the cyclist's knees on the bonnet, i.e., see time points 130ms and 200ms in Figure 2.17 (a).

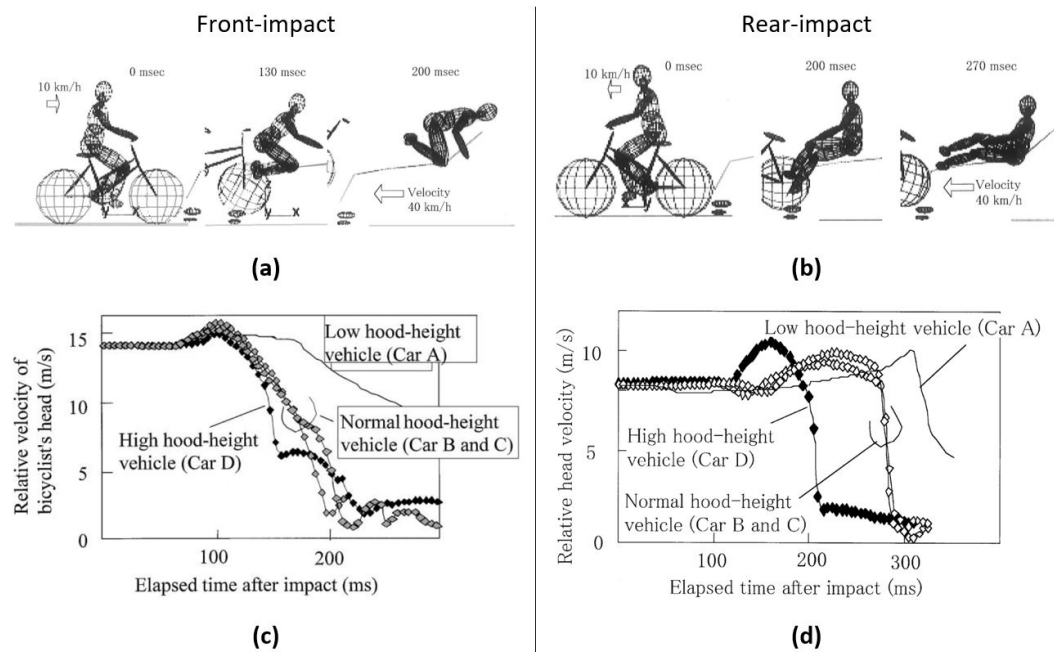


Figure 2.17: Kinematic response of cyclists in front and rear-impacts with a low hood-height vehicle. Adapted from Maki et al. (2001) [101].

Impact locations

The primary focus of the study by Maki et al. (2003) [89] related to how injury outcomes to the head vary by impacting vehicle type, impact velocities, and head impact locations. The study also included an analysis of cyclist impact locations by forensic analysis of dents and scratches seen on the vehicle in police photographs (Figure 2.18). A comparative analysis was performed on the injury outcomes for side-impact cyclist-motorised vehicle cases and pedestrian-motorised vehicle cases. The study demonstrated that for cyclist collisions with bonnet-type vehicles, the locations of head impact included the roof, the windscreen frame, including the A-pillars, whereas for pedestrian collisions the impact locations were located more forward and included the bonnet. However, for cyclist collisions with minivans, the impact locations were similar to those for pedestrians, including a number of impact locations on the front panel.

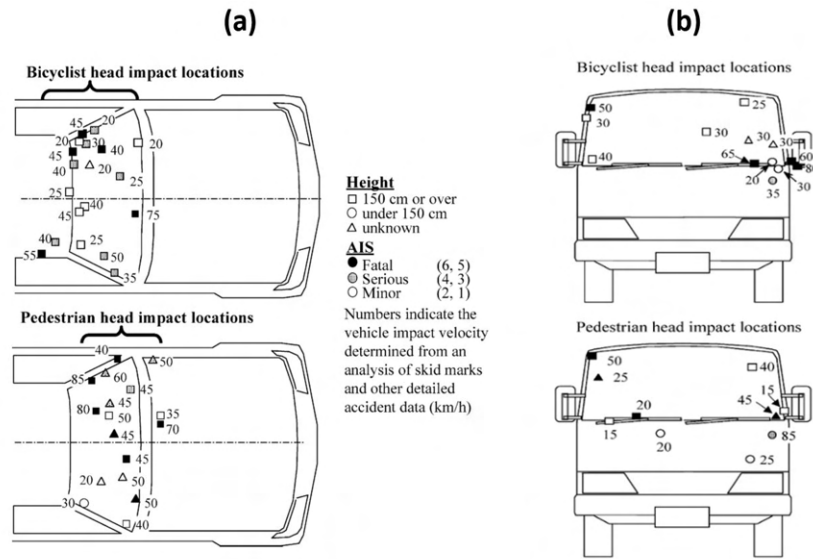


Figure 2.18: Comparison of head impact locations for cyclists and pedestrians in collisions with (a): bonnet-type vehicles, and (b): minivans. Adapted from Maki et al. (2003) [89].

Fredriksson et al. (2012) [90] performed a detailed analysis of injury outcomes for head, neck, chest, upper extremity, and lower extremity impact locations for 139 cyclist and 191 pedestrian collisions with bonnet-type vehicles in GIDAS between 1999 and 2010. Findings indicate that the largest proportion of lower extremity injuries result from impact with the vehicle's front end. Furthermore, a larger proportion of head injuries suffered by cyclists result from impact with the windshield area (Table 2.3).

Table 2.3: AIS 3+ injury source vs. cyclist body region (Cyclists percentages in orange, pedestrian percentages in green). Significant differences are denoted by an asterisk ($p < 0.05$). Adapted from Fredriksson et al. (2012) [90].

	Leg	Arm	Chest	Neck	Head
Front end	22% vs. 41% *	0% vs. 1%	2% vs. 5%	1% vs. 0%	0% vs. 1%
Hood edge	1% vs. 5%	0% vs. 0%	0% vs. 2%	0% vs. 0%	0% vs. 1%
Hood area	4% vs. 7%	2% vs. 3%	11% vs. 13%	0% vs. 1%	1% vs. 5%
Windshield area	1% vs. 2%	1% vs. 1%	11% vs. 14%	1% vs. 3%	23% vs. 27%
Ground	8% vs. 5%	4% vs. 4%	8% vs. 9%	1% vs. 2%	14% vs. 14%
Other/Unknown	4% vs. 3%	0% vs. 0%	4% vs. 3%	1% vs. 1%	4% vs. 2%

Of the AIS 3+ injuries to the head due to impact with the windshield area, 37% were due to impact with the A-pillars, 26% with the glass, 26% roof edge, and 11% with the instrument panel and the low frame. Cyclists experience a lower proportion of impacts to these areas than pedestrians, with the majority of cyclist head injuries resulting from impact with the roof edge.

Secondary/ground impact

Generally, when a cyclist-motorised vehicle collision occurs there are two possible impact phases that can occur, i.e., primary, and secondary impacts. Primary impact refers to an impact with the vehicle itself, and secondary impact refers to a subsequent impact with the road or ground. Two forms of post vehicle impact projection types have been described, 1) wrap projection, where wrapping occurs on impact with a bonnet-type vehicle followed by projection of the cyclist from the bonnet/windshield area via the sides or the top of the vehicle, and 2) forward projection, where the cyclist is impacted by a high bonnet-type or a flat fronted vehicle followed by projection of the cyclist directly forward onto the ground.

A variety of kinematic scenarios can occur within wrap projection, however generally they include three phases: 1) the ‘contact phase’ with the vehicle, 2) the ‘flying phase’ where here the cyclist is projected into the air, and 3) the ‘sliding phase’ on the ground. In a study for the European Integrated Project on Advanced Protection Systems (APROSYS), Carter et al. (2008) [103] found secondary contact with the ground to be responsible for 42% of the injuries sustained by cyclists, and 48% due to primary impact with the vehicle. This proportion was much higher than for pedestrian cases in the same study, for whom secondary impact accounted for only 16% of injuries. Secondary impacts have also been shown to be responsible for a large proportion of head injuries in the United Kingdom, i.e., a detailed review of 55 collision cases indicated that secondary head impact was responsible for 38

(69%) of the head injuries [104]. However, other studies have shown lower importance for ground impact, e.g., as previously presented in Table 2.3.

Vehicle-based prevention strategies

On impact, the mass, front geometry, and material properties of a vehicle affect the injury outcomes for cyclists and pedestrians. In Europe, regulation (EC) 78/2009 sets out the basic requirements for the passive protection of pedestrians and other vulnerable road users in the form of tests and limit values for the type-approval of vehicle fronts. There are also a number of consumer organisations that perform safety assessments on vehicles, i.e., NCAPs in Europe, Japan, South Korea, Latin America, and Australia.

The test procedures (e.g., European regulations - Figure 2.19) involve a number of impact tests using head forms and leg forms. The test methodology for Euro NCAP is largely the same as that described in EC 78/2009, however, there are a number of differences. Most importantly, the test impact area is larger in Euro NCAP, extending to areas rearward of the bonnet including the windscreen, A-pillars, and roof allowing for larger WADs, which as previously detailed, better accounts for cyclist impacts. As described by Mackay et al. (2013) [105], Euro NCAP star ratings have acted as a strong incentive for car manufacturers to implement safer designs. European type-testing regulations generally specify lower safety standards, though their revisions generally follow updates to NCAP standards (*ibid.*). Accordingly, recent revisions to type-testing regulations in Europe include larger head impact zones. Vehicle safety regulations in Europe and consumer testing typically focus on the primary impact of the vehicle, but as previously detailed, the literature suggests that it is important also to consider secondary/ground impacts for a more comprehensive assessment of impacts for VRUs. This may be achieved by including specific tests for secondary/ground impacts in vehicle type-testing. In any case, vehicle front design alterations in recent decades

appear to have improved safety for both pedestrians and cyclists. Richter et al. (2005) [106] found that between the 1970s and the 1990s in Germany, there was a reduction in the severity of injuries sustained by cyclists and pedestrians related to improvements made in vehicle design during that period. More recently, Li et al. (2020) [107] found similar improvements post-2000.

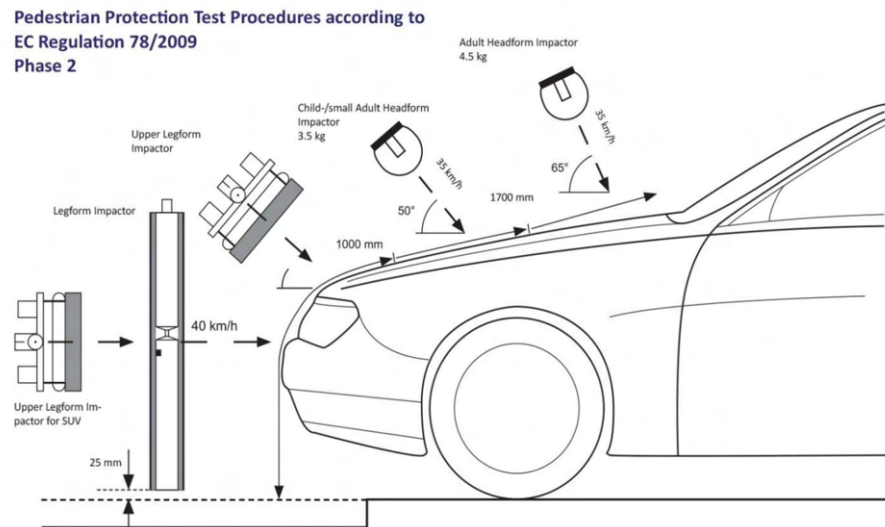


Figure 2.19: Pedestrian impact testing according to EC 78/2009. Figure from Schmitt et al. (2016) [108].

Apart from alterations to the front geometry and structures, in recent years other design alterations have been developed to mitigate cyclist/pedestrian injuries from impacts with bonnet-type vehicles. For example, pop-up hoods [109], or external airbags [110]. These systems aim to modify kinematics, absorb impact energy, and prevent impact with stiffer regions of the vehicle such as the A-pillars. Furthermore, as part of the suite of revisions to the General Safety Regulations¹⁷ a variety of intelligent vehicle-based safety systems are to be introduced. These systems typically use sensors, cameras, and other technologies to detect potential hazards and assist the driver in controlling the vehicle, i.e., ADAS (discussed

¹⁷<https://eur-lex.europa.eu/eli/reg/2019/2144/oj>

in section 2.6.1). Since vehicle speed is an important contributor to both the occurrence and severity of collisions, from 2024, all new vehicles will be required to have a form of Intelligent Speed Assist (ISA)¹⁸. However, these systems will be overridable, leading to concerns over their potential effectiveness. This measure will therefore be reviewed in 2025. Furthermore, informed by findings from European research projects (e.g., PROSPECT - Figure 2.9), since 2019, regulated type-testing has included the Advanced Emergency Braking (AEB) system for automatic detection of and avoidance of imminent forward collisions with cyclists/pedestrians¹⁹. These systems have been projected to save lives, and reduce injuries. In particular, the proliferation of AEB systems in cars is expected to result in far fewer collisions and lower impact speeds. A prospective analysis involving a car kinematic model with AEB and test cases informed by a representative sample of French police reports indicates that these systems have the potential to reduce the occurrence of both fatalities and injuries to cyclists [111]. Specifically, reductions ranged from 35% to 59% for fatalities, 14% to 54% for serious injuries, and 11% to 42% for minor injuries.

2.6.3 Heavy goods vehicles

It is well-known that Heavy Goods Vehicles (HGVs) feature frequently among fatalities and serious cyclist injuries internationally [6], and in Ireland [112] (particularly at junctions in slow-moving traffic). HGVs pose risks to cyclists primarily in urban environments. In 2009, Dublin City Council released a report on cyclist fatalities in Dublin City between the years 2002 and 2006. The main findings were that 8 of the 11 cyclist fatalities during the study period involved HGVs turning left at junctions (nearside-hooks), and of the 28 serious injury collisions, many (29%) were due to left-turning vehicles, of which 63% were HGVs.

Drivers of HGVs rarely have much direct vision of their surroundings from their cabs,

¹⁸<https://eur-lex.europa.eu/eli/reg.del/2021/1958/oj>

¹⁹<https://eur-lex.europa.eu/eli/reg/2020/1597/oj>

and their indirect vision (through their wing mirrors) has large blind zones. Limited direct and indirect vision for HGV drivers poses dangers to all road users. However, due to their relative size and road positioning, cyclists are at a particularly high risk of being in a HGV driver's blind zones. The extent of this effect is illustrated in Figure 2.20.

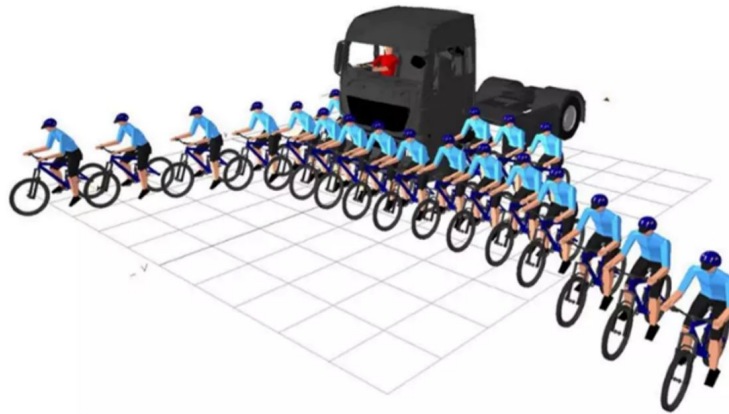


Figure 2.20: Possible positions of cyclists that may be visible to drivers through direct/indirect vision. Figure from a report by Transport for London (2016) [113].

International findings indicate that most cyclist fatalities involving a HGV result from the cyclist being positioned at the front/nearside of the HGV, and indirect/direct vision issues in this region (the blind zone) are a contributing factor in most of these impacts [114]. Historically, European regulations limiting HGV lengths (for trailer and tractor) have led to designs with the driver cabin placed high above the engine. However, cabin height has been shown to reduce direct vision for drivers [113]. Currently, this is primarily mitigated using a range of mirrors, providing an indirect vision of the space around the cabin, and underrun protection systems to prevent cyclists from falling under the wheels in the case of impact. However, incorrectly adjusted mirrors often result in impacts [115], and direct vision is preferable since the need to check multiple mirrors reduces reaction times, resulting in a temporal blind zone. Therefore, recent HGV designs have included ADAS for the blind zone,

i.e., forward collision warning (FCW), and autonomous emergency braking (AEB). Upcoming European regulations will include mandatory blind zone detection systems. Specifically, by 2024 HGVs will be required to have Blind Spot Information Systems (BLIS)²⁰, and Moving Off Information Systems (MOIS)²¹ to warn the driver of cyclists when turning, or moving off from a stop. Alongside current indirect vision standards²², there are also plans to improve direct vision in HGVs through a Direct Vision Standard (DVS) by 2029, i.e., with lower cabs and more windows.

²⁰<https://eur-lex.europa.eu/eli/reg/2020/1596/oj>

²¹<https://eur-lex.europa.eu/eli/reg/2021/829/oj>

²²[https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX:42014X0808\(02\)](https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX:42014X0808(02))

2.7 Single cyclist collisions

2.7.1 Scale of the problem

Single cyclist collisions/single bicycle crashes, i.e., falls and impacts not involving a collision with another road user, are a significantly underestimated road safety problem. Schepers et al. (2015) [116] reviewed 13 international studies and concluded that single cyclist collisions comprised 5–30% of fatalities, and 60–95% of cyclists admitted to hospitals or treated at emergency departments. The proportions among hospital-admitted cyclists are shown in Table 2.4. Furthermore, these rates do not appear to be particularly variable between study locations, nor affected by cycling modal share. A review of cyclist injuries in the Irish emergency department data register reported that only 32% involved collisions with motorised vehicles. Many (42%) were recorded as “unspecified” [117], and many of these are likely to be single cyclist collisions. The risks of single cyclist collisions are underestimated both among researchers/policymakers, and cyclists themselves [118], leading to a dearth of knowledge and research into these cases. Cyclist-motorised vehicle collisions comprise the largest share among fatalities, however, among serious injuries and lower severity cases single cyclist collisions dominate. Historically, drastic improvements in road safety have been achieved through targeted decreases in fatality rates (detailed in section 2.3), by focusing on collision/injury prevention strategies for cyclist-motorised vehicle collisions. However, since reductions in serious and lower severity collisions are now targeted through European road safety strategies (i.e., Vision Zero and the Safe System approach - section 2.2), and called for by international transport organisations, e.g., the International Transport Forum [6], efforts towards reducing the occurrence and severity of single cyclist collisions should now also be prioritised.

Table 2.4: Proportions of single cyclist collision casualties among road casualties admitted to hospital for various countries/locations, including modal shares. Adapted from Schepers et al. (2015) [116].

Study area, study period, ref	Modal share	Share among:		N
		Cyclist collisions	All collisions	
Netherlands (2005–2009) [119, 120]	31%	74%	41%	46,100
Denmark (2011) [120, 121]	19%	74%	33%	18,489
Belgium, Flanders, Brussels (2003–2007) [122, 120]	13%	87%	30%	18,750
England (2011–2012) [120]	2%	80%	23%	16,227
Sweden (1998–2005) [123, 120]	17%	75%	23%	29,788
Finland (1985–1986) [120, 124]	13%	65%	22%	127
Canada (2010–2011) [125, 126]	2%	82%	15%	4,126
USA, Oregon (2002–2006) [125, 127]	1%	67%	11%	414
Australia (2008–2009) [128, 125]	1%	63%	9%	3,811
France, Rhône county (1996–2008) [129, 120]	3%	65%	9%	2,578
Iran (2003) [130]	NA	62%	3%	420
Germany, Münster (2009–2010) [131, 125]	27%	72%	NA	251
New Zealand (2011) [132, 133]	1%	78%	NA	2,260

2.7.2 Direct causes

In recent years, the causal factors for single cyclist collisions have been a focus of research, using emergency department attendee surveys, insurance data, and self-reported surveys [134, 42, 43, 44, 135]. A comprehensive study of single cyclist collisions involved a survey of Dutch emergency department attendees [44]. In this study, ‘direct causes’ were defined as the object, action, or mechanism that caused the cyclist to fall. The coding scheme categorises collision causes by: 1) infrastructure (on-road/off-road obstacles or road surface conditions), 2) road-user related (e.g., avoidance manoeuvres, riding mistakes), or 3) bicycle malfunction. Findings indicated that roughly half of single cyclist collisions are related to infrastructure (cyclists colliding with road furniture, off-road furniture, skidding due to a slippery road, or loss of control due to an uneven road surface). Cyclist factors including low-speed loss of control, baggage catching the front wheel, or risky cycling accounted for roughly a third of collisions, while bicycle malfunction was rare (5%) (ibid.). A significant proportion (18%) involved more than one direct cause (ibid.). The coding scheme developed in this study formed a basis for a study of single cyclist collisions in insurance data in Finland

[135], which presented a much higher proportion due to slipping on snow/ice. International findings indicate that slippery road surfaces are a common contributory factor, however, as demonstrated in a recent review paper priorities between countries and cycling environments can vary [136] (Table 2.5). Thus highlighting the need for localised data collection regimes, i.e., international findings for collision factors may not be appropriate to the Irish context.

Table 2.5: Studies that have examined the characteristics or crash types of single cyclist collisions. Adapted from Utriainen et al. (2022) [136].

Study area, period, ref	Source	N	Three most common contributory factors:		
			1	2	3
Finland (2016–2017) [135]	Insurance	3,448	Skidding due to a slippery road surface, e.g., ice or snow (47%)	Avoidance of other road users (14%)	Colliding with an object, e.g., a bollard or a kerb (9%)
Denmark (2010–2015) [137]	ED/Hospital	1,720	Road-related, e.g., slippery road or potholes in the road (39%)	Cyclist-related, e.g., inattention by the cyclist (29%)	Unknown, specific factor was not specified (25%)
Sweden (2013–2017) [138]	ED/Hospital, Survey	~644	Skidding on, e.g., ice or snow (32%)	Collision with a stationary object, e.g., a curbstone (18%)	Loss of control during a braking or evasive manoeuvre (13%)
Switzerland (NA–2016) [43]	Survey	638	Skidding on, e.g., wet leaves or ice (31%)	Crossing a threshold, or collision with an obstacle, e.g., a kerb or pothole (27%)	Wheel lodging into or skidding on a tram or railway track (13%)
Denmark (2012–2013) [139]	Survey	349	Snow or ice as a contributory factor (48%)	A curve or when turning as a contributory factor (22%)	A kerb as a contributory factor (13%)
Australia (2009–2010) [140]	ED/Hospital, Survey	122	Loss of control on a straight section (49%)	Colliding with an object (20%)	Loss of control on a curve (13%)
Australia (2013) [134]	ED/Hospital, Survey	62	Loss of control, e.g., in slippery conditions	Interaction with tram tracks, e.g., turning across tracks (19%)	Sudden braking to avoid another road user (15%)
Australia (2014–2017) [141]	ED/Hospital, Survey	39	Loss of control (54%)	Colliding with a stationary object (46%)	NA
Netherlands (2012) [40]	ED/Hospital, Survey	27	Colliding with an object (52%)	Fall from a bicycle (48%)	NA

2.7.3 Fall kinematics, & dynamics

Overall, little is known of the fall mechanisms in single cyclist collisions. Though there is a well-developed body of work into the general kinematic forms of falls due to perturbations (not specific to cyclist falls), e.g., Van Den Kroonenberg et al. (1996) [142], and Maki et al. (1996) [143], Hsiao et al. (1997) [144], and Feldman et al. (2007) [145]. Furthermore, single cyclist falls have been computationally modelled for the purposes of estimating head impact conditions and helmet effectiveness, e.g., Bourdet et al. (2012) [146], McNally et al. (2013) [147], Fahlstedt et al. (2016) [148], Feist et al. (2016) [149], and Wang et al. (2022) [73].

As described in section 2.5, computational modelling approaches generally involve either multibody (MB), or finite element (FE) models, and dynamics solvers implement the equations of motion as an initial value problem, i.e., initial conditions for the simulation are specified at a certain point in time. As demonstrated in section 2.6.2, impact kinematics and dynamics from vehicle-cyclist collisions are influenced significantly by initial conditions, i.e., collision configurations, human posture, and motion. The effects of initial conditions for falls have yet to be investigated, however, due to the lower impact speeds, and therefore longer reaction times, initial pose and motion are expected to have a larger relative effect.

The self-protective effects of active response in unplanned sideways falls is a well-established area of research. These studies involve measuring the fall kinematics of human subjects subjected to a perturbation in a motion capture laboratory e.g., Van Den Kroonenberg et al. (1996) [142], Hsiao et al. (1997) [144], and Feldman et al. (2007) [145]. Common 'kinematic forms', i.e., the motion of the falling person and the sequence of impacted body regions, are investigated for injury prevention strategies. However, these vary between experimental studies; Hsiao et al. (1997) [144] found that active trunk rotation during the fall results in landing on the hands and knees, with low incidence of hip impact, whereas Feldman et al. (2007) [145] found hip impact to be common, and while the upper extremities were also

commonly used, less trunk rotation was observed, resulting in landings on the thigh. Both studies involved applying perturbations to human subjects, however in the former, subjects had prior knowledge of the perturbation direction. The study by Van Den Kroonenberg et al. (1996) [142] involved subjects performing a voluntary fall, resulting in similar findings to Feldman et al. (2007) [145], however, the order of ground impact for the hip/upper extremities differed. Nevertheless, across these studies, the general kinematic form of a sideways fall initially involves the fall-side leg extending in an attempt to recover balance, followed by the arms extending to absorb impact energy and avoid head-ground contact (Figure 2.21). However, fall characteristics specific to single cyclist falls have not been well investigated. Higher initial velocity, and the presence of bicycle between the falling cyclist's legs acting as an obstacle likely result in different kinematic forms to static falls from standing heights.

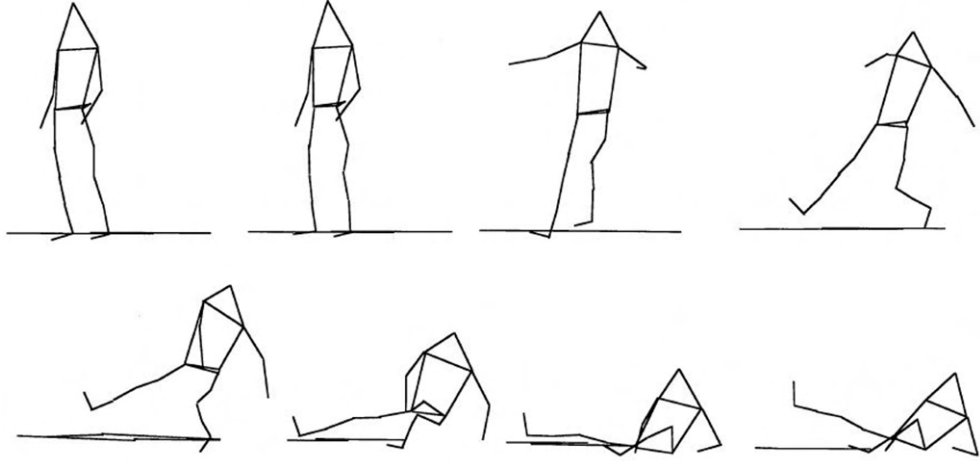


Figure 2.21: Example kinematic form for a sideways fall. Adapted from Hsiao et al. (1997) [144].

Protective response to a fall/perturbation can be decoupled into its kinematic and dynamic components. Here kinematic protective response in modelling is defined as 1) the Degrees of Freedom (DOFs) (q_0 from section 2.5) i.e., linear position specified for the root of the model relative to its environment, and joint angular configurations throughout the body

which specify pose at a certain point in time, and 2) 1st derivatives of these DOFs (d DOFs) ($\dot{q}_0$ from section 2.5) specifying motion throughout the body, i.e., linear velocity of the root, and joint angular velocities throughout the body. The dynamic component involves active muscle response, i.e., muscle activation. There are a number of computational models that include active response, examples include the active MADYMO model [150], and a number of finite element models such as the THUMS, VIVA+, and GHBMC. For modelling active behaviour, the MADYMO model includes hill-type muscle elements, and actuators in the neck, arms, legs, and spine. However, these models have been developed primarily for vehicle occupant impact modelling, e.g., Valdano et al. (2021) [151], Östh et al. (2015) [152], and the control systems defining active responses to kinematic scenarios may not be suited to modelling falls. Neither kinematic nor dynamic components of protective response have been well investigated for cyclist falls [146, 148, 149, 147, 73, 153], nor falls of other Vulnerable Road Users (VRUs) such as electric scooter riders [154, 155]. Most of these studies have modelled fictive fall scenarios, initialising the human body model with an initial velocity on a modelled bicycle/scooter, which is projected into an obstacle. For example, Wang et al. (2022) [73] simulated cyclist falls resulting from impact with a kerb, and skidding, to assess the relative effectiveness of a variety of helmet types in MADYMO. Similarly, Posirisuk et al. (2022) [155] investigated the ground-impact kinematics and dynamics of electric scooter riders in forward falls after impact with a kerb in MADYMO, finding high head-ground impact forces (higher than skull fracture thresholds), and that lower initial scooter velocity reduces impact forces (Figure 2.23). The authors also compared simulated fall kinematics to a staged test from online footage, finding large differences due to the active/protective response of the rider to the fall.

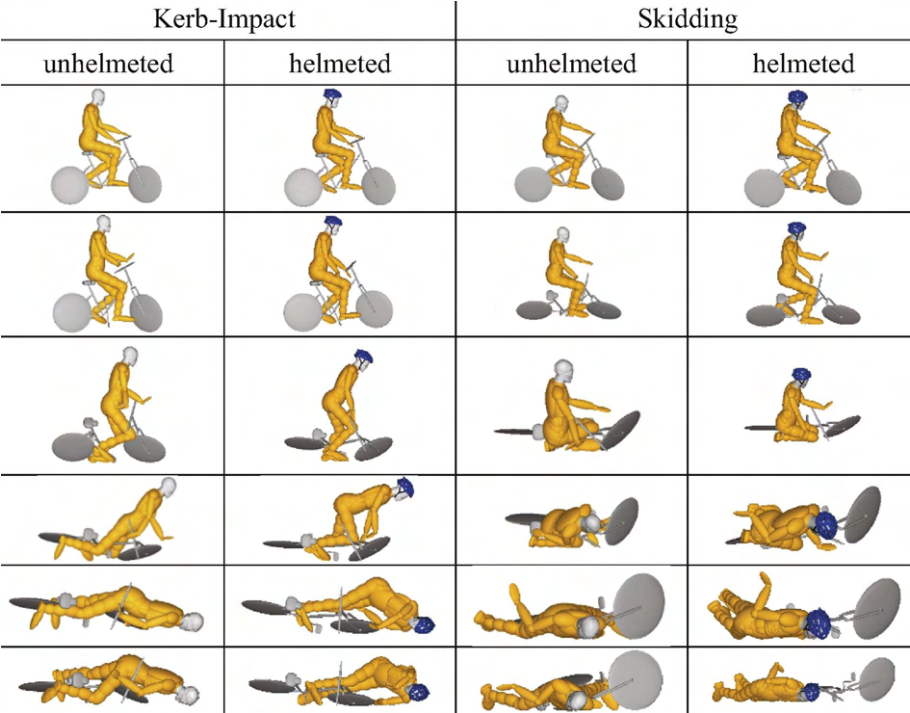


Figure 2.22: Computational modelling of fictive cyclist falls. Adapted from Wang et al. (2022) [73].

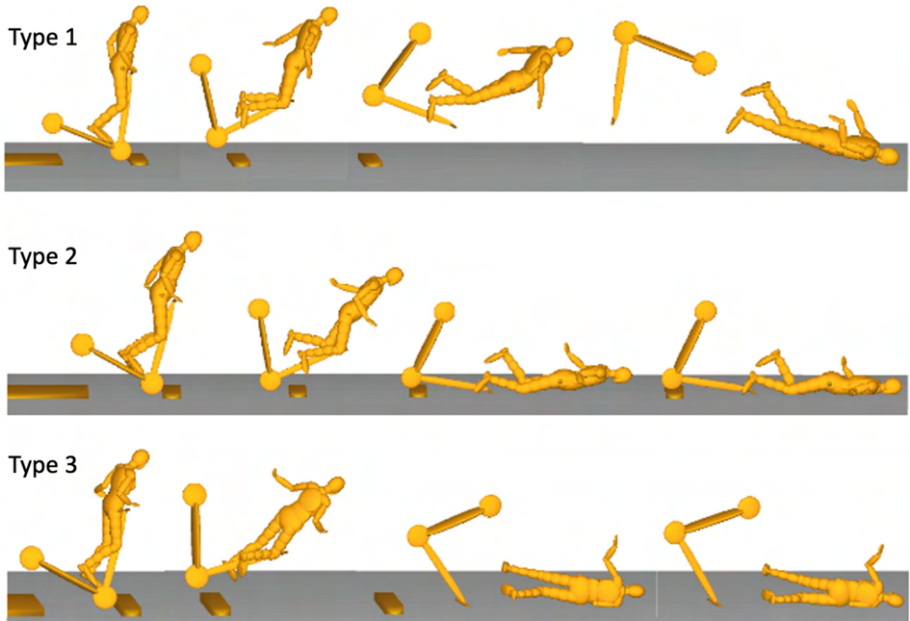


Figure 2.23: Computational modelling of fictive electric scooter falls by Posirisuk et al. (2022) [155].

Findings from Wang et al. (2022) [73] indicate that helmets significantly reduce head injuries in falls. While computational modelling is not the only basis for determining the effectiveness of helmets, and statistical analyses of historical police/hospital data have found significant protective effects, e.g., Høyen et al. (2018) [156], and Foley et al. (2020) [117], current approaches taken to characterise common head impact conditions through computational modelling could be improved, as evident by the unrealistic ragdoll-type motion in Figures 2.22, and 2.23. Therefore, overall predicted effectiveness of novel helmet designs are difficult to assess, and helmet type testing protocols may not be representative of real-life impact conditions. This also limits the assessment of other potential injury prevention strategies such as speed limiters (for electric bikes/scooters), elbow/knee guards, softer road surfaces, or safer road furniture.

As described in section 2.5, MADYMO provides a suite of MB models which allow for user definition of body pose, overall linear velocity, and individual joint angular velocities. While repositioning of FE models is more difficult, recent efforts have allowed for modelling of falls using the THUMS FE model with specification of trunk, pelvis, and knee angles [157] (Figure 2.24). In an investigation of injuries resulting from a fall from height using MADYMO, Milanowicz et al. (2017) [158] developed an approach for initialising the fall kinematics at the instance of loss of balance using motion capture data (Figure 2.25). However, as discussed previously, kinematic forms in falls are difficult to generalise using motion capture data, and are dependent on the experimental design. Therefore, real-world/in-the-wild footage is a preferred source for plausible kinematics. The dearth of studies in this area is in part due to difficulties in capturing human kinematics from video footage. As described in section 2.8, CV/AI based approaches may present opportunities for reconstructing falls, with the inclusion of observed protective responses.

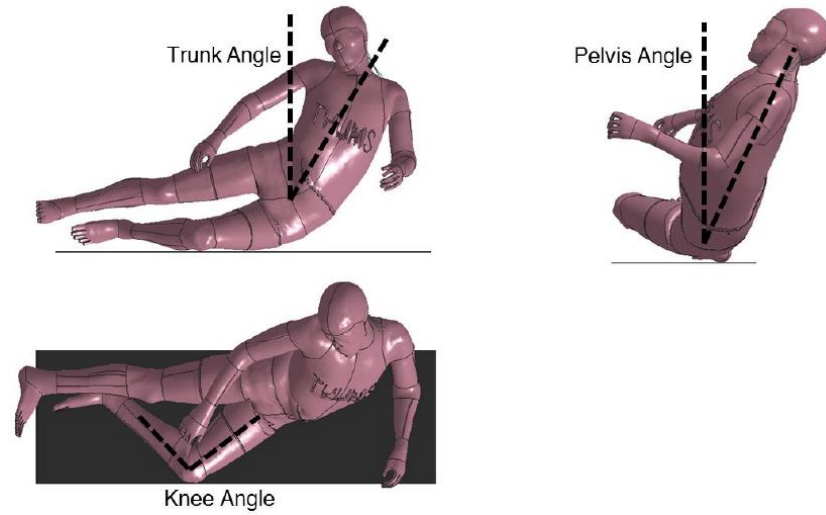


Figure 2.24: FE computational modelling of of a fall. Adapted from Sahandifar et al. (2022) [157].

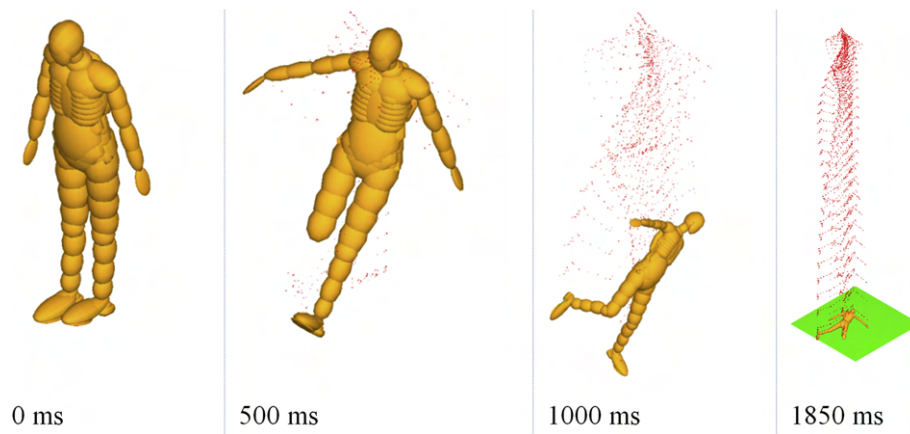


Figure 2.25: Simulated fall from height, with motion capture data informed initial conditions. Adapted from Milanowicz et al. (2017) [158].

2.8 Human motion capture, & pose estimation

Human motion capture technologies are widely used for animation, physiotherapy, sports biomechanics, ergonomics, robotics, and augmented/virtual reality. Marker-based optical or optoelectronic motion capture systems involve tracking passive retroreflective or active LED markers placed on a human subject. These systems require the use of multiple spatially and temporally calibrated high-framerate cameras (200fps) with infrared light emitters (for passive markers) (e.g., Vicon²³, and Optitrack²⁴). There are also a variety of alternative motion capture systems that involve markers/sensors, including 1) the use of inertial measurement units (i.e., combined gyroscope(s), and accelerometer(s), e.g., Xsens), 2) instrumented exoskeletons (with sliders and potentiometers), e.g., Gu et al. (2016) [159], and 3) combining magnetic sensor markers with a magnetic field generator, e.g., Yabukami et al. (2000) [160]. Marker-based motion capture systems obtain 3D coordinates for each marker by algebraic triangulation [161], from which underlying skeletal joint/body positions and orientations are automatically estimated. These joints are positioned to approximate the human skeletal structure, and their kinematic nature with differing degrees of freedom (DOFs), and ranges of motion (ROMs) are specified to limit the axes that the links are free to rotate about; effectively reducing unrealistic poses.

However, in many cases there is a need for markerless forms of motion capture, to allow for more natural subject motion, and capture from conventional video cameras in less experimentally-constrained environments (i.e., outside of a motion capture laboratory). Such systems do exist (e.g., Simi²⁵), however, many of them currently involve the use of calibrated multi-sensor (RGB or RGB-D camera) setups, making them prohibitively expensive and unsuitable for many potential applications. As detailed in section 2.7.3, there is a need

²³<https://www.vicon.com/>

²⁴<https://www.optitrack.com/>

²⁵<http://simi.com/en/>

for a method of markerless motion capture from in-the-wild footage for traumatic injury biomechanics applications, e.g., reconstruction of single cyclist falls, electric scooter falls, or accidental falls in workplaces.

Both multi-camera and single-camera (monocular) 3D human pose estimation methods exist. Generally, they employ a 2D keypoint pose estimator as a backbone and use CV and AI techniques to ‘lift’ the 2D pose into 3D (e.g., Figure 2.26). A simple calibrated multi-camera technique involves classical algebraic triangulation of keypoint/joint positions [161]; The popular 2D pose estimator OpenPose contains a module for this [162]. Many machine learning/regression-based multi-camera pose estimators have also been developed, which use neural networks trained and tested on widely used motion capture datasets (e.g., Human3.6M [163]) to regress for both 2D and 3D keypoints directly from images/videos. Regression-based multi-camera pose estimators have achieved high accuracies of below 2cm Mean Per Joint Position Error (MPJPE) over a variety of tasks in Human3.6M [164, 165]. MPJPE is a commonly used metric to evaluate the accuracy of human pose estimation models. It measures the average Euclidean distance between the predicted and ground-truth positions of each joint in a human skeleton. Considering the inherent depth ambiguities, remarkably high accuracy has also been achieved from monocular pose estimators (in the order of 3-5cm MPJPE) [166, 167, 168, 169, 164, 170, 171, 172, 173, 174]. Code bases for many of these methods are made publicly available on repositories such as GitHub, e.g., HRNet²⁶, and OpenPose²⁷, VideoPose3D²⁸, Gast-Net²⁹.

However, position-based pose representation suffers from several limitations. In particular, joint/link orientations are not included, subject size estimates are inaccurate, and predicted limb lengths are often quite variable, greatly limiting its practical uses, e.g., in

²⁶<https://github.com/leoxiaobin/deep-high-resolution-net.pytorch/>

²⁷<https://github.com/CMU-Perceptual-Computing-Lab/openpose/>

²⁸<https://github.com/facebookresearch/VideoPose3D/>

²⁹<https://github.com/fabro66/GAST-Net-3DPoseEstimation/>

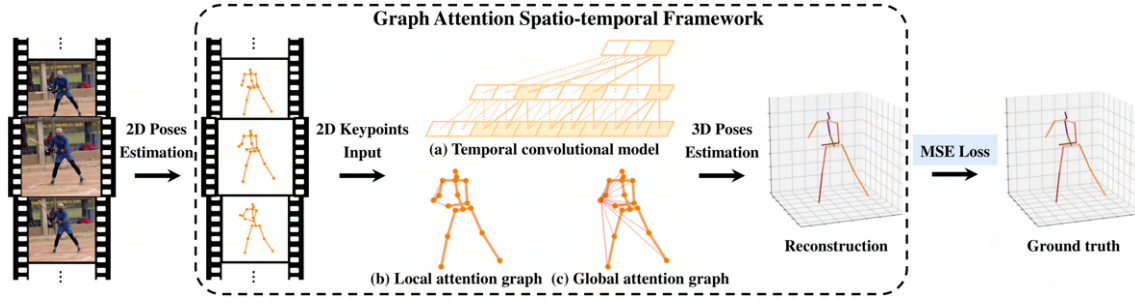


Figure 2.26: Schematic overview of the GAST-Net framework. Figure from Liu et al. (2020) [171].

biomechanics applications. Other regression-based pose estimators address a portion of these limitations through reformulating the pose representation, and instead predicting joint orientations within a kinematic chain, e.g., Zhou et al. (2016) [175], and Pavllo et al. (2018) [176], i.e., through forward kinematics (FK) (see section 7.3.1). There are various ways to parameterise these rotations (e.g., sequential Euler/Cardan angles, Euler/Screw axis-angle), though unit quaternions are generally preferred as they overcome singularities associated with operations in R^3 . Orientation-based 3D pose representation allows for orientation losses to be included, e.g., Mean Per Joint Angular Separation (MPJAS). Similar to MPJPE, MPJAS is a metric to evaluate the accuracy of human pose estimation models, however, it instead measures the average angular difference between the predicted and ground-truth orientations of each joint in a human skeleton. Furthermore, model-based pose estimators allow for other biomechanical constraints such as joint DOFs. Though orientation-based pose representation is more physically meaningful than position-based representation, the results are mostly sub-par in terms of MPJPE. However, these are promising approaches meriting further development. 3D pose and shape estimation methods also exist, i.e., 3D pose with the inclusion of body shape predictions. Promising approaches involve the use of a statistical human body shape model, i.e., a skinned vertex model that represents a wide variety of body shapes in natural human poses, developed via dimensionality reduction techniques, i.e., principal

component analysis (e.g., SMPL, STAR) [177, 178, 179]. However, similar to methods that employ kinematic model-based pose representations, accuracy results for statistical human body model-based methods are lower than position-based ones.

Pose estimation using a statistical human body model (SMPL) has been applied to the task of classifying pedestrian pre-crash pose from monocular footage [180] (Figure 2.27). It is expected that this kind of approach may improve the fidelity of vehicle-pedestrian impact reconstructions, as current approaches rely on fictive estimated poses, e.g., Maki et al. (2003) [89], volunteer test in simulated environments, e.g., Soni et al. (2013) [181], or visual inspection of crash footage, e.g., Han et al. (2017) [182]. This kind of approach may help guide changes to type-testing methodologies, i.e., provide more representative postures.

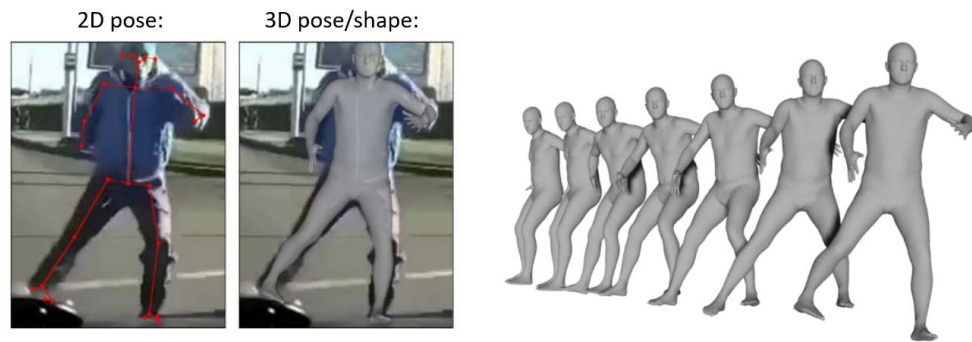


Figure 2.27: Classification of pedestrian pre-crash pose using a statistical human body model (SMPL). Adapted from Schachner et al. (2020) [180].

A crossover field also exists between biomechanics, robotics, and animation, whereby the tracked motion of a subject is applied to a kinematic chain, i.e., a biomechanical model, animated character, or humanoid robot. Some recent approaches employ a position-based 3D pose estimator and apply regression [183, 184] or inverse kinematics (IK) optimisation [185, 186, 187] to infer joint orientations (which are essential in these applications). As detailed in section 7.3.2, there is a kinematic indeterminacy to this problem due to the ambiguous ‘twist’ angle in limbs/links. A previous approach has overcome this ambiguity by limiting this twist angle for animation [184]. However, while the loss functions used produce

animations with visual realism, they are not biomechanically informed.

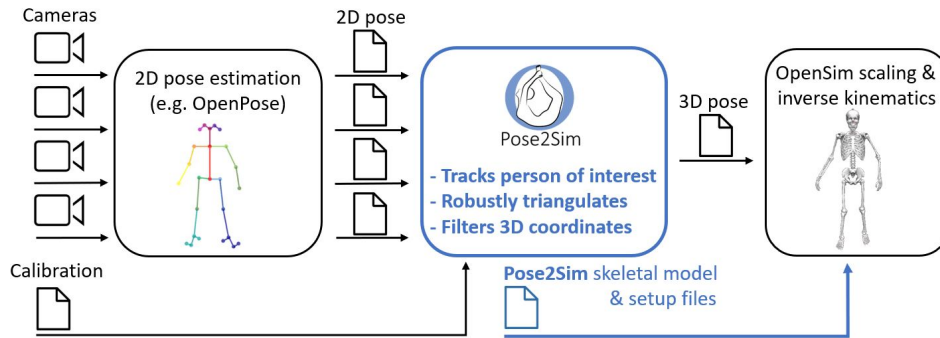


Figure 2.28: The Pose2Sim framework. Figure from Pagnon et al. (2021) [185].

A popular human biomechanics software OpenSim contains an IK tool for prescribing joint positions to a biomechanical model, which has recently been applied to obtain joint orientations from triangulated 2D predictions, i.e., Pose2Sim [185, 186] (Figure 2.28). However, many practical applications, including the use of 3D human pose estimation for reconstruction of fall biomechanics, require a similar tool for 3D pose estimates from a monocular method, which have characteristics that restrict its application. Namely, subject dimensions are inaccurately scaled (since there is no context for the size of the subject), and limb lengths are often variable.

2.9 Conclusions

In summary, while national and international policies aim to encourage more people to cycle, it is crucial to also work towards improving the safety of cyclists. Having a thorough understanding of typical scenarios leading up to crashes and the types of impacts involved is essential for treating the safety hazards faced by cyclists. However, such factors have not been extensively studied in the Irish context. Therefore, this thesis aims to fill this knowledge gap by conducting a comprehensive analysis of common pre-crash scenarios and impact configurations, with the goal of identifying effective strategies for reducing the risk of cycling collisions and enhancing cyclist safety on Irish roads.

Examination of collision data also indicates that due to underreporting, police-reported statistics are skewed toward incidents involving motorised vehicles, and that consideration should also be paid to single cyclist collisions. While significant engineering efforts have been focused on developing collision and injury prevention strategies cyclist collisions with motorised vehicles, there has been inadequate consideration given to single cyclist collisions. Therefore, this thesis takes an engineering perspective to reduce the occurrence and severity of these cases.

Chapter 3

Study A: Collision characteristics, & underreporting biases

Related publication:

- Characteristics of cyclist collisions in Ireland: Analysis of a self-reported survey,
K. Gildea, C. Simms,
Accident Analysis & Prevention (2021)

3.1 Introduction

Due to its numerous health, environmental, and economic benefits [188], cycling has been encouraged in Ireland, and throughout Europe [189, 190]. A key factor affecting the uptake of cycling is safety; perceived risks have been shown to deter the uptake of cycling in Dublin [15]. Moreover, with increased uptake there is also the increased responsibility on road safety stakeholders to ensure a safe cycling environment. Road safety in Ireland has been improving, and Ireland has been awarded the ‘Road Safety PIN Award’ by the European Transport Safety Council for sustained successful strategies in reducing road deaths and injuries. However, as detailed in section 2.3, while overall numbers have reduced in Ireland, the numbers and modal share of cyclist injuries have been increasing (Figures 2.2, and 2.3), reflecting increases in popularity.

Evidently, increased efforts should be made to reduce the occurrence and severity of injuries to cyclists. In Ireland and internationally, safety interventions are generally based on police-reported data. However, as detailed in section 2.4.1, limited detail is available for analysis, and cycling collisions are often not reported to the police [27, 6, 28, 29, 30, 31, 32, 33, 26]. It is known that the vast majority of cyclist collisions in Irish police statistics are with motorised vehicles, and fewer than 10% are single cyclist collisions [23, 24]. However, internationally it is known that collisions where a motorised vehicle is not involved as a collision partner, i.e., single cyclist, cyclist-pedestrian or cyclist-cyclist collisions have lower odds of being reported to the police [6, 29, 30]. The biased nature of cyclist collision reporting has clear implications for policy makers and road safety researchers, who generally rely on police data to determine road safety priorities.

As detailed in section 2.4.2, self-reported surveys are often used to gain a greater understanding of cycling collisions not present in police, hospital, or insurance data (e.g., Madsen et al. (2018) [28], and Shinar et al. (2018) [30]). The self-reported nature of these surveys presents challenges, but they are a valuable mechanism for assessment of otherwise unobserved cases and unrecorded information.

3.2 Study aims

There is a large body of international research into the factors that contribute to both the occurrence and severity of cyclist collisions, and their associated prevention strategies, however, given the large disparity in cycling rates and cycling environments between countries it is unclear how applicable international findings are to the Irish context. Accordingly, the overall aim of this study is to use an online survey to investigate cyclist collisions in Ireland, and inform future prevention priorities. Specifically, this study has two aims:

1. Investigate the factors biasing the reporting of cyclist collisions, informing further investigation into collision types that are least represented in police statistics.
2. Compare collision characteristics and injury outcomes for collisions with motorised vehicles and non-motorised vehicle collisions (which have lower odds of being reported to the police).

3.3 Methods

3.3.1 Survey design & dissemination

The online survey was designed following an extensive literature review, a focus group session, and survey trialling to collect collision information from a target population of adult cyclists (>18) in Ireland who had been involved in a collision(s) in the past five years (as per Hollingworth et al. (2015) [191], and Useche et al. (2019) [46]). The survey seeks collision details under the headings of road factors, environmental factors, and human factors, as well as outcome details such as police reporting, injury severity, and hospital attendance. Behavioural and attitudinal information was collected for cyclists who had not been involved in a collision, where cyclists were defined as people who had cycled on a public road in the previous 12 months. However, this chapter only contains information relating to the collisions. Behavioural and attitudinal information was only sought for those not involved in collisions to limit each individual's response time (and hence increasing response numbers and completion rates). Injury severities were coded as 'minor' or 'serious' according to the definitions used in police statistics in Ireland and the UK (see Table A.1).

A flowchart of the survey showing a bifurcation section, a collisions pipeline, and a behaviours and attitudes pipeline is shown in Figure A.1. Respondents were directed to the collisions pipeline if they had a collision since the 1st of January 2013. Cyclists were directed to enter their most recent collisions. The full survey questionnaire is available¹. The survey was open March 24th - August 2nd, 2018. Dissemination was via mailing lists of several cycling organisations, employers, and universities, and was also circulated through social media. In an effort to reduce sampling bias, the study was advertised simply as a cyclist safety survey. Ethical approval for the survey and focus group were provided by the Trinity College Dublin Faculty of Health Sciences Ethics Committee.

¹<https://kevgildea.github.io/assets/Thesis/3.3.1-Questionnaire.pdf>

3.3.2 Data cleaning

Three techniques were applied to identify invalid responses as either ‘inconsistent’, ‘wrong turns’, or ‘substantially incomplete’, similar to methods used by Hertach et al. (2018) [43]. Within the survey are groups of two or more questions with mutually exclusive answers, which should be answered in a certain pattern. Cases deviating from these expected patterns were excluded (e.g., the respondent selects that the collision occurred both on the ‘Weekend’ and on ‘Wednesday’). Since the survey uses piping, and directs respondents based on their responses to certain questions, some respondents made errors and were sent to an inappropriate page. These erroneous responses were excluded. Responses may be considered ‘substantially incomplete’ if the respondent did not engage with the survey sufficiently, as these respondents may leave many questions unanswered. Such responses were excluded from the survey. Respondents were also excluded if they were under 18 years old or if their collision had occurred outside of the Republic of Ireland. For further details see Figure A.1. Collisions were also examined for miscoded collision types (according to the definitions in Table A.1).

3.3.3 Statistical analysis

Univariable analysis

For categorical variables, Chi-square testing was used to identify significant differences between two groups: 1) collisions with motorised vehicles versus non-motorised vehicle collisions, and 2) injury patterns for the different collision types. Fisher’s exact test was applied in cases where more than 20% of cells had expected frequencies < 5 . For the continuous variable age, an independent-samples t-test was used to compare the means between the groups.

Multivariable analysis

Binary logistic regression modelling was used to establish the effects of various collision details on whether a collision was reported to the police:

$$p = P(Y=1 | X_1 = x_1, \dots, X_i = x_i) = \frac{e^{\beta_0 + \beta_1 x_1, \dots, \beta_i x_i}}{1 + e^{\beta_0 + \beta_1 x_1, \dots, \beta_i x_i}}, \quad (3.1)$$

where the dependent variable Y takes two values (1, 0), β_i are the coefficients estimated using the method of maximum likelihood and x_i are the predictor variables. This can be rearranged as:

$$OR = \frac{p}{1-p} = e^{\beta_0 + \beta_1 x_1, \dots, \beta_i x_i}, \quad (3.2)$$

where OR is the odds ratio used to estimate the change in outcome per unit increase in the corresponding predictor variable, while keeping remaining variables fixed.

Many questionnaire studies handle missing data by performing listwise deletion: simply using cases with fully populated responses and discarding cases with missing values. However, the distribution of missing values may not be random. Rubin et al. (1976) [192] describes three types of missing data: 1) missing completely at random (MCAR), 2) missing at random (MAR), and 3) missing not at random (MNAR). Since access to unobserved data is unavailable, neither MAR nor MNAR can be tested, however MCAR can be tested using Little's multivariate test [193]. A method called multiple imputation is applied, which fills missing data with plausible values [194]. This method is commonly used in analysis of data which has a degree of missingness as it has been shown to yield more accurate results than listwise deletion for MNAR and MAR data, and improvements in statistical power for MCAR data [195].

3.3.4 Data descriptions & summary of methodological approach

There were 3,904 respondents to the survey. A total of 860 fully completed collisions were available for analysis, along with a further 562 partially completed collision cases where the respondent exited the survey prior to completion (giving a total of 1,422 collision cases) (see Figure A.1). In section 3.4.1, collision characteristics of collisions with motorised vehicles vs. collisions not with motorised vehicles are compared. In section 3.4.2, injury outcomes are compared between collision types (for the 564 collisions involving injuries). In section 3.4.3, police reporting biasing factors were investigated for all collision cases, and police reporting/hospital attendance were further investigated for injurious cases Figure 3.1.

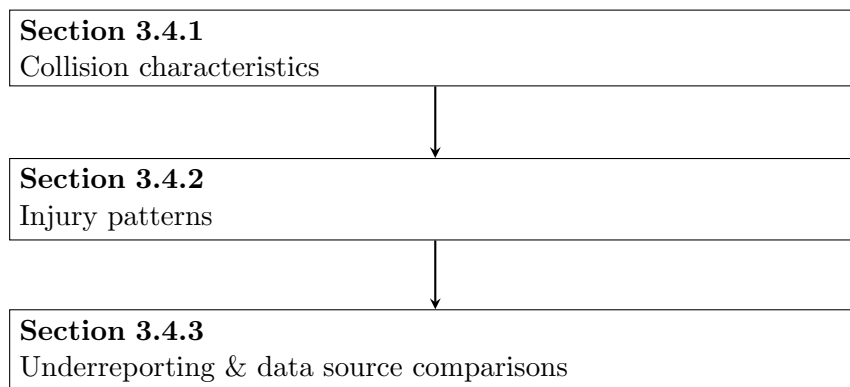


Figure 3.1: The methodological approach used in this study.

3.4 Results

3.4.1 Collision characteristics

Of the 1,030 collisions for which the collision partner was specified, the largest proportion of collisions was between cyclists and motorised vehicles (MVC) (55.9%), followed by single cyclist collisions (SCC) (29.0%), collisions with other cyclists (CCC) (7.9%) and pedestrians (CPC) (7.2%). Table 3.1, Table 3.2, Table 3.3 show the distributions of the various characteristics in two groups: 1) cyclist collisions with motorised vehicles and 2) cyclist collisions with anything other than a motorised vehicle (i.e., single cyclist collisions, collisions with pedestrians, or with other cyclists).

Comparisons of road factors are shown in Table 3.1. Chi-square statistics were used for inter-group comparisons, and odds ratios were calculated. The speed limits on roads differ between collision groups: collisions in environments with speed limits of 60 km/h or less had higher odds of being with motorised vehicles (OR 3.3, 95% CI:2.0–5.3). Collisions on roads without cycling facilities had lower odds of being with motorised vehicles (OR 0.6, 95% CI:0.5–0.8), however, for those who stated they were using the cycling facility (if available) there was no significant difference between groups (OR 1.3, 95% CI:0.6–2.9). Collisions on bending roads had lower odds of being with motorised vehicles (OR 0.3, 95% CI:0.2–0.5), similarly for collisions on roads with downhill gradients (OR 0.5, 95% CI:0.3–0.9). Collisions at junctions had higher odds of being with motorised vehicles (OR 2.7, 95% CI:2.0–3.5).

Comparisons of environmental factors are shown in Table 3.2. Chi-square statistics were used for inter-group comparisons, and odds ratios were calculated. Collisions on weekdays had higher odds of being with motorised vehicles (OR 2.3, 95% CI:1.7–3.1), as had collisions in environments flagged as urban by the respondent (OR 3.3, 95% CI:2.2–5.0). Understandably, collisions in no/light traffic had lower odds of being with motorised vehicles (OR 0.3, 95%

CI:0.3–0.4) (corresponding to the higher prevalence of rural environments among collisions not involving motorised vehicles), as had collisions in inclement weather (OR 0.4, 95% CI:0.3–0.6), or on hazardous road surfaces (i.e., not dry) (OR 0.3, 95% CI:0.2–0.4) (likely because these are common contributory factors in single cyclist collisions).

Comparisons of human factors are shown in Table 3.3. For categorical variables, Chi-square statistics and Fisher’s exact test (where applicable) were used for inter-group comparisons, and odds ratios were calculated. For the continuous variable (age), an independent-samples t-test was performed. There was no significant difference in respondent age for collisions with motorised vehicles ($M = 37$, $SD = 11.7$) and collisions without motorised vehicles ($M = 38$, $SD = 12.4$), $t(938) = -1.84$, $p = 0.07$. Collisions involving male cyclists had slightly higher odds of being with motorised vehicles (OR 1.3, 95% CI:1.0–1.8). Collisions in unfamiliar locations had much lower odds of being with motorised vehicles (OR 0.1, 95% CI:0.1–0.3). There was no significant difference in use of helmets (OR 0.9, 95% CI:0.6–1.2), or high visibility equipment (OR 0.9, 95% CI:0.4–2.1) and bicycle lights (during dusk/dark conditions) ($p = 0.28$) between groups. Reporting of alcohol use or mobile phone use on the part of the cyclist was extremely low ($<2\%$), and there were no significant differences between groups; $p = 0.26$, and $p = 1.0$, respectively. Cyclists reported earphone usage was also low (8%), however cyclists wearing earphones had higher odds of being in collisions with motorised vehicles (OR 1.6, 95% CI:1.0–2.7). Cyclists travelling for commuting/utility/work purposes had higher odds of being in collisions with motorised vehicles (OR 2.1, 95% CI:1.6–2.9), as were cyclists using hybrid/mountain bicycles (OR 1.3, 95% CI:1.0–1.7). Collisions involving cyclists travelling at speeds of 20 km/h and over had lower odds of being with motorised vehicles (OR 0.5, 95% CI:0.4–0.7).

Table 3.1: Road factors for collisions with and without the involvement of motorised vehicles.

	Motorised vehicle collisions		Non-motorised vehicle collisions		Overall	
	No.	%	No.	%	No.	%
Speed limit (km/h)***						
30	126	26.8%	93	28.4%	219	27.4%
50	281	59.8%	166	50.6%	447	56.0%
60	34	7.2%	12	3.7%	46	5.8%
80	25	5.3%	43	13.1%	68	8.5%
100	4	0.9%	14	4.3%	18	2.3%
Total	470	100.0%	328	100.0%	798	100.0%
Cycling facility**						
Segregated lane	5	0.9%	8	1.9%	13	1.3%
Dedicated on road lane	151	27.4%	90	21.4%	241	24.8%
Combined cycle/bus lane	78	14.2%	42	10.0%	120	12.3%
Contraflow lane	7	1.3%	0	0.0%	7	0.7%
No facility	310	56.3%	281	66.7%	591	60.8%
Total	551	100.0%	421	100.0%	972	100.0%
Using cycling facility*						
Yes	221	92.1%	129	92.1%	350	92.1%
No	19	7.9%	11	7.9%	30	7.9%
Total	240	100.0%	140	100.0%	380	100.0%
Road curve***						
Straight	516	89.9%	338	75.4%	854	83.6%
Bending	54	9.4%	86	19.2%	140	13.7%
Sharp Bends	4	0.7%	24	5.4%	28	2.7%
Total	574	100.0%	448	100.0%	1022	100.0%
Road incline*						
Flat	506	88.2%	373	83.3%	879	86.0%
Uphill	27	4.7%	18	4.0%	45	4.4%
Downhill	37	6.4%	53	11.8%	90	8.8%
Hillcrest	4	0.7%	4	0.9%	8	0.8%
Total	574	100.0%	448	100.0%	1022	100.0%
Junction type***						
T Junction	112	19.5%	44	9.8%	156	15.3%
Y Junction	19	3.3%	16	3.6%	35	3.4%
Other Junction	82	14.3%	36	8.0%	118	11.5%
Roundabout	34	5.9%	11	2.5%	45	4.4%
Entrance	42	7.3%	16	3.6%	58	5.7%
Not at Junction	285	49.7%	325	72.5%	610	59.7%
Total	574	100.0%	448	100.0%	1022	100.0%
Road type***						
Cyclist-Pedestrian Area	11	2.0%	42	9.5%	53	5.3%
Dual Carriageway	24	4.3%	7	1.6%	31	3.1%
Footpath/Pedestrianised	0	0.0%	5	1.1%	5	0.5%
Greenway	0	0.0%	3	0.7%	3	0.3%
Housing Estate	11	2.0%	7	1.6%	18	1.8%
One-way	61	10.8%	84	19.0%	145	14.4%
Private road	0	0.0%	4	0.9%	4	0.4%
Two-way	456	81.0%	290	65.6%	746	74.2%
Total	563	100.0%	442	100.0%	1005	100.0%

a: for collisions where there was cycling infrastructure available to be used, *significant at the 5% level, **significant at the 1% level ***significant at the 0.1% level

Table 3.2: Environmental factors for collisions with and without the involvement of motorised vehicles.

	Motorised vehicle collisions		Non-motorised vehicle collisions		Overall	
	No.	%	No.	%	No.	%
Day***						
Weekday	483	84.9%	321	72.1%	804	79.3%
Weekend	86	15.1%	124	27.9%	210	20.7%
Total	569	100.0%	445	100.0%	1014	100.0%
Time						
00:00-06:00	11	1.9%	11	2.5%	22	2.2%
06:00-12:00	277	48.5%	215	48.9%	492	48.7%
12:00-18:00	190	33.3%	138	31.4%	328	32.4%
18:00-00:00	93	16.3%	76	17.3%	169	16.7%
Total	571	100.0%	440	100.0%	1011	100.0%
Urban/rural (opinion) ***						
Urban	527	93.1%	359	80.5%	886	87.5%
Rural	39	6.9%	87	19.5%	126	12.5%
Total	566	100.0%	446	100.0%	1012	100.0%
Traffic conditions***						
No Traffic	29	5.1%	70	15.7%	99	9.7%
Light Traffic	150	26.3%	185	41.4%	335	32.9%
Moderate Traffic	221	38.7%	120	26.8%	341	33.5%
Heavy Traffic	171	29.9%	72	16.1%	243	23.9%
Total	571	100.0%	447	100.0%	1018	100.0%
Weather conditions***						
Dry	486	86.0%	307	70.9%	793	79.5%
Wet	71	12.6%	88	20.3%	159	15.9%
Windy	0	0.0%	5	1.2%	5	0.5%
Foggy	0	0.0%	2	0.5%	2	0.2%
Snowy/Icy	2	0.4%	20	4.6%	22	2.2%
Multiple	6	1.1%	11	2.5%	17	1.7%
Total	565	100.0%	433	100.0%	998	100.0%
Road conditions***						
Dry	485	84.9%	281	63.1%	766	75.4%
Wet	81	14.2%	112	25.2%	193	19.0%
Frost/Ice	3	0.5%	22	4.9%	25	2.5%
Gravel	1	0.2%	8	1.8%	9	0.9%
Oil	0	0.0%	9	2.0%	9	0.9%
Other	0	0.0%	6	1.3%	6	0.6%
Multiple	1	0.2%	7	1.6%	8	0.8%
Total	571	100.0%	445	100.0%	1016	100.0%
Light conditions***						
Dark, no street lighting	0	0.0%	3	0.7%	3	0.3%
Dark, poorly-lit	3	0.5%	20	4.5%	23	2.3%
Dark, well-lit	55	9.6%	41	9.2%	96	9.4%
Dusk	38	6.7%	10	2.2%	48	4.7%
Daylight, poor visibility	16	2.8%	19	4.3%	35	3.4%
Daylight, good visibility	455	79.7%	353	79.1%	808	79.4%
Daylight, low sun	4	0.7%	0	0.0%	4	0.4%
Total	571	100.0%	446	100.0%	1017	100.0%

*significant at the 5% level, **significant at the 1% level ***significant at the 0.1% level

Table 3.3: Human factors for collisions with and without the involvement of motorised vehicles.

	Motorised vehicle collisions		Non-motorised vehicle collisions		Overall	
	Median	IQR ^a	Median	IQR ^a	Median	IQR ^a
Age (years)	37	26-45	38	26.75-46	37	26-46
	No.	%	No.	%	No.	%
Sex*						
Female	147	27.3%	138	33.3%	285	29.9%
Male	392	72.7%	276	66.7%	668	70.1%
Total	539	100.0%	414	100.0%	953	100.0%
Familiarity with the location***						
Not Familiar	7	1.2%	43	9.6%	50	4.9%
Familiar	566	98.8%	405	90.4%	971	95.1%
Total	573	100.0%	448	100.0%	1021	100.0%
Helmet use						
No	107	18.8%	91	20.2%	198	19.4%
Yes	463	81.2%	360	79.8%	823	80.6%
Total	570	100.0%	451	100.0%	1021	100.0%
High-vis apparel use^b						
No	17	17.7%	16	21.9%	33	19.5%
Yes	79	82.3%	57	78.1%	136	80.5%
Total	96	100.0%	73	100.0%	169	100.0%
Bicycle light use^b						
Front and Rear	89	92.7%	70	94.6%	159	93.5%
Rear	3	3.1%	2	2.7%	5	2.9%
Front	1	1.0%	2	2.7%	3	1.8%
None	3	3.1%	0	0.0%	3	1.8%
Total	96	100.0%	74	100.0%	170	100.0%
Alcohol use						
No	567	99.0%	441	98.2%	1008	98.6%
Yes	6	1.0%	8	1.8%	14	1.4%
Total	573	100.0%	449	100.0%	1022	100.0%
Mobile Phone use						
No	567	99.1%	448	99.3%	1015	99.2%
Yes	5	0.9%	3	0.7%	8	0.8%
Total	572	100.0%	451	100.0%	1023	100.0%
Earphones use***						
No	518	90.6%	425	94.2%	943	92.2%
Yes	54	9.4%	26	5.8%	80	7.8%
Total	572	100.0%	451	100.0%	1023	100.0%
Trip purpose***						
Commuting/Utility/Work	448	78.0%	289	64.2%	737	72.0%
Leisure/Training/Racing	126	22.0%	161	35.8%	287	28.0%
Total	574	100.0%	450	100.0%	1024	100.0%
Bicycle type*						
Road bicycle	362	63.1%	313	69.2%	675	65.8%
Hybrid bicycle	172	30.0%	111	24.6%	283	27.6%
Mountain bicycle	40	7.0%	28	6.2%	68	6.6%
Total	574	100.0%	452	100.0%	1026	100.0%
Cyclist speed (km/h)***						
0	13	2.3%	2	0.5%	15	1.5%
0-10	148	26.0%	118	26.6%	266	26.3%
10-20	250	43.9%	145	32.7%	395	39.0%
20-30	129	22.6%	126	28.4%	255	25.2%
30-40	24	4.2%	40	9.0%	64	6.3%
40-50	6	1.1%	8	1.8%	14	1.4%
50+	0	0.0%	4	0.9%	4	0.4%
Total	570	100.0%	443	100.0%	1013	100.0%

a: Interquartile range b: for collisions in dusk or dark conditions, *significant at the 5% level, **significant at the 1% level ***significant at the 0.1% level

3.4.2 Injury patterns

In Figure 3.2, injury patterns and overall injury severities are presented for each collision type. For overall injury severities, 977 cases were available for analysis (i.e., minor, serious, or no injury), and for the analysis of injury patterns, 564 cases were available for analysis (i.e., injury occurrence for each body region). Chi-square statistics were used for inter-group comparisons, and odds ratios were calculated. Approximately 70% of respondents sustained injuries to the upper and lower limbs, 48% to the torso, 37% to the head and 14% to the neck. Injuries ranged from minor bruises and abrasions to fractures and severe internal injuries. Single cyclist collisions had the highest level of injury occurrence (73% involved injuries); compared to collisions with vehicles, the odds of injury occurrence for single cyclist collisions were almost 3 times greater (OR 2.8, 95% CI:2.0–3.9). Collisions with other cyclists also had high odds compared to collisions with vehicles (OR 1.8, 95% CI:1.1–3.1). Collisions with pedestrians had the lowest levels of both overall injury occurrence (46%) and serious injury occurrence (7%). Injury patterns were generally similar across all collision types, though those involving pedestrians had lower injury levels for all body regions. Injuries to the upper and lower extremities dominate, with injuries to these regions in over 70% of cases (except for collisions with pedestrians). Single cyclist collisions and collisions with motorised vehicles had similar levels of head injury.

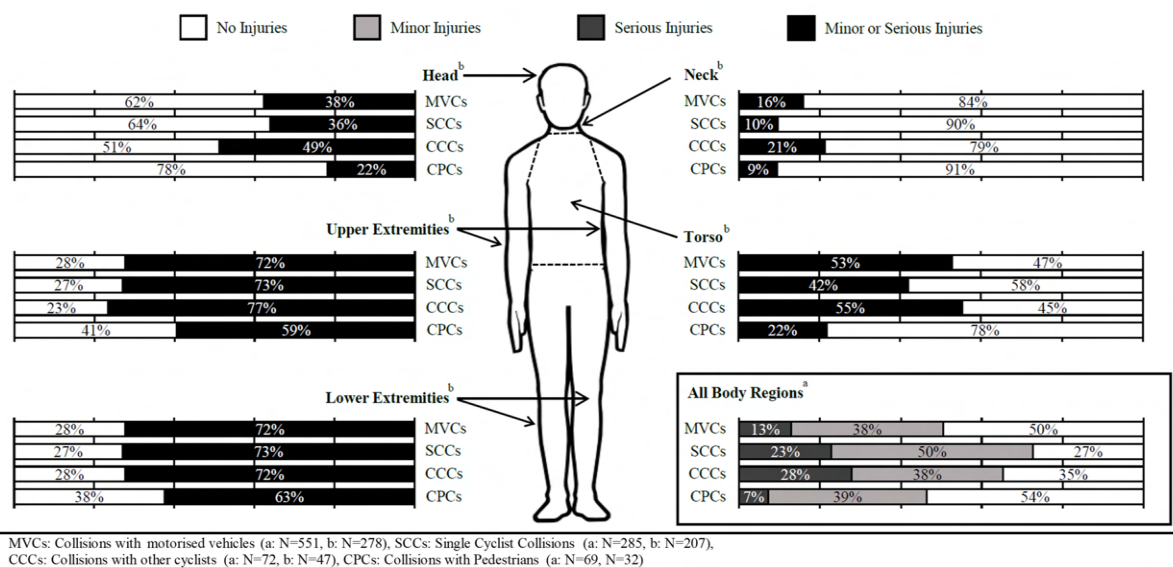


Figure 3.2: Injury patterns for injured cyclists, overall and for each collision type.

3.4.3 Underreporting & data source comparisons

Table 3.4 shows the results of a binary logistic regression with police reporting as the dependent variable and age, sex, location (county Dublin/outside county Dublin), locus familiarity, i.e., whether the cyclist was familiar with the particular location, setting (urban/rural), day (weekend/weekday), time of day, trip purpose, collision type and injury severity as independent variables (see Table A2). The Variance Inflation Factor (VIF) was found to be <10 for all variables, suggesting that the level of multicollinearity is not problematic. The continuous variable age was found to be linearly related to the logit of the dependent variable via the Box-Tidwell procedure, with $p > 0.05$. Information was missing for one or more variables for 565 cases (40%). The null hypothesis for Little's test (that the missing data is MCAR) was not rejected with $p > 0.05$, suggesting that multiple imputation will work well. Multiple (30) imputations were performed, as recommended by White et al. (2011) [196]. Only location, collision type, and injury severity were found to be significant, see Table A.2. Since modelling is performed for effect estimation, both significant and insignificant variables were included in the final model, i.e., inclusion of insignificant variables increases the likelihood that the confidence interval for the effect of interest has the stated coverage [197]. The model was statistically significant, $X^2(15) = 211.922$, $p < 0.0001$. The model explained 37.1% (Nagelkerke R^2) of the variance in police reporting and correctly classified 87% of cases. The area under the Receiver Operating Characteristic (ROC) curve was 0.840 (95% CI: 0.803–0.876) (considered an excellent level of discrimination according to Hosmer et al. (2013) [198]), with a corresponding Gini coefficient of 0.680 (95% CI: 0.606–0.752). Five outliers (0.4% of cases) were found, indicated by an absolute value of standardised residual greater than 2.5 in the regression output, with values ranging between 2.7 and 3.0. These cases were investigated and were retained as there was no obvious reason for removal, and their presence had low influence on the model, as indicated by Cook's distance values between 0.32 and 0.54, and

Leverage values between 0.006 and 0.012. The findings show that the odds of police reporting for collisions outside of county Dublin was 2.2 times greater than those in county Dublin. The odds of police reporting for collisions between cyclists and motorised vehicles were the highest; 20.0 times greater than single cyclist collisions, 9.8 times greater than cyclist-cyclist collisions, and 4.1 times greater than collisions with pedestrians. The odds of police reporting for serious injury collisions were the highest; 7.0 times greater than minor injuries, and 24.4 times greater than non-injurious collisions.

Table 3.4: Underreporting of collisions to the police.

	Reporting to the Police						Univariable Analysis		Multivariable Analysis	
	Not reported		Reported		Total		OR	95% CI	OR ^a	95% CI
	No.	%	No.	%	No.	%				
County										
Rest of Ireland	173	78.3%	48	21.7%	221	100.0%	1.665**	(1.134 – 2.444)	2.226**	(1.234 – 4.017)
County Dublin	679	85.9%	111	14.1%	790	100.0%	ref	ref	ref	ref
Total	852	84.3%	159	15.7%	1011	100.0%				
Collision type										
Cyclist-Motorised Vehicle (MVC)	434	75.7%	139	24.3%	573	100.0%	ref	ref	ref	ref
Single Cyclist (SCC)	280	96.2%	11	3.8%	291	100.0%	0.133***	(0.070 – 0.251)	0.050***	(0.024 – 0.105)
Cyclist-Cyclist (CCC)	74	92.5%	6	7.5%	80	100.0%	0.261***	(0.111 – 0.613)	0.102***	(0.036 – 0.292)
Cyclist-Pedestrian (CPC)	69	93.2%	5	6.8%	74	100.0%	0.241***	(0.095 – 0.611)	0.243**	(0.087 – 0.676)
Total	857	84.2%	161	15.8%	1018	100.0%				
Injury severity										
No Injury	379	92.7%	30	7.3%	409	100.0%	0.104***	(0.063 – 0.173)	0.041***	(0.022 - 0.076)
Minor	340	84.8%	61	15.2%	401	100.0%	0.410***	(0.253 – 0.662)	0.143***	(0.084 - 0.246)
Serious	93	58.5%	66	41.5%	159	100.0%	ref	ref	ref	ref
Total	812	83.8%	157	16.2%	969	100.0%				

a: multivariable odds ratios calculated by binary logistic regression, *significant at the 5% level, **significant at the 1% level ***significant at the 0.1% level

A cross comparison of police reporting and hospital attendance for collisions involving injuries is shown in Figure 3.3. For 4 injurious collisions no indications of police reporting, or hospital attendance were given ($N = 560$). Overall, only 23% were reported to the police, and 30% resulted in a hospital attendance. Only 14% of collisions were both reported to the police and resulted in a hospital attendance, and 61% were neither reported to the police nor resulted in a hospital attendance. A large proportion of serious injuries (82%) resulted in either hospital attendance or police reporting, compared to only 21% of minor injuries.

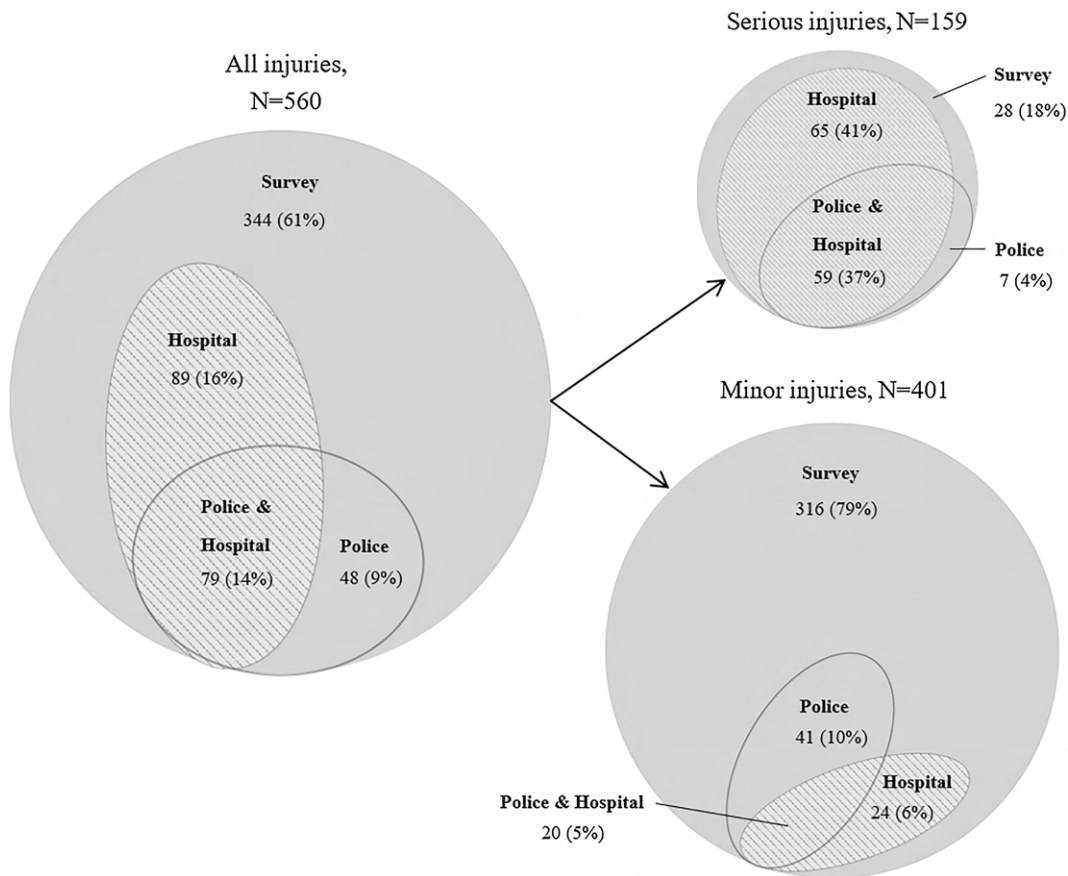


Figure 3.3: Reporting of injurious collisions to the police and hospital attendance, represented as a proportional area Euler Diagram (generated using the approach by Micallef et al. (2014) [199]).

3.5 Discussion

This chapter presents findings of the first self-reported survey of cycling collisions in Ireland. With details of over 1,000 cycling collisions, the results demonstrate this approach is effective at augmenting our understanding by providing detail for cases not seen in police or hospital data.

3.5.1 Underreporting biases

These survey results provide further evidence that cycling collisions are substantially under-reported: only 23% of collisions with injuries were coded as having been reported to the police, and only 30% reported a hospital attendance. Bedford et al. (2011) [32], Short et al. (2014) [26], and Foley et al. (2016) [33] previously presented analyses of police and hospital data, implying underreporting in an Irish context, and these findings provide further evidence through the addition of survey-based data. Using probabilistically matched police and hospital data, Short et al. (2014) [26] estimated that there are roughly 6 times as many cyclist injuries than recorded in police statistics (reporting rate of roughly 17%), which is similar to, albeit slightly lower than the finding of 23% in this study. By comparison, findings from an international survey on underreporting of cyclist's most severe collisions found reporting rates ranging between 0% (Israel) and 35% (Germany) [30]. The International Transport Forum recently recommended that cyclist injuries be monitored using a combination of police, hospital and insurance data [200]. In self-reported data, only 39% of collisions involving injuries were either reported to the police or resulted in a hospital attendance (or both). The results indicate that the combined monitoring of police and hospital data may be effective for serious injury collisions (as suggested by Foley et al. (2016) [33]), however this is not the case for minor injuries (see Figure 3.3). Although inclusion in insurance data is unknown, these statistics highlight the important contribution surveys can make in assessing the burden of cyclist injuries.

Although collisions with motorised vehicles are the largest cohort in the survey, comprising just over half of the total, they are less dominant than commonly understood [23, 24], and the survey results emphasise the importance also of non-motorised vehicle collisions in the Irish context. Shinar et al. (2018) [30] found that the odds of police reporting for collisions with motorised vehicles is 15 times greater than for single cyclist collisions, compared to a factor of 20 in the findings from this study (see Table 3.4). Shinar et al. (2018) [30] also found injury severity to be the strongest predictor of cyclist collision reporting, and findings from the current study indicate similar, with 42% of serious injuries reported to the police. Findings from this study also indicate that the odds of police reporting for serious injury collisions are 7 times greater than minor injury collisions.

3.5.2 Comparisons of collision characteristics

A substantial proportion (56%) of the survey cases were collisions with motorised vehicles, and other survey studies have found the proportion to be lower: 13% in a survey of cyclists in Queensland, Australia [42], and 23% in an internationally distributed survey [30]. This implies the need for interventions to reduce their occurrence, such as traffic separation (segregated cycle lanes), improvements to junction designs, or reductions in speed limits (in areas of mixed traffic) [201, 6, 202], though further investigation is required to identify effective strategies for the Irish context. Findings from this study indicate that compared to collisions with motorised vehicles, a larger proportion of non-motorised vehicle collisions occurred in rural environments with higher posted speed limits and lighter traffic conditions. They also have lower odds of occurring at junctions, and higher odds of occurring in unfamiliar locations, on roads with curves or downhill gradients, in inclement weather conditions, or on roads with hazardous surface conditions. A higher proportion of cyclists involved in non-motorised vehicle collisions were females, and occurred during leisure, training, racing trips as opposed to utility, commuting, or work trips. These collisions also occurred at higher cycling speeds

than collisions with motorised vehicles. The resulting injuries are generally at a higher severity level for non-motorised vehicle collisions (with the exception of cyclist-pedestrian collisions), contrary to previous findings [42, 30]. For example, only 27% of single cyclist collisions involve no injury, and 23% involved a serious injury. This may be influenced by recall bias, whereby collisions resulting in injuries or involving other road users may be inherently more memorable, biasing the reporting of injurious single cyclist collisions to the survey. Nevertheless, it emphasises the importance of single cyclist collisions and injuries due to ground contact in the overall cycling injury burden.

Due to differences in collision characteristics, prevention strategies for collisions with motorised vehicles are not likely to be as effective for non-motorised vehicle collisions (single cyclist collisions in particular). Furthermore, decreases in cyclist-motorised vehicle collision risk has been shown to accompany increasing cyclist modal share, according to the so-called ‘Safety in Numbers’ effect [39], however internationally it is known that risk for single cyclist collisions does not decrease in the same way [116]. Therefore, Irish policymakers should be aware that safety strategies are needed to address increasing numbers of single cyclist collisions that may accompany increasing modal share of cycling in Ireland. For example, 43% of people in the Netherlands cycle every day (compared to 5% in Ireland) [203], and single cyclist collisions are a significant contributor to the road safety problem, comprising 74% of cyclist injuries and 41% of all road crash injuries [116]. In the Netherlands a large proportion of single cyclist collisions are related to infrastructure, by way of the cyclist colliding with road furniture, or skidding/loss of control due to a hazardous road surface [44]. A large proportion are also caused by cyclist related factors, including loss of control at low speed, or risky riding behaviours (ibid.). The Safe System approach must be taken to address the causes of single cyclist collisions, however, further investigation is required to identify appropriate prevention strategies for Ireland.

3.5.3 Descriptive comparisons to Irish police statistics

In police statistics, 87% of injurious cyclist collisions occurred on urban roads with lower speed limits (less than or equal to 60 km/h) [23]. Similarly, in the survey results where speed limit was indicated/known, 83% were on roads with speed limits less than or equal to 60 km/h. The majority (78%) of collisions reported to the survey occurred in county Dublin, compared to 61% in police statistics (*ibid.*), though findings also indicate that collisions in county Dublin have lower odds of being reported to the police. Situations where cyclists are required to cross paths with other transport modes are common sources of cyclist collisions: 40% of self-reported collisions occurred at junctions, which is lower than the proportion in police statistics (51%) (*ibid.*). This is likely a result of non-motorised vehicle collisions being underreported in police statistics, supported by the fact that half of collisions with motorised vehicles in the survey occurred at junctions. In police statistics 74% of cyclists are male (*ibid.*), similar to respondents involved in collisions in the survey (70%). In police statistics 79% of collisions occurred on weekdays (*ibid.*), equal to the survey results. However, in police statistics 33% of collisions occurred between 06:00-12:00 (*ibid.*), compared to half in the survey results, and correspondingly fewer were between 12:00-00:00.

In police statistics between 2014 and 2015, the ratio of serious to minor injuries was 1:5.9 [204, 205], compared to 1:2.5 in self-reported cases. This is counterintuitive in that findings indicate that minor injuries have lower odds of being reported than serious injuries, which should result in a higher proportion of minor injuries for the survey cases. This may in part be a result of recall bias, whereby collisions involving serious injuries are inherently more memorable than those involving minor injuries. It is also known that injury severity according to the definitions used in this study (Table A.1) is sometimes misclassified by police in the United Kingdom [206], resulting in some serious injuries being misclassified as minor.

3.5.4 Limitations

For this study there was no means of obtaining a fully representative sample of the population of cyclists in Ireland. The Irish census contains a module on the commuting travel preferences which can be used to compare to the survey results [207], and the membership details of Cycling Ireland (the national body for sports cycling in Ireland) can be used as a proxy for leisure/racing cyclists. The proportions of survey respondents by county are similar to those for the commuting population of cyclists in Ireland (Figure A.2), though there are differences for the leisure/racing population, with a disproportionate number of survey respondents coming from Dublin. A smaller proportion of survey respondents were male (63%), when compared to both the commuting population in Ireland (73%), and the membership of Cycling Ireland (80%). Since no child cyclists (<18) were included in this study, collision factors that may be specific to younger cyclists are not available in these results. However, as detailed in section 3.5.3, after accounting for underreporting biases, broad collision characteristics for cyclist collisions in the survey are similar to those seen in police statistics.

Self-reporting has associated biases, one of which (recall bias) may have the effects of 1) underrepresenting the overall share of single cyclist collisions, 2) overrepresenting the proportion of injurious single cyclist collisions, and 3) increasing the overall severity of injuries in the survey results. For sensitive questions, social desirability bias may be a factor [208], which may contribute to the low reporting of mobile phone and alcohol usage in these findings. Furthermore, although helmets are not mandatory in Ireland, a high proportion of survey respondents reported wearing a helmet (81%), compared to 47% in police statistics [23]. However, it is also possible that self-selection bias may be a factor, whereby cyclists who chose to take part in the survey may be more safety conscious than the general population of cyclists in Ireland. Since only cyclists were surveyed, the police reporting rates for collisions involving a second road user (vehicle driver, pedestrian, or other cyclist) are likely underestimates.

Clearly these results do not include fatal cyclist collisions, and an analysis of fatalities should be included as part of a more complete impression of cyclist safety priorities in the Irish context. Therefore, police investigation files for fatal and serious cyclist collisions are analysed in chapter 5. It was not possible to code the injuries according to the Abbreviated Injury Scale (AIS), which is used to standardise injury outcomes, making international comparisons more difficult. The definitions used for minor and serious injuries in this chapter are the same as those used in Ireland and the United Kingdom, though they differ by varying degrees to those used across the Europe [209].

3.6 Conclusions

Cyclists in Ireland are responsive to self-reported surveys relating to collision events, suggesting they are an engaged cohort for road safety. Due to difference in road environments, and cycling levels, safety priorities vary between countries. However, the findings of this study may have international relevance for countries with an increasing popularity of cycling starting from a relatively low base.

The results demonstrate that serious injury collisions may be well addressed by the combined monitoring of police and hospital data, however, self-reporting is highlighted as an important data source for minor injuries. Just over half of cyclist collisions reported to the survey were with a motorised vehicle, and this proportion holds even for serious injuries. Single cyclist collisions accounted for roughly a third of the total, and only a small proportion of these were reported to the police. This suggests that police-based statistics on the burden of cyclist collisions in Ireland are biased towards those involving motorised vehicles, and policymakers should be aware of the considerable burden of single cyclist collisions. Less severe injuries have also been shown to be underreported, and to contribute to the safety problem to a far greater degree than observed in police statistics. In efforts to inform prevention strategies, future work should focus on identifying the configurations of these underreported collision types.

CRedit authorship contribution statement [210]

Kevin Gildea: Conceptualisation, Data curation, Formal analysis, Software, Investigation, Methodology, Resources, Validation, Visualisation, Writing - original draft, Writing - review & editing, Project administration. **Ciaran Simms:** Conceptualisation, Funding acquisition, Methodology, Project administration, Resources, Writing - original draft, Writing - review & editing.

Chapter 4

Study B: Collision configurations, with the inclusion of underreported cases

Related publication:

- Configurations of underreported cyclist-motorised vehicle and single cyclist collisions: Analysis of a self-reported survey,
K. Gildea, D. Hall, C. Simms,
Accident Analysis & Prevention (2021)

4.1 Introduction

Analysis of the survey responses identified that injury severity and collision type have a biasing effect on police reporting [211] (chapter 3), with only 42% of cyclist collisions involving serious injuries and 15% of those involving minor injuries being reported by the cyclist to the police (See Table A.1 for injury definitions). Similar rates have been reported internationally [30]. In contrast, almost all fatal collisions are reported to the police. Furthermore, only 39% of collisions involving injuries in self-reported data were either reported to the police or available for inclusion in hospital data [211], highlighting the contribution self-reported survey data can make to our understanding of the overall cyclist safety problem. The largest proportion of cyclist collisions in the survey was with motorised vehicles (56%), followed by single cyclist collisions (29%) (i.e., cases not involving a collision with another road user). A minority of cyclist-motorised vehicle collisions involving injuries were reported to the police (40%), and accounting for other collision factors, the adjusted odds of police reporting for collisions with motorised vehicles was 20 times greater than for single cyclist collisions (5% were reported). Thus, further research into the configurations of these underreported yet frequent collisions is required.

As detailed in section 2.6, internationally there has been extensive analysis of cyclist collisions with motorised vehicles (e.g., Simms et al. (2009) [86]). Collisions with bonnet-type vehicles (Sedans, Hatchbacks, SUVs, or Vans) are the most frequent cause of injuries and fatalities, though heavy goods vehicles (HGVs) account for disproportionate shares of fatalities/serious injuries [6]. Vehicle type-testing for active and passive safety in Europe relies on pan-European research projects which characterise common pre-crash manoeuvres and impact configurations (i.e., AsPeCSS, PROSPECT, and CATS) (see section 2.6.1). However, due to underreporting, the nature of lower severity cyclist-motorised vehicle collisions are

poorly understood. Since lower severity collisions are less likely to be included in official data sources [211, 30], current priorities for infrastructural interventions, and vehicle type-testing may be biased towards collision types more prone to result in severe injuries/fatalities. Furthermore, safety priorities for pre-crash scenarios and impact configurations are known to vary substantially by cycling environment [74, 76, 75], and are only relevant to certain countries with data collection systems that allow for a detailed level of analysis.

The survey findings indicate that a high proportion (29%) of cyclist collisions on roadways in Ireland are single cyclist collisions [211] (chapter 3), compared to studies involving police data, both in Ireland [23] and internationally [6]. As detailed in section 2.7, in recent years, the causal factors for single cyclist collisions have been a focus of research, using emergency department attendee surveys, insurance data, and self-reported surveys [134, 42, 43, 44, 135]. The survey findings from chapter 3 highlighted that collisions not involving impact with motorised vehicles have higher odds of occurring in rural environments with higher posted speed limits, and lighter traffic conditions [211]. They also have lower odds of occurring at intersections, and higher odds of occurring in unfamiliar locations, on roads with curves or downhill gradients, in inclement weather conditions or on roads with hazardous surface conditions (ibid.). However, to determine appropriate prevention strategies for single cyclist collisions further investigation is required into the mechanisms that caused the cyclist to fall (direct causes). Furthermore, similar to collisions with vehicles, common collision factors for single cyclist collisions may vary by cycling environment (demonstrated in section 2.7.2).

4.2 Study aims

This analysis builds on previous findings which indicated that road, environmental, and human collision factors differ between collision types (i.e., single cyclist, cyclist-pedestrian,

cyclist-cyclist, or cyclist-motorised vehicle collisions) (ibid.). For collisions with bonnet-type vehicles, both pre-crash scenarios/manoeuvres and impact configurations are presented and ranked according to frequency of occurrence. Severity of injury outcome, police reporting level, and summary details are also presented (see section 4.4.1). For single cyclist collisions direct causes, the mechanisms of impact, and the injury outcomes are investigated (see section 4.4.2). Injury patterns and serious injuries are presented for the most common impact configurations and fall types (see section 4.4.3). Finally, 11 representative collision scenarios are summarised, which together comprise a significant proportion of the cyclist safety problem (see section 4.5.1).

4.3 Methods

4.3.1 Survey design & cleaning

An online survey was designed to collect on-road collision information from cyclists in 2018. The sample contained adult cyclists (>18) who had been involved in a collision while cycling in Ireland in the previous 5 years. As described in chapter 3 [211], validation techniques were applied to the collected collision cases, which included identification and removal of inconsistent or incomplete responses, and recoding of collision types according to the definitions in Table A.1.

4.3.2 Collision taxonomy

Causal factors for collisions relate to the environment (weather, time, lighting conditions, traffic conditions etc.), road (road type, cycling infrastructure, road furniture etc.), human/behavioural (distraction, fatigue, speed, manoeuvres etc.) and the vehicle (malfunction, vision issues etc.). However, there is often overlap. Road factors and vehicle driver/cyclist

manoeuvres that result in collisions are primarily considered here. For collisions with bonnet-type vehicles, ‘pre-crash scenarios’ are defined as driver/cyclist manoeuvres directly before the collision, and for single cyclist collisions ‘direct causes’ are defined as the object, action, or mechanism that caused the cyclist to fall. The analysis also includes injury outcomes and impact configurations which may guide future injury reduction/prevention strategies (e.g., less aggressive vehicle geometries and structures). For this purpose, the survey involved both closed and open text responses for detailed descriptions of both the lead-up to a collision and how the cyclist impacted the vehicle/object/ground, as well as GPS coordinates, road configuration, road type, the cyclist’s actions, and the driver’s actions (as reported by the cyclist). Representative diagrams of pre-crash scenarios, impact configurations, and fall types presented throughout this chapter are generalised examples intended as visual aids. For inter-coder reliability, a second researcher coded a randomly selected set of cases, comprising 10% of the total number. Both researchers discussed the codes for this subsample and came to a consensus on any changes to be made to 1) coder 1s codes in the case of mistakes, and 2) categories to add/adapt based on ambiguities in the scheme.

Cyclist-Motorised vehicle collisions

The overall taxonomy flowchart for collisions with bonnet-type vehicles is shown in Figure 4.1. Nearly all ($N = 512$, 94%) cyclist-motorised vehicle collisions involved bonnet-type vehicles, so pre-crash collision scenarios were coded only for these cases. A coding scheme (Table B.1) was devised according to the traffic environment: 1) ‘same direction’, where prior to impact vehicle and cyclist travelled in the same direction, 2) ‘lateral direction’, for crossing directions of travel 3) ‘oncoming direction’, for opposing directions of travel, or 4) ‘Other’ (e.g., doorings - vehicle occupant opening a door in the cyclist’s path). The traffic environment codes are similar to those used in CATS [76], and specific pre-crash scenario codes are similar to those

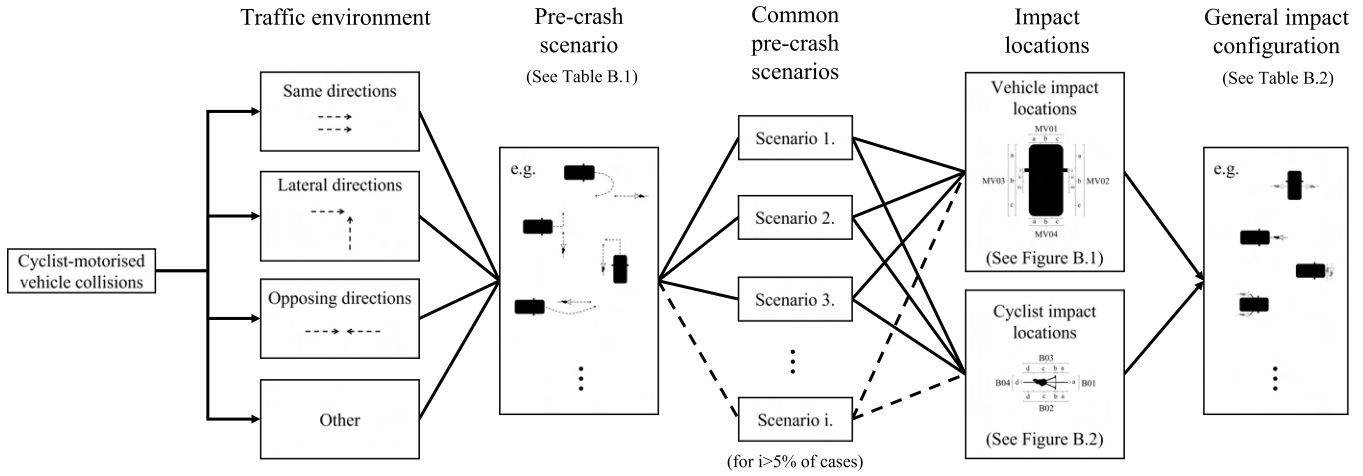


Figure 4.1: Taxonomy flowchart for collisions with bonnet-type vehicles.

used in Volvo cars accident database (V CAD) [83]. There was 98% agreement between coders on coded traffic environment, and 91% agreement on specific pre-crash scenarios, with 90% of cases categorised, the remaining cases being unclear. Impact configurations (locations on the vehicle and bicycle) were coded according to the impact location maps (Figures B.1, and B.2) and categorised into general kinematic forms (Table B.2), with 94% agreement between coders. There were no overrun collisions. This methodology is similar to previously performed studies [88, 212, 213, 87]. An analysis of impact configurations and injury outcomes was performed for both the general traffic environment and the most common pre-crash scenarios (those which each comprise $> 5\%$ of cases).

Single cyclist collisions

The overall coding flowchart for single cyclist collisions is shown in Figure 4.2. Direct causes were coded using a scheme similar to [44, 135] (Table B.3), with up to two direct causes for each case. This scheme categorises collision causes by: 1) infrastructure (on-road/off-road obstacles or road surface conditions), 2) road-user related (e.g., avoidance manoeuvres, riding

mistakes), or 3) bicycle malfunction. Using this scheme 92% of the 295 collisions were coded, with 92% agreement between coders, with the remaining cases being unclear. These codes and paired impact partners/risky manoeuvres (e.g., tram tracks, kerb, wet road markings, abrupt braking) were used to define crash scenarios (Table B.4) with 97% agreement. Limited research has been performed into the kinematic forms of single cyclist falls, therefore a categorisation scheme was devised with three common fall types:

1. ‘pitch-over’, involving a sudden bicycle deceleration causing the cyclist to be projected forwards due to inertia, typically over or to the side of the handlebars (e.g., “I went over the handlebars”, “I was thrown forward from the bike”). Common causes are braking too hard, hitting an obstacle or something getting entangled in the front wheel.
2. ‘topple-over’, involving a cyclist falling to the side due to a loss of balance (e.g., “I lost my balance”, “I fell to the side”).
3. ‘skid-out’, occurring when the tire loses traction and the bicycle falls beneath the cyclist (e.g., “The bike went out from under me”, “I skidded out”). Skidding can be initiated by braking, rapid steering or banking and is more likely in downhill gradients and/or poor road conditions (water, frost/ice, gravel or oil).

Fall types were coded with 86% agreement between coders.

4.3.3 Injury outcomes

Injury severities were coded as ‘minor’ or ‘serious’ according to definitions in police statistics in Ireland and the United Kingdom (Table A.1). The most significant injuries (e.g., concussion, skull fracture, leg fracture, internal organ damage) by impact configuration/fall type are presented in section 4.4.3.

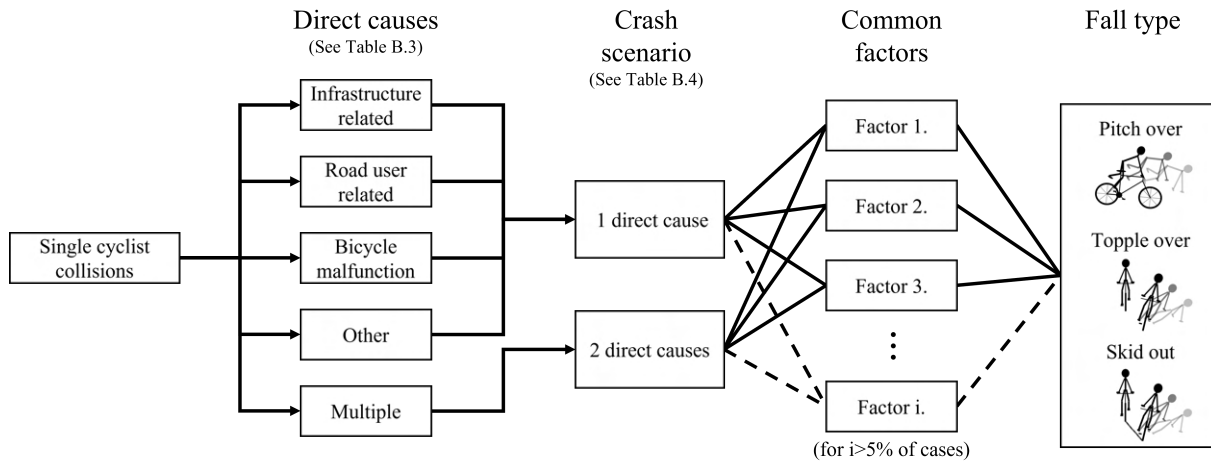


Figure 4.2: Taxonomy flowchart for single cyclist collisions.

4.4 Results

4.4.1 Configurations of cyclist collisions with motorised vehicles

Collision Partners

Nearly all cyclist-motorised vehicle collisions ($N = 512$, 94%) involved a bonnet-type vehicle ($N = 432$, 79% Sedans/Hatchbacks, $N = 35$, 6% SUVs, and $N = 45$, 8% Vans), the remainder being buses ($N = 17$, 3%), HGVs ($N = 10$, 2%), and Motorbikes/scooters ($N = 5$, 1%).

Pre-crash scenarios and impact configurations

Table 4.1 shows the injury outcomes and impact configurations categorised by pre-crash directions of travel of the vehicle/cyclist. For interpretation, consider the example of collisions resulting from lateral directions of travel (Table 4.1 - rank 2):

Fifty one percent of collisions with bonnet-type vehicles were preceded by the vehicle/cyclist travelling in the same direction, followed by lateral (25%) and opposing directions of travel (10%). The latter had most injuries (84%), followed by lateral directions (59%) and same direction (41%). The level of reporting to police for collisions involving injuries varied with direction of travel, with same direction of travel collisions being the least reported (31%).

The majority of collisions with the vehicle/cyclist travelling in opposing or lateral directions resulted in the cyclist impacting the side of the vehicle (Side-MV) (Table B.2), or the vehicle impacting the side of the cyclist (Side-Cyclist). In contrast, collisions with the vehicle/cyclist travelling in the same direction mostly resulted in the cyclist and vehicle impacting side to side (Side-Side). Side-Side impacts were most common (34% of the total), but Side-MV collisions and Side-Cyclist also comprise significant shares (18% and 17% respectively) and have higher injury levels, with Side-Cyclist cases having a large proportion of serious injuries (29%). Dooring impacts comprise 15% of cases and have higher injury levels than Side-Side impacts, however injuries are primarily minor (55%).

Table 4.2 also shows injury outcomes and impact configurations for the eight most prevalent collision scenarios for bonnet-type vehicles, comprising 79% of these collisions (Table B.1 shows all collision scenarios). The largest share (19%) involved a cyclist and vehicle initially travelling in the same direction, with the vehicle initiating a left turn across the cyclist (LT/SD), but only 16% of cases with injuries were reported to the police. This most commonly resulted in a Side-Side impact, or a Side-MV impact. Ireland is a left-hand traffic country, and this scenario is commonly referred to as a ‘left-hook’, whereas in right-hand traffic countries it would be referred to as a ‘right-hook’. For generality, LT/SD cases are referred to as ‘nearside-hook’ collisions. The second most common scenario (12%) involved dooring (D) which were also seldom reported to police (22% of collisions with injuries). It

was mostly unspecified whether dooring occurred on the vehicle's nearside or offside, though where it is specified the proportions are similar. The next most common pre-crash scenarios involved the vehicle changing lanes while travelling in the same direction as the cyclist (CL/SD) (11%), and the vehicle overtaking the cyclist (OT/SD) (8%), mostly resulting in Side-Cyclist impacts. The reported mode speed for both cyclists and vehicles was 10–20 km/h. However, for OT/SD collisions the reported mode vehicle speed was much higher (30–40 km/h), with a higher proportion in rural environments (21%). Collisions involving a right turning vehicle and an oncoming cyclist (RT/OD) (offside-hook collisions) comprise a minor share (8%), but they have the highest injury levels (64% minor injuries and 25% serious injuries).

4.4.2 Configurations of single cyclist collisions

Table 4.3 shows direct causes for single cyclist collisions, the fall types and resulting injury outcomes. For interpretation, consider the example of collisions involving bicycle malfunction. (Table 4.3 - '1 direct cause' - rank 6):

There were $N = 6$ collisions which involved only bicycle malfunction as a direct cause (code '3'), comprising 2% of coded single cyclist collisions. The majority ($N = 4$) resulted in a pitch-over fall.

Many single cyclist collisions involved two direct causes (32%). Most (87%) related to infrastructure, either involving an on-road obstacle (1ai), off-road obstacle (1aii) or linked to road surface quality (1bi/1bii). Many (31%) were road-user related (avoidance manoeuvring or mistakes) (2a/2b/2c/2d). They were seldom a result of a bicycle malfunction (3.) (2%). The most common fall type was skidding (39% of those coded), followed by pitch-over (35%) and topple-over (20%). All fall types had high injury levels. Pitch-over falls were the most injurious (88%) and severe (33% serious injuries).

Table 4.4 shows the five most prevalent single cyclist collision factors, consisting of grouped pre-crash scenarios from Table B.4. Since up to 2 contributing factors are coded, there is some overlap. For interpretation, consider the example of collisions involving kerbs. (Table 4.4 - rank 3):

These comprised 21% of coded single cyclist collisions. Summary details show that the majority occurred in urban environments (96%). The mode cyclist speed was 0–10 km/h. twenty two percent of these collisions resulted in no injury. Considering resulting fall types, the largest share resulted in the cyclist toppling over ($N = 18$), with similar proportions of pitch-over and skid-out falls.

Table 4.2: Impact configurations and injury outcomes (for categories with 10 cases or more) of collisions with bonnet-type vehicles for the eight most common collision scenarios, ranked by frequency.

Rank	Pre-crash scenario, N, %	Description: Cyclist and vehicle initially travelling in the Same Direction, with a collision resulting from the vehicle taking a Left Turn across the cyclist's path.	Resulting impact configurations, N	Summary details
1	LT/SD, 88, 19%		Side-Side, 45 Side-MV, 15 Rear-MV, 7 Rear-Cyclist, 1 Unknown, 20	Police reporting level (injuries): 16% Mode {cyclist speed} = 10-20 km/h Mode {vehicle speed} = 10-20 km/h In urban environment = 98% Environment: Entrance (18%), T-junction (15%), Y-junction (10%)
2	D, 56, 12%	Description: Collision resulting from a vehicle occupant opening their Door, with the cyclist approaching from behind.	Dooring-Unspecified, 37 Dooring-Offside, 11 Dooring-Nearside, 8	Police reporting level (injuries): 22% Mode {cyclist speed} = 10-20 km/h Mode {vehicle speed} = stationary In urban environment = 98% Environment: Not at intersection (91%)
3	CL/SD, 50, 11%	Description: Cyclist and vehicle initially travelling in the Same Direction, with a collision resulting from the vehicle Changing Lanes.	Side-Side, 30 Rear-MV, 3 Rear-Cyclist, 1 Side-Cyclist, 1 Unknown, 15	Police reporting level (injuries): 29% Mode {cyclist speed} = 10-20 km/h Mode {vehicle speed} = 0-10 km/h In urban environment = 98% Environment: Not at intersection (86%)
4	OT/SD, 38, 8%	Description: Cyclist and vehicle initially travelling in the Same Direction, with a collision resulting from the vehicle attempting to OverTake the cyclist.	Side-Side, 30 Rear-Cyclist, 3 Unknown, 5	Police reporting level (injuries): 50% Mode {cyclist speed} = 10-20 km/h Mode {vehicle speed} = 30-40 km/h In urban environment = 79% Environment: Not at intersection (82%)
5a	RT/OD, 36, 8%	Description: Cyclist and vehicle initially travelling in Opposite Directions, with a collision resulting from the vehicle taking a Right Turn across the cyclist's path.	Side-MV, 21 Side-Cyclist, 11 Head on, 1 Unknown, 3	Police reporting level (injuries): 53% Mode {cyclist speed} = 10-20 km/h Mode {vehicle speed} = 10-20 km/h In urban environment = 100% Environment: T-junction (33%), Entrance (22%)
5b	LT/RD, 36, 8%	Description: Collision resulting from a vehicle taking a Left Turn and cyclist approaching from the vehicle driver's Right Direction.	Side-Cyclist, 16 Side-MV, 6 Rear-MV, 3 Side-Side, 2 Rear-Cyclist, 1 Unknown, 8	Police reporting level (injuries): 65% Mode {cyclist speed} = 10-20 km/h Mode {vehicle speed} = 30-40 km/h In urban environment = 94% Environment: Roundabout (56%), T-junction (28%)
7	SCP/RD, 34, 7%	Description: Collision resulting from a cyclist and vehicle travelling with Straight Crossing Paths, with the cyclist approaching from the vehicle driver's Right Direction.	Side-Cyclist, 17 Side-MV, 10 Unknown, 7	Police reporting level (injuries): 52% Mode {cyclist speed} = 10-20 km/h Mode {vehicle speed} = 0-10 km/h In urban environment = 91% Environment: T-junction (41%), Entrance (24%)
8	RT/RD, 27, 6%	Description: Collision resulting from a vehicle taking a Right Turn and cyclist approaching from the vehicle driver's Right Direction.	Side-Cyclist, 10 Side-MV, 6 Side-Side, 2 Other, 1 Unknown, 8	Police reporting level (injuries): 45% Mode {cyclist speed} = 10-20 km/h Mode {vehicle speed} = 0-10 km/h In urban environment = 92% Environment: T-junction (48%), Entrance (15%)

Table 4.3: Direct causes for single cyclist collisions, the resulting fall types, and resulting injury outcomes.

			Fall types			
			No injuries Minor injuries Serious injuries			
Overall	N, %		Skid-out, 84	Pitch-over, 75	Topple-over, 42	Other, 13
	271, 100%		20% 57% 23%	12% 55% 33%	17% 64% 19%	No fall, 1 Unknown, 56
Cases with 1 direct cause						
Rank	N, %	Code: Description				
1	52, 19%	1ai: Colliding with an obstacle on the roadway (deliberately) designed and build by road authorities.				
2	43, 16%	1bi: Loss of traction due to the road surface conditions.				
3	30, 11%	1aii: Riding off the road and colliding with a kerb or an off-road obstacle.				
4	22, 8%	1bii: loss of control due to an uneven road-surface, or a loose object on the road surface.				
5	20, 7%	2ci: Involving an abrupt or adventitious steering/braking avoidance manoeuvre.				
6	6, 2%	3: Bicycle malfunction.				
7a	2, 1%	2b: Due to something becoming lodged or hitting the front wheel.				
7b	2, 1%	2ciii: Cyclist making a turning mistake.				
9a	1, 0%	2cii: Cyclist making a braking mistake.				
9b	1, 0%	2civ: Cyclist doing a stunt/trick.				
	4, 1%	4: Other.				
Cases with 2 direct causes						
Rank	N, %	Codes: Description				
1	30, 11%	1aii & 2ci: Riding off the road and colliding with a kerb or off-road obstacle, involving an abrupt or adventitious steering/braking avoidance manoeuvre.				
2	23, 8%	1ai & 1bi: Colliding with an obstacle on the roadway (deliberately) designed and build by road authorities, and loss of traction due to the road surface conditions.				
3	8, 3%	1ai & 2ci: Involving an abrupt or adventitious steering/braking avoidance manoeuvre, and colliding with an obstacle on the roadway (deliberately) designed and build by road authorities.				
4	7, 3%	1bi & 2ci: Involving an abrupt or adventitious steering/braking avoidance manoeuvre, and loss of traction due to the road surface conditions.				
5	6, 2%	1aii & 1bi: Riding off the road and colliding with a kerb or off-road obstacle, and loss of traction due to the road surface conditions.				
6	4, 1%	1bii & 2d: Cyclist boxed in by traffic, and loss of control due to an uneven road-surface, or a loose object on the road surface.				
7	3, 1%	1bi & 2cv: Involving an abrupt or adventitious steering/braking avoidance manoeuvre, while cycling too fast for the conditions.				
8a	2, 1%	1aii & 2d: Cyclist boxed in by traffic, and riding off the road and colliding with a kerb or off-road obstacle.				
8b	2, 1%	1ai & 2d: Cyclist boxed in by traffic, and colliding with an obstacle on the roadway (deliberately) designed and build by road authorities.				
8c	2, 1%	1bii & 2ci: Involving an abrupt or adventitious steering/braking avoidance manoeuvre, and loss of control due to an uneven road-surface, or a loose object on the road surface.				
11	1, 0%	1bii & 2a: Involving an abrupt or adventitious steering/braking avoidance manoeuvre, at low speed.				

Table 4.4: Most prevalent factors for single cyclist collisions, and the resulting fall types, including the injury outcomes, ranked by frequency.

Rank	N, %	Collision factor groupings and descriptions	☐ No injuries ☐ Minor injuries ☒ Serious injuries	Fall Types
				Skid-out, 72 Pitch-over, 5 Topple-over, 2 Other, 1 Unknown, 3
1	83, 31%	Collisions involving slippery roads. Summary details Police reporting level (injuries): 2% Mode {cyclist speed} = 10-20 km/h In urban environment = 80% N, % Description: Specific scenario codes (see Table B.4 for descriptions) 51, 61% Wet road: WR/T(7), WTT/C(8), WRM/T(6), WMD(6), WR(4), WK/EX(3), WRT/C(3), WR/TF(2), WR/AVVM(2), WRM(2), WTT(2), WTT/S(2), WLK(1), WR/B(1), WSB(1), WRM/TF(1) 19, 23% Icy road: IR(6), IR/T(4), IR/B(3), IR/AVVM(2), IK/EXC(1), IR/AVPH(1), IRM/T(1), ITT/C(1) 5, 6% Gravel on road: G/T(2), G(1), G/D(1), GK/EXC(1) 3, 4% Muddy road: MR/AVB(1), MR/AVVM(1), MR/T(1) 3, 4% Oily road: OR/T(2), OR/B(1) 2, 2% Other: RM/T(1), RS/B(1)		
2	62, 23%	Collisions involving tram tracks. Summary details Police reporting level (injuries): 2% Mode {cyclist speed} = 10-20 km/h In urban environment = 100% N, % Description: Specific scenario codes (see Table B.4 for descriptions) 44, 71% Crossing or cycling alongside tram tracks (no other factor): TT/C(29), TT(10), TT/S(5) 13, 21% Crossing or cycling alongside slippery tram tracks: WTT/C(8), WTT/S(2), WTT(2), ITT/C(1) 5, 8% Crossing or cycling alongside tram tracks due to an avoidance manoeuvre or being boxed in: TT/AVVM(3), TT/AVP(1), TT/BI(1)		
3	56, 21%	Collisions involving kerbs. Summary details Police reporting level (injuries): 7% Mode {cyclist speed} = 0-10 km/h In urban environment = 96% N, % Description: Specific scenario codes (see Table B.4 for descriptions) 26, 46% Cycling over or clipping a kerb (no other factor): K/EXC(10), K/T(7), K/EX(4), K(3), K/S(2) 24, 43% Cycling over or clipping a kerb due to an avoidance manoeuvre or being boxed in: K/AVVM(16), K/AVP(3), K/AVVP(2), K/BI(2), K/AVB(1) 6, 11% Cycling over or clipping a slippery kerb: WK/EX(3), GK/EXC(1), IK/EXC(1), WLK(1)		
4	53, 20%	Collisions involving avoidance manoeuvres from vehicles. Summary details Police reporting level (injuries): 11% Mode {cyclist speed} = 0-10 km/h In urban environment = 89% N, % Description: Specific scenario codes (see Table B.4 for descriptions) 25, 47% Colliding with a road feature after avoiding a moving vehicle: K/AVVM(16), TT/AVVM(3), D/AVVM(1), MD/AVVM(1), PH/AVVM(1), PV/AVVM(1), RT/AVVM(1), WG/AVVM(1) 12, 23% An abrupt avoidance manoeuvre from a moving vehicle: AB/AVVM(9), AVVM(2), AT/AVVM(1) 8, 15% Colliding with a road feature due to being boxed in by a vehicle: PH/BI(4), K/BI(2), CE/BI(1), TT/BI(1) 5, 9% Taking an avoidance manoeuvre from a moving vehicle on a slippery road: IR/AVVM(2), WR/AVVM(2), MR/AVVM(1) 3, 6% Taking an avoidance or adventitious manoeuvre from a parked vehicle: K/AVVP(2), AVVP(1)		
5	20, 7%	Collisions involving potholes. Summary details Police reporting level (injuries): 0% Mode {cyclist speed} = 0-10 km/h In urban environment = 84% N, % Description: Specific scenario codes (see Table B.4 for descriptions) 9, 45% Cycling into a pothole (no other factor): PH(9) 5, 25% Cycling into a pothole due to an avoidance manoeuvre or being boxed in by a vehicle: PH/BI(4), PH/AVVM(1) 4, 20% Cycling into a submerged pothole: PH/SM(4) 2, 10% Taking an avoidance manoeuvre from a pothole: AVPH(1), IR/AVPH(1)		

The injury severity outcomes for all single cyclist collisions were broadly similar. Slippery surface conditions were the most common factor (31%). Many were either wet (61%) or icy (23%), and they mostly resulted in skidding. The next most common factor was tram tracks, (23% of single cyclist collisions), for which the most common fall type was pitch-over. Most (71%) involved the cyclist crossing or cycling alongside tram tracks, with no other factor disclosed, but a significant share (21%) also related to slippery surface conditions along with interacting with tram tracks (i.e., crossing or cycling alongside), and the remainder involved interacting with tram tracks after an avoidance manoeuvre. Cyclist speeds were similar across all collision factors but were somewhat higher for collisions involving slippery roads or tram tracks (10–20 km/h compared to 0–10 km/h for the others). Kerbs were a factor in 21% of collisions, many of which (46%) involved no other factor and mostly resulted from clipping/impacting the kerb while exiting the roadway, often to enter a cycle track. Many kerb impacts (43%) involved an avoidance manoeuvre or being boxed in by a vehicle, and the remainder involved slippery road surface conditions. Collisions involving kerbs most commonly resulted in the cyclist toppling over. Many single cyclist collisions (20%) involved an avoidance manoeuvre from a motorised vehicle, the largest share (47%) of which then also involved an impact with a road feature (most commonly kerbs). Similarly, 15% of collisions involving avoidance manoeuvres involved the cyclist impacting with a road feature due to being boxed in by a vehicle. Many (23%) avoidance manoeuvres involved an abrupt or adventitious steering/braking action leading to the cyclist falling, with no other impact partner. Finally, potholes were involved in 7% of single cyclist collisions and 45% of these involved no other factor. Twenty five percent of collisions with potholes resulted from the cyclist taking an avoidance manoeuvre or being boxed in, and a further fifth (20%) were resulted from the pothole being submerged, reducing its visibility. All categories of single cyclist collisions had much lower levels of police reporting than cyclist-motorised vehicle collisions, however, single

cyclist collisions involving an avoidance manoeuvre from a motorised vehicle had the highest reporting level (11% reported to the police).

4.4.3 Injury patterns

Of the coded collisions, 53% (N = 261) of those with bonnet-type vehicles and 75% (N = 204) of single cyclist collisions resulted in injuries. Injury patterns for the four most common impact configurations with bonnet-type vehicles and the three defined fall types for single cyclist collisions are shown in Figure 4.3 and Table 4.5. For interpretation, consider the example of head injuries in Side-Side impacts:

There were N = 60 Side-Side collisions, of which 35% (N = 21) involved a head injury, N = 20 involved a direct head impact. Seven cases resulted in a concussion, and 3 cases resulted in a skull fracture, comprising 44% and 19% of Side-Side serious injury cases respectively.

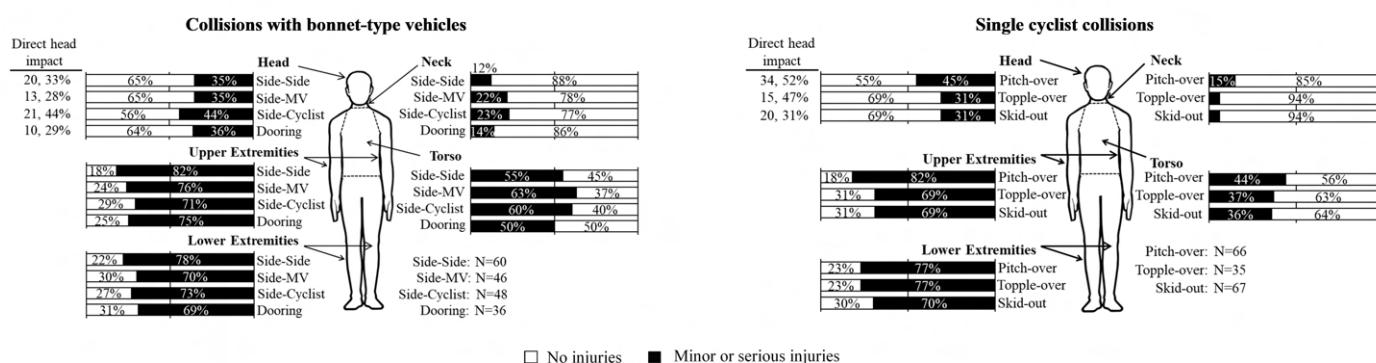


Figure 4.3: Injury patterns for injured cyclists, for the four most common impact configurations in collisions with bonnet-type vehicles, and the three defined fall types in single cyclist collisions.

Patterns are generally similar across the impact configurations. Side-Cyclist collisions have higher levels of head injury than the other impact configurations (8–9% difference) and also have the highest level of direct head impact (44%). Side-Side impacts have the highest

level of upper/lower extremity injuries. Dooring impacts have the lowest levels of lower extremity and torso injury. Side-Cyclist and Side-MV impacts have the highest levels of neck injury. Forty-five percent ($N = 30$) of pitch-over falls resulted in head injury, compared to 31% for skid-out and topple-over falls. Pitch-over falls were the single cyclist fall type with the highest levels of head injury (45%) and direct head impact (52%), and also had the highest levels of upper/lower extremity and torso injury.

Table 4.5: A comparison of the occurrence of selected serious injuries in the four most common impact configurations in collisions with bonnet-type vehicles, and the three defined fall types in single cyclist collisions.

	Collisions with bonnet-type vehicles										Single cyclist collisions							
	Side-Side		Side-MV		Side-Cyclist		Dooring		Overall ^b		Pitch-over		Topple-over		Skid-out		Overall ^c	
	No.	% ^a	No.	% ^a	No.	% ^a	No.	% ^a	No.	% ^a	No.	% ^a	No.	% ^a	No.	% ^a	No.	% ^a
Head																		
Concussion	7	44%	3	33%	10	53%	3	60%	29	46%	7	28%	2	25%	4	21%	15	24%
Skull fracture	3	19%	1	11%	3	16%	0	0%	10	16%	6	24%	1	13%	3	16%	14	22%
Neck																		
Neck fracture	0	0%	0	0%	0	0%	0	0%	1	2%	2	8%	0	0%	0	0%	2	3%
Torso																		
Rib fracture	2	12%	0	0%	3	16%	0	0%	10	16%	3	12%	0	0%	4	21%	9	14%
Spine fracture	0	0%	0	0%	2	11%	0	0%	2	3%	0	0%	0	0%	0	0%	0	0%
Internal organ damage	0	0%	0	0%	1	5%	0	0%	1	2%	1	4%	0	0%	1	5%	2	3%
Upper extremities																		
Upper arm fracture	1	6%	1	11%	1	5%	0	0%	4	6%	2	8%	0	0%	3	16%	5	8%
Lower arm fracture	1	6%	1	11%	0	0%	0	0%	3	5%	2	8%	0	0%	1	5%	3	5%
Hand/wrist fracture	2	13%	2	22%	3	16%	0	0%	8	13%	8	32%	3	38%	6	32%	18	29%
Lower extremities																		
Upper leg fracture	1	6%	0	0%	0	0%	0	0%	1	2%	0	0%	1	13%	2	11%	3	5%
Lower leg fracture	0	0%	0	0%	1	5%	0	0%	2	3%	0	0%	0	0%	0	0%	0	0%
Foot/ankle fracture	0	0%	0	0%	0	0%	1	20%	2	3%	0	0%	0	0%	0	0%	0	0%
Total	16		9		19		5		63		25		8		19		63	

a: column percentages do not add to 100% as cases can have multiple or none of the listed injuries, b: including all coded cases with known and unknown impact configurations, c: including all coded cases with known and unknown fall types.

For both collision types (single cyclist and bonnet-type vehicle collisions), similar proportions of injuries were serious (see definition in Table A.1): 31% ($N = 63$) for coded single cyclist collisions and 24% ($N = 63$) for coded collisions with bonnet-type vehicles. For those seriously injured in single cyclist collisions, 24% ($N = 15$) sustained a concussion and 22% ($N = 14$) sustained a skull fracture, compared to the 46% ($N = 29$) concussions and 16% ($N = 10$) skull fractures from collisions with bonnet-type vehicles. Twenty-nine percent (N

= 18) of serious injury single cyclist collisions involved a hand/wrist fracture, compared to 13% (N = 8) of collisions with bonnet-type vehicles. For collisions with bonnet-type vehicles, concussion/skull fracture rates among serious injury cases were similar across impact configurations. Serious injury dooring impacts were rare. Side-Cyclist cases had a higher level of torso injuries (rib fracture, spine fracture or internal organ damage). Fractures in Side-MV cases were primarily to the upper extremities (upper/lower arms, or hand/wrist). Lower extremity fractures were less common than upper extremity fractures. For serious injury single cyclist collisions, concussion/skull fracture was most common among pitch-over falls, where 28% involved a concussion and 24% involved a skull fracture. There were 2 neck fractures in single cyclist collisions, both from pitch-over falls. Fractures in topple-over falls were primarily to the hand/wrist, and these were also common for skid-out and pitch-over falls.

4.5 Discussion

In this study, a detailed analysis of pre-crash configurations, impact configurations, and injury outcomes for cyclist collisions with motorised vehicles and single cyclist collisions is performed. Unlike previous studies of single cyclist collisions, and cyclist-motorised vehicle collisions, this study includes many minor injury and non-injurious cases that would not appear in other data sources. These findings strengthen our understanding of the cyclist safety problem and can be used as a comprehensive basis to develop collision/injury prevention strategies.

4.5.1 Representative cyclist impact scenarios

Representative pre-crash scenarios and collision factors have been identified both for cyclist-motorised vehicle collisions and for single cyclist collisions (Table 4.6), including an estimate for the proportion of collisions that each scenario/factor represents. Overall, the 8 selected

cyclist-motorised vehicle collisions comprise 42% of all cyclist collisions and the selected single cyclist collision factors comprise 23% of all cyclist collisions. Together these comprise a total of 65% of the overall safety problem posed to cyclists reflected from the survey. These results do not include fatal collisions, and future work should extend this analysis to include fatalities (see chapter 5).

Table 4.6: Representative cases for cyclist-motorised vehicle collisions and single cyclist collisions.

Cyclist-motorised vehicle collisions			Single cyclist collisions		
Pre-crash scenarios	% ^a	% ^c	Collision factors	% ^{b,d}	% ^c
LT/RD (36) & SCP/RD (34) & RT/RD (27): Collision resulting from a vehicle taking a left turn, a right turn or travelling straight ahead, and cyclist approaching from the vehicle driver's right direction.	20%	11%	Collisions involving slippery roads. (83) e.g. skidding out due to skidding on wet, icy, gravelly road surface conditions.	31%	9%
LT/SD (88): Cyclist and vehicle initially travelling in the same direction, with a collision resulting from the vehicle taking a left turn across the cyclist's path.	18%	10%	Collisions involving tram tracks. (62) e.g. falling forward over the handlebars due to a bicycle wheel becoming lodged in tram tracks while crossing.	23%	7%
D (56): Collision resulting from a vehicle occupant opening their door, with the cyclist approaching from behind.	11%	6%	Collisions involving kerbs. (56) e.g. clipping/hitting a kerb while exiting the roadway onto a cycle track, or due to avoiding a vehicle and toppling over.	21%	6%
CL/SD (50): Cyclist and vehicle initially travelling in the same direction, with a collision resulting from the vehicle changing lanes.	10%	6%	Collisions involving avoidance manoeuvres from motorised vehicles. (53) e.g. colliding with a road feature or falling after abrupt or adventitious steering/braking while avoiding a vehicle.	20%	6%
OT/SD (38): Cyclist and vehicle initially travelling in the same direction, with a collision resulting from the vehicle attempting to overtake the cyclist.	8%	4%	Collisions involving potholes. (20) e.g. cycling into a pothole and falling forward over the handlebars.	7%	2%
RT/OD (36): Cyclist and vehicle initially travelling in opposite directions, with a collision resulting from the vehicle taking a right turn across the cyclist's path.	7%	4%	Total	81%	23%
Total	75%	42%			

a: proportion of coded cyclist collisions with motorised vehicles (including non-bonnet-type vehicles) (N=461), b: proportion of coded single cyclist collisions (N=271), c: estimated proportion of all survey collisions (including cyclist-cyclist, and cyclist-pedestrian collisions) (N=1,030), d: proportions do not add to 81% as there is overlap between collision factors.

4.5.2 Collision configurations

In order to consolidate the insights and findings from chapters 3, 4, and 5, discussions on collision factors and prevention strategies have been migrated into sections 9.2, and 9.3 in the discussion chapter. This approach avoids repetition, and allows for a more comprehensive analysis of the research, as the discussion can draw connections between the different chapters and explore any overarching themes or patterns.

4.5.3 Recommendations for monitoring cyclist safety

Chapter 3 highlighted that single cyclist collisions and less severe injuries have lower odds of being reported to the police [211]. This is emphasised here in more detail. It is recommended that road users are encouraged to report collisions, e.g., self-reporting of collisions via an online platform (as is available to road users in London). Furthermore, increases in the level of detail recorded in official statistics is recommended, and the cyclist collision categories developed here could be used to inform coding in police/official collision statistics. Additionally, it is recommended that a similar survey be performed in different jurisdictions on a regular basis, to allow for longitudinal monitoring of safety priorities.

4.5.4 Limitations

The representative collision scenarios developed in this study are useful for developing engineering solutions for cyclist collisions, however the factors examined in this study are not exhaustive and there are a number of collision causes which were not included in the analysis (e.g., weather, lighting) or not available for examination (e.g., distraction, fatigue). Furthermore, the collisions reported to this survey are from the perspective of the cyclist, and further insights into cyclist-motorised vehicle collisions could be gained by including self-reporting by vehicle drivers. Due to the self-reported nature of this study, fatalities are not included in

this analysis. However, representative collision scenarios differ for fatal and life threatening collisions, e.g., it is known that HGVs feature frequently among fatalities and serious injuries [6] (see chapter 5). Furthermore, only adult cyclists (>18) were included in the study, so safety priorities specific to younger cyclists are not available.

As acknowledged in chapter 3 [211], there was no means to ensure the sample of cyclists included in this study was representative of cyclists in Ireland. However, the demographics (location, sex) of survey respondents are similar to those of commuting cyclists in Ireland (according to census data) [207], implying that the survey respondents are broadly representative of cyclists in Ireland. Since the responses in this study rely on the perception and memory of the cyclist, there may be some inaccuracies for certain variables which may be more difficult to estimate (e.g., speed, driver's intended action). Furthermore, accurate memory recall of collision details may be affected by the length of time that has passed since collision occurrence. A period of 5 years was chosen, as per Hollingworth et al. (2015) [191], and Useche et al. (2019) [46], which both involved self-reported cyclist collisions. However, other studies use shorter periods [42, 28, 30]. To limit inaccuracies, in reliability checks significant attempts were made to identify and exclude inconsistent responses, which may be symptomatic of inaccurate recollection. Furthermore, in this work, collision scenarios are coded using open-text responses, noting cases where the description was unclear.

4.6 Conclusions

This analysis of self-reported survey data on cyclist collisions in Ireland has led to the identification of a range of representative collision scenarios both for collisions with motorised vehicles and for single cyclist collisions, with the inclusion of underreported and lower severity collisions. The dataset generated in this study is available from the authors on reasonable request.

Findings indicate that current and proposed ADAS systems and type-testing protocols may adequately address many collisions that present in lower severity and non-injurious collisions. However, findings indicate that priorities for pre-crash scenarios and impact configurations shift with the inclusion of lower severity collisions. This study highlights the relative importance of collisions resulting from the cyclist and vehicle travelling in the same direction, specifically, nearside-hook, vehicle lane changing, and overtaking manoeuvres are emphasised. Furthermore, cases involving a cyclist struck from the side by vehicle fronts comprise a smaller share than previous studies; specifically, impacts with the sides of vehicles, and dooring impacts emerge as important impact configurations with the inclusion of self-reported collisions.

For single cyclist collisions, the importance of loss of traction of the tires due to slippery road conditions, and interactions with tram tracks, kerbs, and potholes are emphasised. Findings indicate that common collision scenarios vary between countries and cycling environments, agreeing with international findings (Table 2.5) [136], however, the coding scheme devised here for single cyclist collisions can act as a basis for identifying common collision scenarios in other countries.

CRedit authorship contribution statement [210]

Kevin Gildea: Conceptualisation, Data curation, Formal analysis, Software, Investigation, Methodology, Resources, Validation, Visualisation, Writing - original draft, Writing - review & editing, Project administration. **Daniel Hall:** Validation, Writing - review & editing. **Ciaran Simms:** Supervision, Conceptualisation, Funding acquisition, Methodology, Project administration, Methodology, Resources, Validation, Visualisation, Writing - review & editing.

Chapter 5

Study C: Collision configurations for fatal & serious injuries

Related publication:

- Characteristics of fatal and serious cyclist collisions in Ireland: Analysis of police investigation files,
K. Gildea, A. Kervick, C. Simms,
International Research Council on Biomechanics of Injury Europe (IRCOBI Europe) (2022)

5.1 Introduction

In chapters 3 [211], and 4 [214], underreporting of cyclist collisions to Irish police was investigated using a nationally distributed self-report collision survey. This study highlighted underreporting biases and classified the most common pre-crash manoeuvres and impact scenarios for injurious and non-injurious cyclist collisions. These findings highlight the relative prevalence of nearside-hooks, overtakings and doorings, and raise the importance of single cyclist collisions, which are particularly underreported in police statistics. However, due to the self-reported nature of this survey, these findings are not based on fatalities or some life-threatening injuries.

5.2 Study aims

Therefore, this study aims to provide a detailed taxonomy of pre-crash road-user manoeuvres and impact configurations, and an analysis of causative factors for serious and fatal cycling collisions in Ireland using data from police investigation reports.

5.3 Methods

An analysis of a convenience sample of 59 fatal and 45 serious cyclist collisions that occurred in Ireland between the years of 2005 and 2015 is presented. The data relating to fatal cases correspond to 57% of the overall cyclist fatalities, and a small proportion of serious injuries in Irish police statistics for 2005-2015. All data were extracted from files provided by the Irish National Roads Policing Bureau. Hardcopy files contain a forensic collision investigation report, a vehicle investigation report and a coroner's report/medical report. Detailed information was extracted from these files for analysis. The taxonomy scheme developed in chapter 4 [214] is applied to code pre-crash manoeuvres and impact configurations based

on the findings of police and forensic investigations. Pre-crash scenarios are defined by the directions of travel that the cyclist/vehicle were travelling, and the manoeuvres each road user was undertaking immediately before impact (see Table B.1). Pre-crash directions of travel are defined by the relative directions of travel that the cyclist/vehicle were travelling in before the collision: 1) same directions of travel (SD), 2) opposing directions of travel (OD), or 3) crossing directions of travel. Ireland is a left-hand traffic country, therefore, for comparability to right-hand traffic environments, in the text references are made to vehicle driver's 'nearside' (vehicle side nearest the kerb) or the vehicle driver's 'offside' (side farther from the kerb). Impact configuration categories were coded by the regions impacted on the cyclist/vehicle (Table B.2). Cases generally involve one vehicle and one cyclist, however, cases with multiple cyclists/vehicles, secondary impacts, or bicycle passengers are highlighted in table footnotes. Road environmental details (road characteristics and lighting) are also presented for common pre-crash scenarios involving bonnet-type vehicles (Table 5.4) or Heavy Goods Vehicles (HGVs) (Table 5.7). In case files involving HGVs, a detailed investigation of direct/indirect vision was often included, these findings are also presented in Table 5.7.

For single cyclist collisions, 'direct causes' are coded, as per chapter 4 (Table B.3). These are general categories describing the object, action, or mechanism that caused the cyclist to fall, as indicated in the investigation file.

5.4 Results

5.4.1 Collision partners

The majority of fatal and serious collisions, 84 (81%) were with motorised vehicles (MVCs) (Figure 5.1). Single cyclist collisions (SCCs) comprised N=9, 15% of fatalities and N=7, 16% of serious injury cases. For cases involving a motorised vehicle (including both MVCs, and SCCs resulting in MVCs), 64 (72%) were with bonnet-type vehicles (Sedans/Hatchbacks, SUVs, and Vans), 18 (20%) with HGVs, and 4 (5%) with Buses. A larger proportion of fatal collisions involved HGVs than serious injuries, N=16, 31% vs. N=2, 5%.

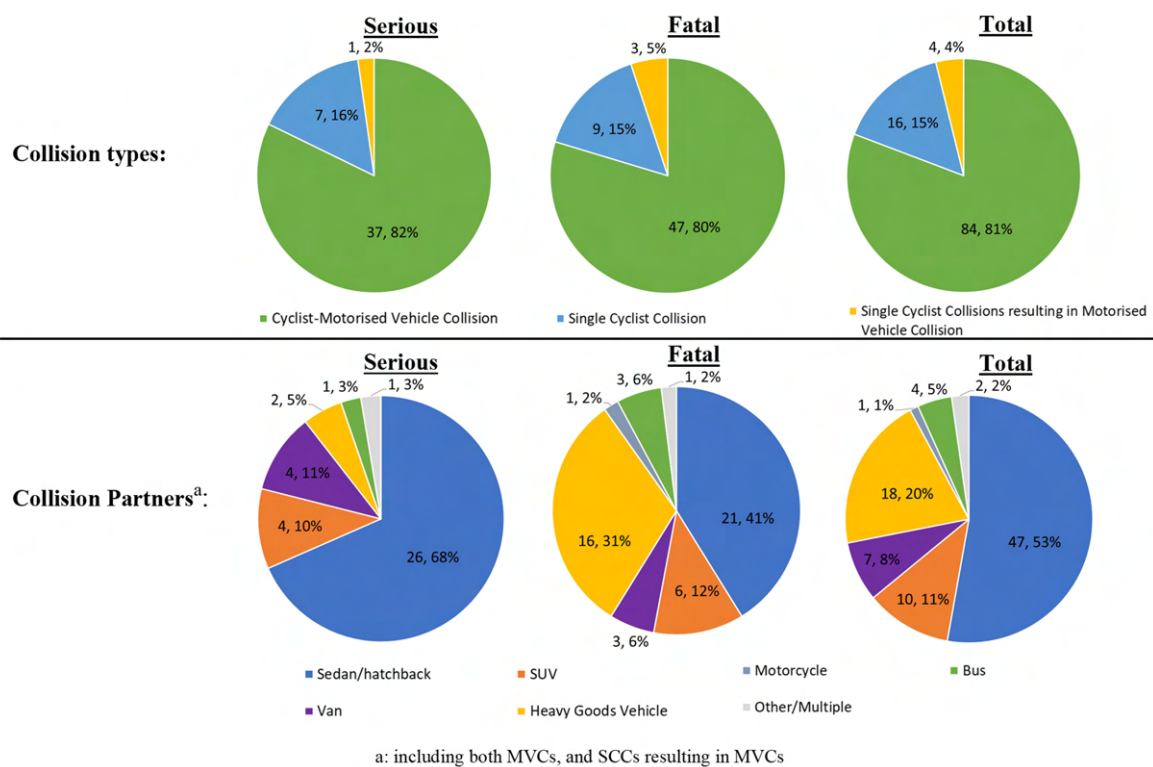


Figure 5.1: Breakdown of collision types, and collision partners (for all cases involving a motorised vehicle) for serious and fatal cyclist cases.

5.4.2 Directions of travel

This sample includes all MVCs (N=84). For serious injuries, the largest proportion involved both the cyclist and vehicle travelling in the same direction (N=19, 51%), followed by both travelling in opposing directions (N=12, 32%) and lateral/crossing directions (N=5, 14%) (Table 5.1). Similarly, for fatal collisions the majority involved same directions of travel (N=29, 62%), followed by lateral/crossing directions (N=10, 21%) and opposing directions (N=8, 17%).

Table 5.1: Pre-crash directions of travel for serious and fatal collisions.

Directions of travel	Serious		Fatal		Total	
	N	%	N	%	N	%
Same directions	19	51%	29	62%	48	57%
Opposing directions	12	32%	8	17%	20	24%
Lateral/crossing	5	14%	10	21%	15	18%
Other	1	3%	0	0%	1	1%

5.4.3 Collisions with bonnet-type vehicles

This sample includes only MVCs involving bonnet-type vehicles (N=62). For both fatal and serious collisions with bonnet-type vehicles, the most common scenario was overtaking/passing (OT/SD) (N=20, 32%) (Table 5.2). For fatal collisions, the second most common scenario involved straight crossing paths with the cyclist approaching from the left, i.e., the vehicle driver's nearside (SCP/LD) (N=6, 21%). For serious collisions, the second most common scenario involved both travelling in opposing directions with the vehicle taking a right turn across the cyclist, i.e., an offside-hook (RT/OD) (N=6, 18%). The most common impact configurations for bonnet-type vehicles involved the vehicle impacting with the cyclist from the rear (Rear-Cyclist) (N=19, 31%) (particularly common for fatalities), or the vehicle frontally impacting with the side of the cyclist (Side-Cyclist) (N=15, 24%) (Table 5.3).

Table 5.2: Pre-crash manoeuvres for cyclist collisions involving bonnet-type vehicles.

Pre-crash scenario	Serious		Fatal		Total	
	N	%	N	%	N	%
OT/SD	9	27%	11	38%	20	32%
RT/OD	6	18%	1	3%	7	11%
SCP/LD	1	3%	6	21%	7	11%
OD	1	3%	3	10%	4	6%
CL/SD	2	6%	1	3%	3	5%
LT/RD	1	3%	2	7%	3	5%
OD/RT	3	9%	0	0%	3	5%
SD/CL	1	3%	2	7%	3	5%
LT/SD	1	3%	1	3%	2	3%
SCP/RD	1	3%	1	3%	2	3%
Other	6	18%	1	3%	7	11%
Unknown	1	3%	0	0%	1	2%

Table 5.3: Impact configurations for cyclist collisions involving bonnet-type vehicles.

Impact configuration	Serious		Fatal		Total	
	N	%	N	%	N	%
Rear-Cyclist	7	21%	12	41%	19	31%
Side-Cyclist	8	24%	7	24%	15	24%
Side-MV	5	15%	4	14%	9	15%
Head on	3	9%	4 ^c	14%	7	11%
Side-Side	5	15%	2 ^a	7%	7	11%
Rear-MV	2 ^b	6%	0	0%	2	3%
Dooring	1 ^c	3%	0	0%	1	2%
Unknown	2	6%	0	0%	2	3%

a: one case in this cell involved overrunning from a second vehicle

b: one case in this cell involved multiple impacted cyclists with serious injuries

c: one case in this cell involved a passenger on the bicycle who was seriously injured

Table 5.4 shows environmental details for common pre-crash scenarios with bonnet-type vehicles. The majority of collisions involving overtaking/passing manoeuvres (OT/SD) occurred on straight roads (N=18, 90%) without traffic separation for cyclists (N=14, 70%) in rural environments (speed limit greater than 60km/h) (N=14, 70%). A relatively high proportion of these cases involved dark/dusk light conditions (N=7, 35%), or low sun ahead of the driver (N=4, 20%).

Table 5.4: Environmental details for common scenarios of cyclist collisions with bonnet-type vehicles.

	OT/SD		RT/OD		SCP/LD		All	
	N	%	N	%	N	%	N	%
Road configuration								
Straight road	18	90%	0	0%	0	0%	33	53%
Bending road	0	0%	0	0%	0	0%	3	5%
Roundabout	0	0%	0	0%	0	0%	2	3%
Entrance	0	0%	1	14%	3	43%	4	6%
Junction (other)	2	10%	6	86%	4	57%	20	32%
Traffic separation								
None	14	70%	3	43%	5	71%	40	65%
Off-road segregated cycle lane	0	0%	0	0%	1	14%	2	3%
On-road painted cycle lane	0	0%	1	14%	0	0%	1	2%
Hard-shoulder	1	5%	0	0%	0	0%	2	3%
Unknown	5	25%	3	43%	1	14%	17	27%
Setting								
Urban	2	10%	5	71%	1	14%	20	32%
Rural	14	70%	1	14%	3	43%	26	42%
Unknown	4	20%	1	14%	3	43%	16	26%
Lighting								
Dark, poor/no street lighting	5	25%	2	29%	1	14%	12	19%
Dark, well-lit	1	5%	0	0%	0	0%	5	8%
Dusk, poor/no street lighting	1	5%	1	14%	0	0%	3	5%
Dusk, well-lit	0	0%	0	0%	0	0%	1	2%
Daylight, good visibility	7	35%	2	29%	3	43%	24	39%
Daylight, low sun ^a	4	20%	1	14%	0	0%	5	8%
Daylight, unspecified	2	10%	1	14%	2	29%	11	18%
Unknown	0	0%	0	0%	1	14%	1	2%

Urban: roads with a speed limit of 60 km/h or less, Rural: otherwise

a: low sun ahead of the driver

5.4.4 Collisions with heavy goods vehicles

The following analysis involves cyclist-HGV collisions involving impact between a cyclist and an in-use HGV (not parked), and therefore includes 2 fewer cases than the number presented in Figure 5.1. Most collisions with HGVs involved both travelling in the same direction (N=14, 87%), and most commonly involved the vehicle turning left across the path of the cyclist (LT/SD) (nearside-hook) (N=7, 44%) (Table 5.5).

Table 5.5: Pre-crash manoeuvres for cyclist collisions with HGVs.

Pre-crash scenario	Serious		Fatal		Total	
	N	%	N	%	N	%
LT/SD	2	100%	5	36%	7	44%
CL/SD	0	0%	2	14%	2	13%
OT/SD	0	0%	2	14%	2	13%
SD (other)	0	0%	3	21%	3	19%
Other	0	0%	2	14%	2	13%

Table 5.6 shows impact configurations for collisions with HGVs were commonly initiated by side to side contacts (Side-Side) (N=8, 50%), or initiated by the HGV impacting frontally with the rear of the cyclist (Rear-Cyclist) (N=5, 31%). The majority of cases (N=11, 69%) also resulted in the HGV overrunning the cyclist.

Table 5.6: Impact configurations for cyclist collisions with HGVs.

Impact configuration	Serious		Fatal		Total	
	N	%	N	%	N	%
Side-Side (overran)	2	100%	6	43%	8	50%
Rear-Cyclist	0	0%	3	21%	3	19%
Rear-Cyclist (overran)	0	0%	2	14%	2	13%
Side-Cyclist (overran)	0	0%	1	7%	1	6%
Head on	0	0%	1	7%	1	6%
Unknown	0	0%	1	7%	1	6%

Table 5.7 shows environmental details for common pre-crash scenarios with HGVs. All nearside-hook (LT/SD) collisions occurred at junctions/entrances, and the majority occurred in urban environments (speed limit 60km/h or less) (N=6, 86%) in daylight conditions with good visibility (N=5, 71%). Overall, based on investigations, 3 cases (19%) resulted from the

cyclist being in the blind zone at the front or the nearside of the HGV, and 7 cases (44%) involved the cyclist being available to be seen by the driver at some point before impact, through either direct (line-of-sight), or indirect vision (mirrors).

Table 5.7: Environmental details for common scenarios of cyclist collisions with HGVs.

	LT/SD		SD (all)		All	
	N	%	N	%	N	%
Road configuration						
Straight road	0	0%	4	29%	6	38%
Entrance	1	14%	1	7%	1	6%
Junction (other)	6	86%	9	64%	9	56%
Traffic separation						
None	2	29%	7	50%	9	56%
Off-road segregated cycle lane	1	14%	1	7%	1	6%
On-road painted cycle lane	3	43%	3	21%	3	19%
Advanced stop box	1	14%	2	14%	2	13%
Unknown	0	0%	1	7%	1	6%
Setting						
Urban	6	86%	9	64%	10	63%
Rural	0	0%	3	21%	4	25%
Unknown	1	14%	2	14%	2	13%
Lighting						
Dark, poor/no street lighting	0	0%	1	7%	1	6%
Daylight, good visibility	5	71%	10	71%	12	75%
Daylight, unspecified	0	0%	1	7%	1	6%
Daylight, overcast	1	14%	1	7%	1	6%
Unknown	1	14%	1	7%	1	6%
Vision						
Visible, direct vision	0	0%	2	14%	2	13%
Visible, indirect vision	3	43%	4	29%	4	25%
Visible, unspecified	0	0%	0	0%	1	6%
In blind zone, at front	0	0%	1	7%	1	6%
In blind zone, at side	1	14%	2	14%	2	13%
Not visible, poor lighting	0	0%	1	7%	1	6%
Unknown, no direct vision	1	14%	1	7%	1	6%
Unknown	2	29%	3	21%	4	25%

Urban: roads with a speed limit of 60 km/h or less, Rural: otherwise

5.5 Discussion

In order to consolidate the insights and findings from chapters 3, 4, and 5, discussions on collision factors and prevention strategies have been migrated into sections 9.2, and 9.3 in the discussion chapter. This approach avoids repetition, and allows for a more comprehensive analysis of the research, as the discussion can draw connections between the different chapters and explore any overarching themes or patterns.

5.6 Conclusions

This is the first detailed analysis of police investigation files for serious and fatal cyclist collisions in Ireland. Though the sample size is small, these findings emphasise the prevalence of 1) left/nearside-turning HGVs at junctions in urban environments resulting in side to side impacts and cyclist overrunning, and 2) overtaking manoeuvres from bonnet-type vehicles in rural environments resulting in rear impacts. Furthermore, single cyclist collisions are an important component of fatal cycling cases. Future countermeasures and test protocols should address these pre-crash scenarios and impact scenarios.

CRedit authorship contribution statement [210]

Kevin Gildea: Conceptualisation, Data curation, Formal analysis, Software, Investigation, Methodology, Resources, Validation, Visualisation, Writing - original draft, Writing - review & editing, Project administration. **Aoife Kervick:** Conceptualisation, Project administration, Writing - review & editing. **Ciaran Simms:** Supervision, Conceptualisation, Funding acquisition, Methodology, Project administration, Resources, Writing - review & editing.

Chapter 6

Study D: Video-based assessment, predictive modelling, & SMoS for cyclist-tram track interactions

Related publication:

- Video-based assessment of cyclist-tram track interactions in wet road conditions,
K. Gildea, C. Mercadal-Baudart, B. Caulfield, C. Simms,
International Cycling Safety Conference (ICSC) (2022)

6.1 Introduction

Common cyclist collision configurations and contributory factors have been investigated in chapter 4 [214], with findings indicating that falls involving interactions with light rail tram tracks are common in the city of Dublin. Tram tracks were the most common infrastructural collision partner, and a contributing factor in 23% of single cyclist collisions (ibid.). Internationally, other self-reporting studies also highlight their importance, with 19% of cases in a study in Melbourne [134], and 13% of cases in a study in Switzerland [43] involving tram tracks. A previous video analysis of cyclists crossing railway tracks found that the minimum safe approach angle for crossing railway tracks is 30° [55], however, this study relied on visual assessments of crossing angles (10° bins), and it is unclear whether these findings also translate to light-rail tram tracks.

Along with the increasing popularity of cycling, many new light rail systems are being implemented across Europe as part of a broader move towards sustainable transport [215]. Accordingly, further investigation is required to understand potential conflicts. As detailed data on crossing angles are not routinely captured in police, hospital, or insurance databases, and given the prevalence of traffic cameras along tram systems, video-based approaches have obvious potential for these cases. Traffic camera footage is often used for the analysis of near-collision or near-miss incidents and Surrogate Measures of Safety (SMoS) or Surrogate Safety Measures (SSM), i.e., a safety-related indicator without the need for collision footage, allowing for rapid proactive assessment of potential areas of conflict (detailed in section 2.4.4).

6.2 Study aims

Therefore, this study aims to use traffic camera footage to identify site-specific safety issues between cyclists and tram tracks, correlate unsuccessful crossing risk with crossing trajectories, and devise a SMoS algorithm for future use in safety assessments.

6.3 Methods

6.3.1 Data collection

Traffic camera footage was collected in October/November 2021 following ethical approval from the School of Engineering, Trinity College Dublin. This involved manual screening, annotation, and extraction of cyclist interactions with tram tracks from 9 locations (10 cameras) in Dublin city centre (Figure 6.1). Locations with an established likelihood of cyclist-tram track conflicts were chosen based on findings from chapter 3 [214], and feedback from experts in the city council. The analysis focuses on weekdays, daylight conditions, and peak commuting hours [211]. Initially, a sample that included both dry and wet conditions was assessed, but a significant preliminary analysis found no unsuccessful crossings during dry conditions. Wet road conditions are a significant factor for cyclist falls on tracks [214, 55]. Therefore, the final analysis focused on periods with wet road conditions.

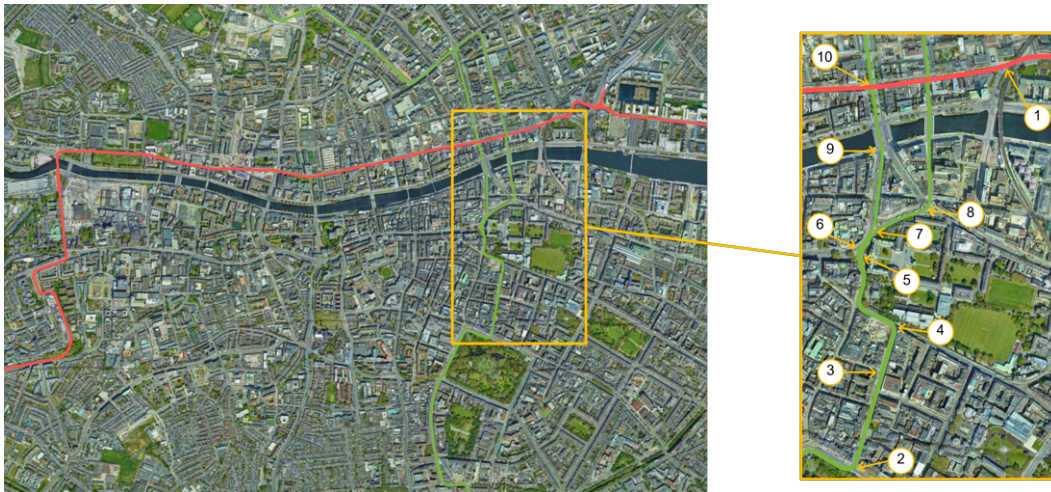


Figure 6.1: Study locations in Dublin city centre.

6.3.2 Track description and effective groove gap width

Various light rail track profiles exist. The popular girder grooved rail types are limited to the European standards: Ri 59N, Ri 60N, IC, Ri52N, Ri53N, NP4a, and 35G. Rail heads are similar across all types, however, the width of the groove gap differs. The Irish tram service (Luas) uses the Ri59N (Ri 59-R13) girder grooved rail in shared-space environments, i.e., most street-running sections and stops (Figure D.1). Pavement/asphalt is set around the rail to support the shared use of the road. Larger groove gap widths present larger risks to crossing cyclists, and this is exacerbated by more off-perpendicular crossing angles ($<90^\circ$). This increased risk can be expressed in the form of an effective width of the groove gap (EW) when crossing at an angle (θ) [216]. The relationship between θ and EW is plotted for various track types in Figure 6.2, showing EW tends to infinity as angle approaches 0° . Furthermore, as crossing angle reduces the differences between effective widths of the track types widens.

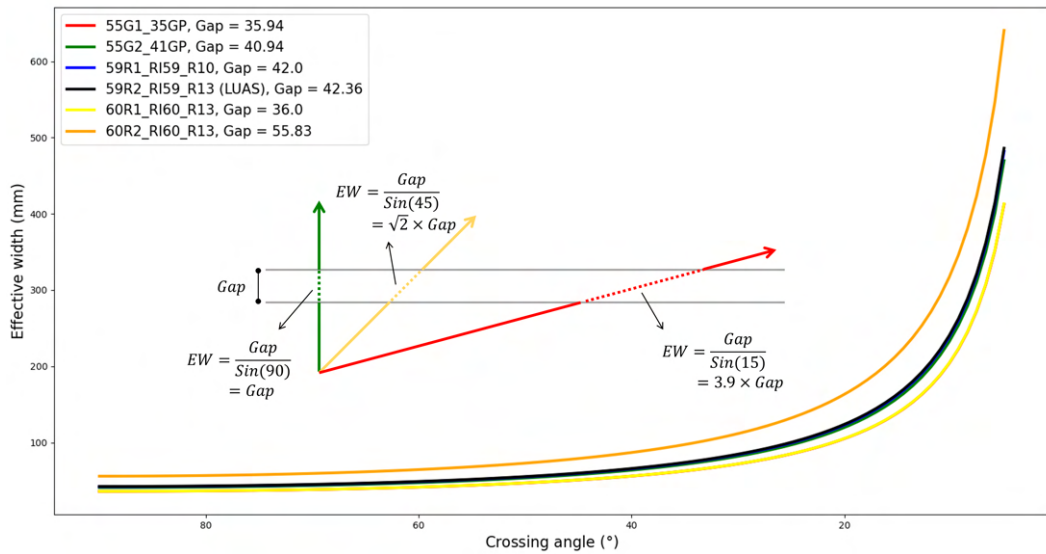


Figure 6.2: Effective track groove gap width (EW) by crossing angle (θ) for various track types. Some of the curves overlap.

6.3.3 Frequency & risk analysis

Using the collected footage, exposure and time-based risk analyses were performed to assess the rate of Unsuccessful Crossings (UCs) compared to Successful Crossings (SCs) at each recording site. UCs are here defined as falls and near-falls involving evidence of loss of control.

6.3.4 Fall type taxonomy

Three broad categories were defined for UCs (Figure 6.3).



Figure 6.3: The three defined categories for unsuccessful crossings (UCs).

6.3.5 Crossing angles & trajectories

Footage of UCs, and a random sample of SCs were extracted for analysis. T-Analyst software (developed in the European InDev project¹) was used to calculate cyclist velocities and trajectories [60]. In this framework, T-calibration allows for ground-plane calibration of

¹<https://cordis.europa.eu/project/id/635895/>

monocular traffic camera footage from manually annotated scene points in both the traffic camera footage and a satellite image (with scale) of the recording location (e.g., Google Earth) [217] (see Figure 6.4). Once calibrated, 3D bounding boxes were annotated for each frame, corresponding to cyclist positions over time on the X-Y plane (ground). Tracks were annotated in a similar way, using points on the ground plane. For cases involving straight tracks a cardinal axis along the track was defined during calibration, and for curved tracks, pixel coordinates were annotated along the track and a 2nd order polynomial was fitted in post-processing. For the calculation of crossing angles (0-90°) and velocities (m/s), a time window was defined based on visual inspection using frames before and after crossing for SCs and only frames before crossing for UCs. Crossing angles were calculated as angles between line segments representing the track and the cyclist trajectory at that location. Frame-based velocity estimates were calculated from trajectories using the central difference method and the camera framerate, and averaged across the window. Cases were excluded if the view of the cyclist was obstructed, the initial track interaction occurred out of frame, or if tracking confidence was affected by distance from the camera (image or calibration quality).

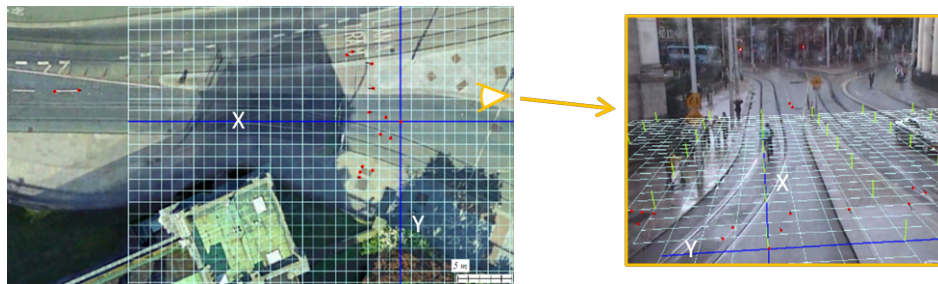


Figure 6.4: Ground plane calibration for Westmoreland St./College St. (Camera 7).

6.3.6 Statistical analysis & predictive modelling of crossing success

Binary logistic regression modelling was used to establish the combined effects of crossing angle and velocity on crossing success (Equation 3.1). In modelling, a random sample of SCs across the study locations was used. To satisfy the assumption of 'independence of observations', only one crossing of one track is included for each cyclist. Both effect estimation and predictive modelling were considered, and three models were created, one for effect estimation (a) and two for predictive modelling (b and c). Model (b) was derived using crossing angle (θ) as the independent variable, whereas for model (c) θ was transformed into EW (Figure 6.2). For effect estimation (model (a)), all variables were included, while for predictive modelling only significant variables were included, as per Harrell et al. (2015) [197]. A Pearson correlation coefficient was computed to determine the relationship between independent variables, indicating non-significant relationships between velocity and (1) θ ($r(108) = -0.046$, $p=0.64$), and (2) EW ($r(108) = -0.008$, $p=0.936$). They were found to be linearly related to the logit of the dependent variable (crossing success) via the Box-Tidwell procedure, with $p > 0.05$. No outliers were found (absolute value of standardised residual greater than 2.5). Predictive models are used in the definition of a SMoS for cyclist-tram track interactions. For this purpose, Equation 6.1 is defined for predicting the number of UCs (N_{UC}) at a site over a period of time using a representative random sample of estimated crossing angles ($\underline{\theta} = [\theta_1, \dots, \theta_M]$), and a count of cyclist numbers (N_C).

$$N_{UC} = N_C \times \frac{\sum_{m=1}^M \left\{ 1 - \frac{e^{\alpha + \beta x_m}}{1 + e^{\alpha + \beta x_m}} \right\}}{M} \quad (6.1)$$

where α, β are taken from the modelling, and $\underline{x} = \underline{\theta}$ for model (b), or $\left[\frac{Gap}{\sin(\theta_1)}, \dots, \frac{Gap}{\sin(\theta_M)} \right]$ for model (c).

6.3.7 Domain-specific cyclist detection

Many deep learning-based object detection algorithms exist. YOLO (You Only Look Once) is relatively easy to use and is considered state-of-the-art for real-time detection [218]. The native model² has a general-purpose object detector trained on the Microsoft Common Objects in Context (MS COCO) dataset [219]. YOLO has been extensively used for road user detection and tracking using an algorithm such as SORT [220] or DeepSORT [221], e.g., [222, 223, 224, 61].

However, differences in image viewpoints, qualities, and textures between MS COCO training images and domain-specific images may result in sub-optimal performance. Therefore, for the purposes of domain transfer, a Convolutional Neural Network (CNN) which is pre-trained on a large dataset can be retrained using a comparatively small amount of data for the same task but in a different domain. The YOLO object detection model has been shown to yield successful domain-specific results after further learning on domain-specific examples, e.g., Tabassum et al. (2020) [225]. The YOLOv5x model was used as a base for the task. This is the largest (166MB) and best-performing YOLO model in terms of Mean Average Precision (50.7mAP_{coco}), i.e., the object detector predicts classes with bounding boxes, and the mAP is a single value used to score how well detections are made across all classes. Average precision (AP) has an optimal value of 1, and requires the setting of an Intersection over Union (IoU) threshold. AP_{0.5} has a threshold of 0.5, whereas AP_{0.5:0.95} averages AP across IoU thresholds between 0.5 to 0.95 for a stricter metric (as per Huang et al. (2017) [226]).

For training, person and bicycle classes were annotated for a sample of images across the collected data³. An investigation into the required number of cases for retraining is

²<https://github.com/ultralytics/yolov5/>

³<https://github.com/ManivannanMurugavel/Yolo-Annotation-Tool-New-/>

performed. The training was performed using various numbers of training examples (30, 50, 70, 90, 110, 130, 150, 200), and a further 26 for validation over 50 epochs. A further 26 images were held for testing the models. As a proof of concept, automatic tracking was assessed using the SORT algorithm [220], and inferred crossing angles were compared to those from manually annotated trajectories using T-Analyst [60].

6.4 Results

6.4.1 Data summary

Table 6.1 shows a summary of the collected data. A total of 2,905 cyclist interactions with tram tracks were surveyed over two periods with wet road conditions. Extracted footage includes 13 UCs (4 Cat. 1, 5 Cat. 2, and 4 Cat. 3 – see Table D.1), and a random sample of the total (2,891) SCs. A total of 9 UCs were identified over Period 1 (7 hours) out of 2,741 cyclists, corresponding to an UC rate of 3.3×10^{-3} (approx. 3 in a 1000). A higher rate was observed in Camera 7 (Westmoreland St./College St.) (4 UCs for 213 cyclists), and a further 5 hours of footage was examined in this location (Period 2), during which a further 4 UCs were noted. Overall, this location has a UC rate of 2.1×10^{-2} , or 21 in 1,000.

Table 6.1: Summary description of the study data, and UC risk estimates.

Camera	No. cyclists	Hours	UC	UC/No. cyclists	UC/Hour
1	198	7	1	0.005	0.143
2	145	7	0	0	0
3	181	7	1	0.005	0.143
4	116	7	0	0	0
5&6	410	7	1	0.002	0.143
7	377	12	8	0.021	0.667
8	324	7	1	0.003	0.143
9	551	7	1	0.002	0.143
10	603	7	0	0	0
Total	2,905	68	13	0.004	0.191

6.4.2 Site study: Camera 1

The majority of crossings at this location (Abbey St./Beresford St.) were at the nearside of the road at a safe crossing angle ($\bar{\theta} = 38^\circ$) (Figure 6.5). The single fall at this location occurred further down the tracks where the cyclist travelled more parallel to the tracks, and was passed by a motorised vehicle while crossing ($\theta = 14^\circ$) (Figure 6.6).

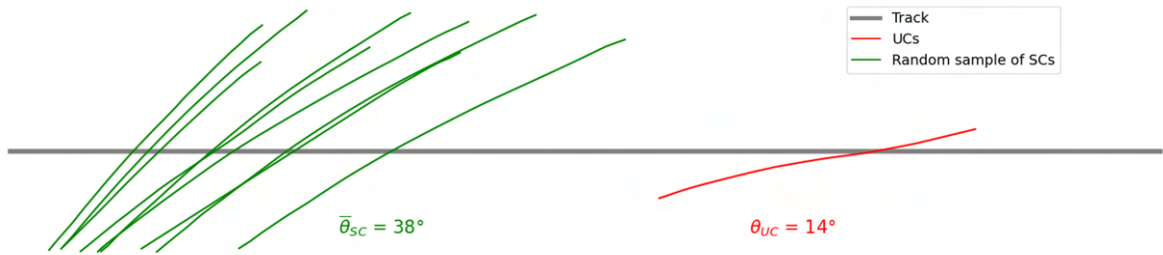


Figure 6.5: Trajectory analysis of cyclist interactions with a track at Abbey St./Beresford St. (Camera 1).

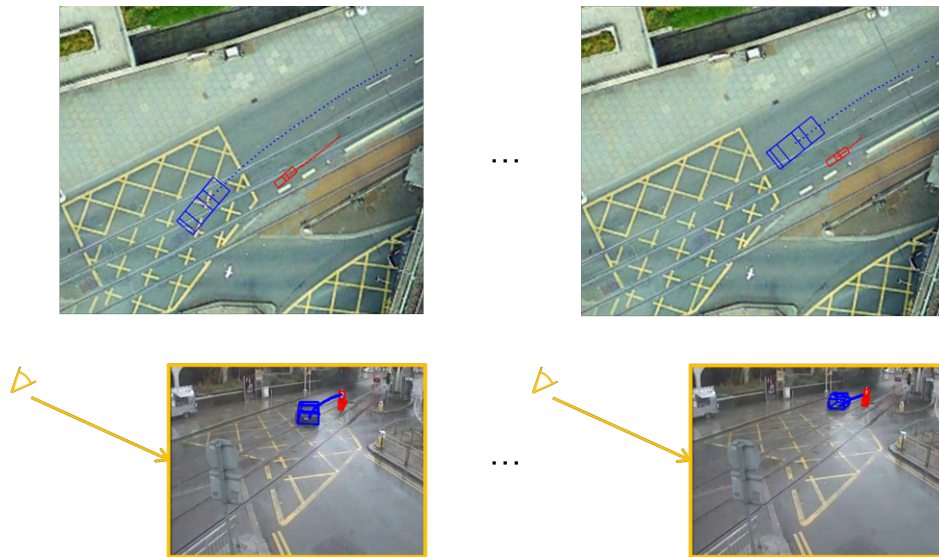


Figure 6.6: Cat. 3 fall at Abbey St./Beresford St. (Camera 1).

6.4.3 Site study: Camera 7

Most UCs at this location occurred on the inside track (N=7, 87%), and the analysis focused on these cases. Trajectories of 6 UCs and a random sample of 7 SCs over the inside track were annotated for Camera 7 (Figure 6.7). Mean crossing angles were higher for SCs ($\bar{\theta} = 17^\circ$, SD = 3.5), compared to UCs ($\bar{\theta} = 10^\circ$, SD = 5.9). The results of a Mann-Whitney U test indicate a significant difference between groups (U = 8, p = 0.03). Average velocities were similar: 4.2m/s for SCs vs. 4.0m/s for UCs. Falls on the inside kerb were common, and crossing angles were low for both SCs and UCs ($\leq 20^\circ$ - excluding one case with intentional mounting of the kerb). This is likely due to the proximity of the nearside kerb (1.16m from the track on average), which limits crossing angle.

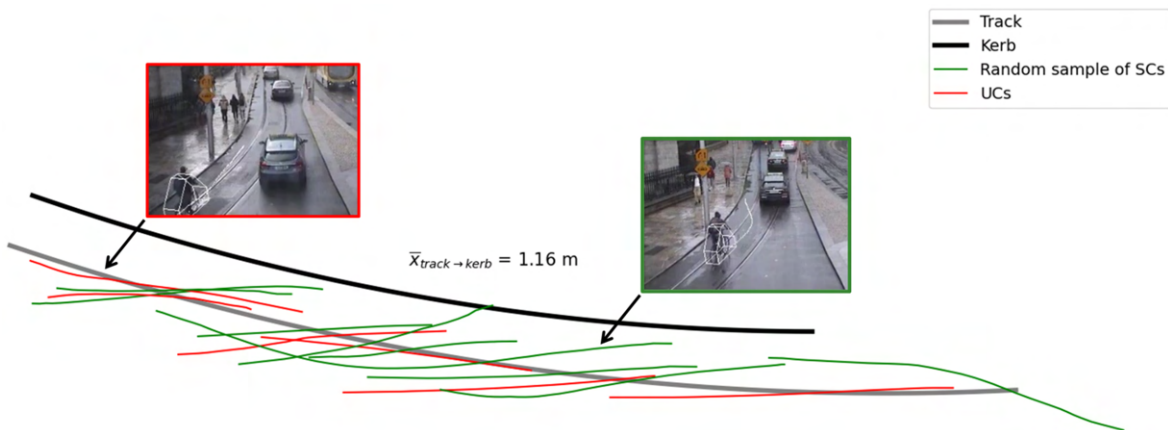


Figure 6.7: Trajectory analysis of cyclist interactions with the inside track at Westmoreland St./College St. (Camera 7).

6.4.4 Multivariable testing & predictive modelling for crossing success

Vectors representing the trajectories for UCs and SCs included in the modelling analysis are shown in Figure 6.8. Mean crossing angles and velocities (and their standard deviations) are also included. Mean crossing angles are notably shallower for UCs (10° vs. 43°), while mean velocities are very similar (4.7m/s vs. 4.8m/s).

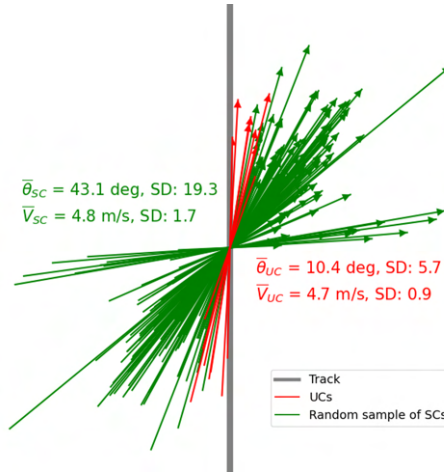


Figure 6.8: Crossing angles and velocities (vector magnitudes).

Model (a): Effect Estimation

Binary logistic regression modelling was used to assess the combined effect of crossing angle and velocity, and to define a predictive model for crossing success. Only crossing angle was significant, see Table D.2. The model was statistically significant $\chi^2(2) = 39.017$, $p < 1 \times 10^{-8}$, Nagelkerke R^2 : 74%.

Model (b): Predictive Modelling Using crossing angle as the independent variable

Model (b) was also statistically significant, $\chi^2(1) = 37.980$, $p < 1 \times 10^{-9}$, Nagelkerke R^2 : 72% (Figure 6.9). It correctly classified 96% of cases, and the area under the Receiver Operating Characteristic (ROC) curve was 0.98 (95% CI: 0.956-1.000), considered an outstanding level of discrimination, as per Hosmer et al. (2013) [198].

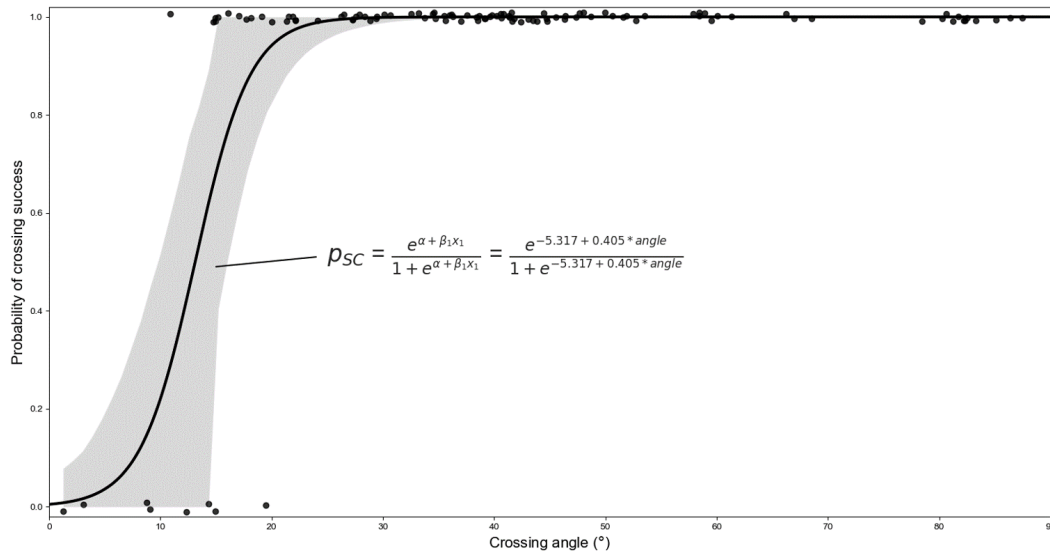


Figure 6.9: SC probability risk curve by crossing angle with 95% confidence levels for model (b).

SC probabilities for various crossing angles based on model (b) are shown in Figure 6.10. Results place the boundary for the definition of a minimum ‘safe’ crossing angle in the region of 25-30°. Below this, the probability of a SC decreases dramatically. Most notably, between 17.5° and 10° the probability of a SC drops from 0.85 to 0.22.

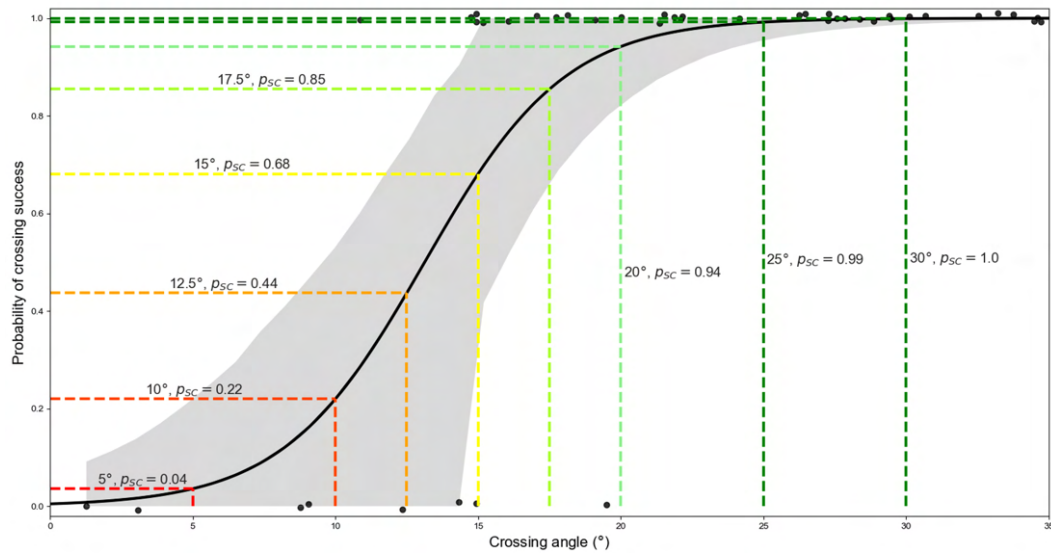


Figure 6.10: SC probabilities for various crossing angles from model (b).

Model (c): Predictive Modelling Using effective groove gap width as the independent variable

Model (c) was also statistically significant, $\chi^2(1) = 33.987$, $p < 1 \times 10^{-8}$, Nagelkerke R^2 : 70%, and the area under the Receiver Operating Characteristic (ROC) curve was the same as model (b) 0.98 (95% CI: 0.956-1.000). Using this, approximate risk curves can be defined for a variety of track types (Figure 6.11).

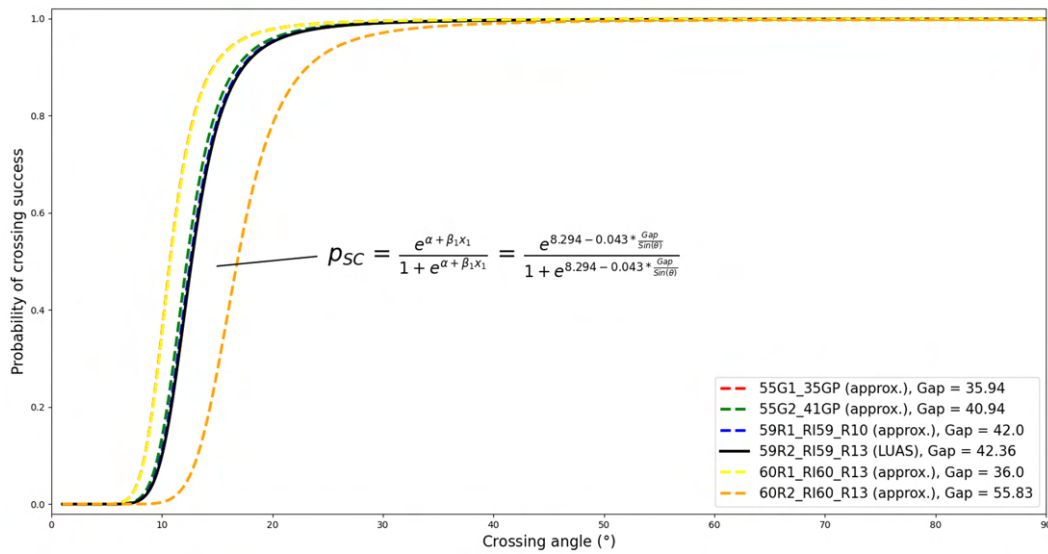


Figure 6.11: Approximate SC probability risk curves for various track types, vs. crossing angle, calculated as a function of effective track width from model (c).

SC probabilities for various crossing angles based on model (c) are shown in Figure 6.12, showing slightly different results to model (b) (Figure 6.10). Although these findings also place the boundary for minimum ‘safe’ crossing angles in the region of 25-30°, for lower crossing angles the associated SC probabilities drop more rapidly. For example, between 17.5° and 10° the probability of a SC drops from 0.9 to 0.1.

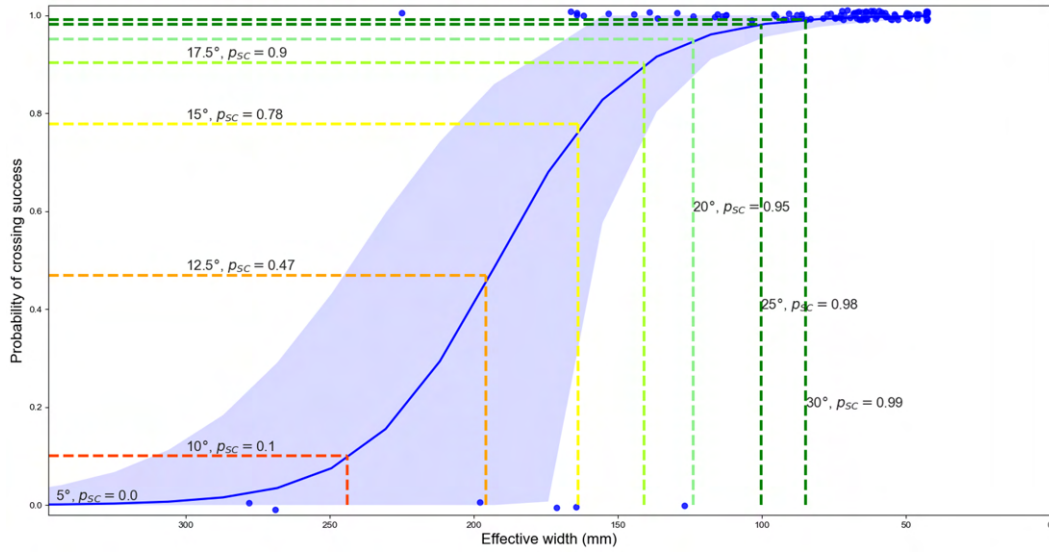


Figure 6.12: SC probabilities for various crossing angles from model (c) (Groove gap = 42.36mm).

6.4.5 Application of predictive models for SMOs

Section 6.4.4 showed there are some differences in risk curves between predictive models (b) and (c). Table 6.2 shows the effect of the chosen model on the prediction of UC numbers, i.e., in the application of Equation 6.1. Although the models deviate somewhat for shallower crossing angles (<25°), in application they predict very similar N_{UC} levels.

Table 6.2: Predicted numbers of UCs for models (b) and (c), where $N_C=1,000$, and $M=100$, with randomly generated angles (θ) within a stated range.

θ range	Model (b)	Model (c)	% diff
0-10°	946	993	2%
0-20°	614	617	0%
0-30°	527	537	1%
0-40°	327	336	1%
0-50°	309	322	2%
0-60°	268	269	0%
0-70°	145	149	1%
0-80°	142	149	2%
0-90°	191	194	1%

6.4.6 Further training for domain-specific cyclist detection

Figure 6.13 shows the accuracy results for YOLOv5x after further training on domain-specific Dublin city images. Substantial improvements are achieved on average precision for bicycle detection up to $0.98AP_{0.5}$, and $0.65AP_{0.5:0.95}$, compared to $0.31AP_{0.5}$, and $0.11AP_{0.5:0.95}$ on the native YOLOv5x model before retraining. The optimal number of cases for retraining is around 100, i.e., where minimal improvements are achieved with extra data.

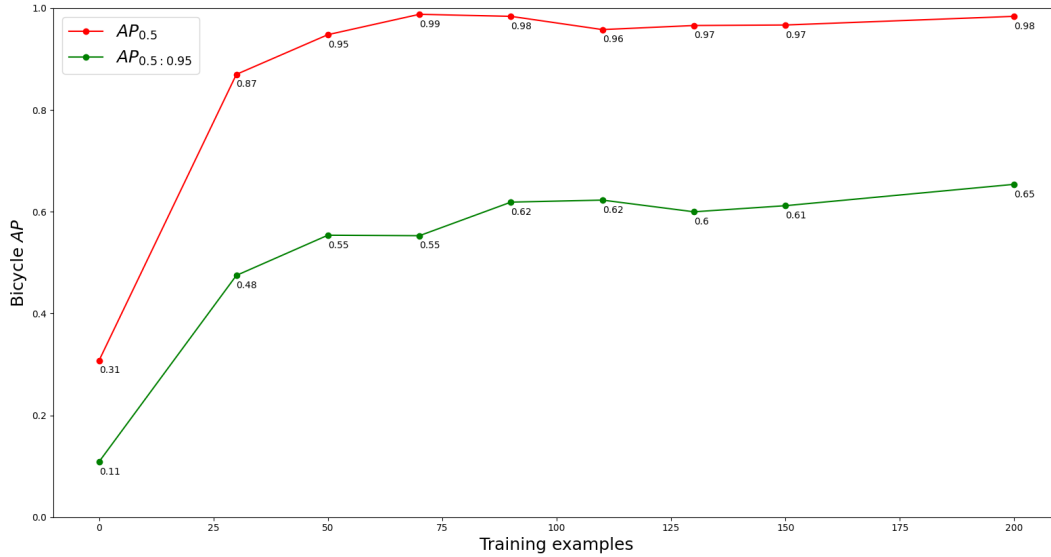


Figure 6.13: Accuracy results for YOLOv5x after further training on various dataset sizes.

Figure 6.14 shows a qualitative comparison of inference accuracy between the native YOLOv5x, and the retrained model YOLOv5xDCC trained on 100 examples (confidence threshold=0.6) for a sample of unseen cases.

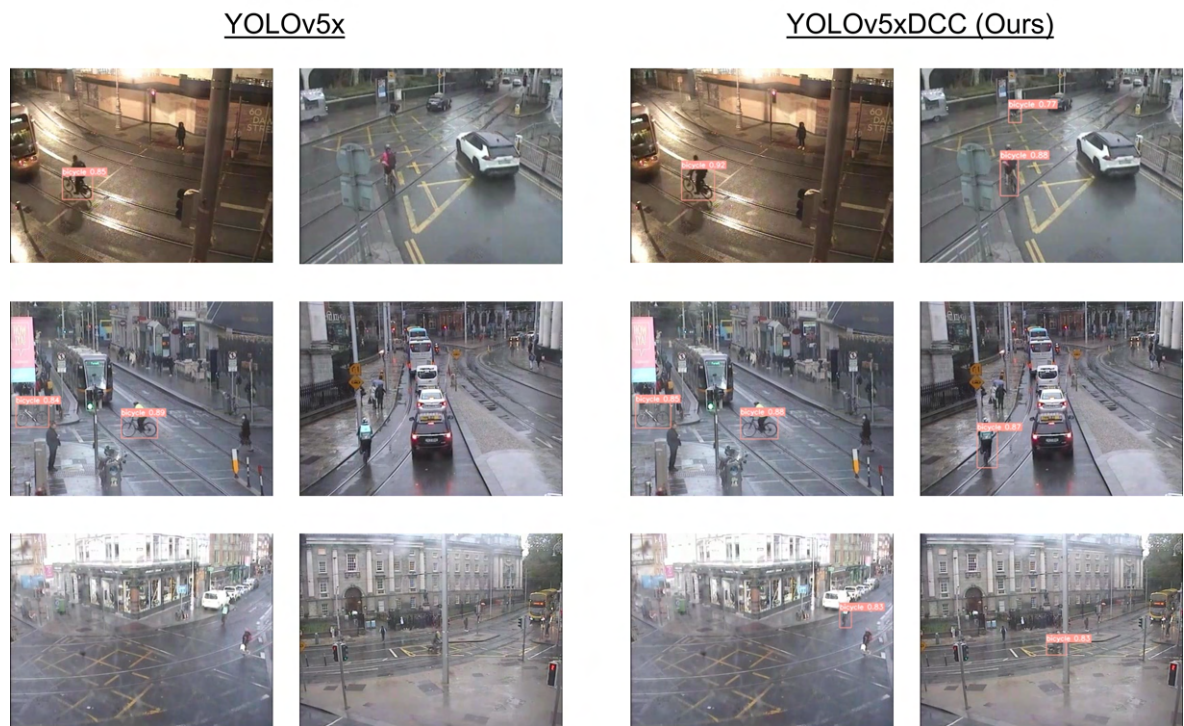


Figure 6.14: Visualisation of model improvements between YOLOv5x and YOLOv5xDCC for a sample of unseen images.

6.4.7 Automatic vs. manual tracking

Inference was performed using model YOLOv5xDCC for a sample of 5 SCs, and 1 UC at camera 1 to compare estimated crossing angles between manual and automatic approaches. A point at the lower end of the bounding box ($y = 0.25h$, $x = 0.5w$) was used for the ground position in each frame, and a Savitzky-Golay filter was used for smoothing. Calculated crossing angles were very similar; automatic tracking yielded an average of 36° , compared to 37° for manual tracking (see Table 6.3, and Figure 6.15).

Table 6.3: Comparison of crossing trajectories for a sample of cases at camera 1.

Case	Manual	Automatic
SC 1	44°	43°
SC 2	33°	34°
SC 3	41°	38°
SC 4	36°	35°
SC 5	32°	31°
UC 1	14°	15°

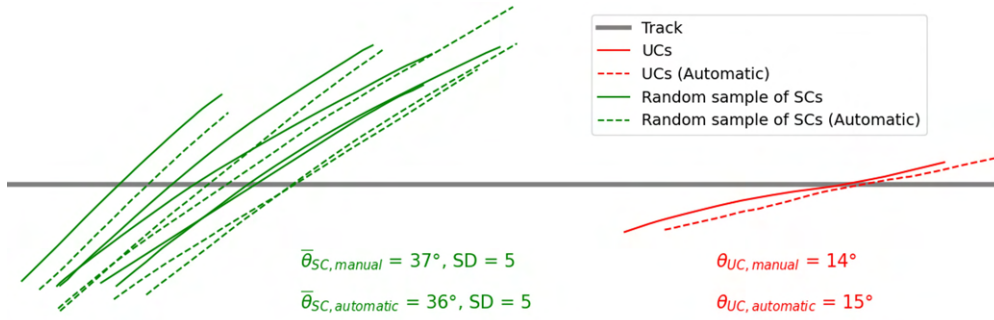


Figure 6.15: Comparison of crossing trajectories for a sample of cases at camera 1.

6.5 Discussion

The current study should serve as a demonstration that video analysis can be useful for investigating and understanding single cyclist collisions, and can help road safety stakeholders identify contributory factors and determine appropriate remedial measures to prevent similar crashes from occurring in the future.

High overall incidence of unsuccessful crossings was observed over this short study period with limited coverage of the track network, highlighting the significance of the safety issue. Supporting results from a self-reporting collision survey [214], and a recent analysis of hospital data [227]. One study location had a particularly high risk (Camera 7: Westmoreland St./College St), and an additional unsuccessful crossing was noted for an adjacent study location (Cameras 5 and 6: College Green). This location was also emphasised in a recent analysis of hospital data in Dublin (ibid.). Overall unsuccessful crossing rates were approx. 21/1000 cyclists at Camera 7, vs. approx. 3/1000 overall. These findings are similar to a study in the US for railway tracks, which found fall rates of 2/1000 at one location, and 15/1000 at another [55]. At Camera 7: Westmoreland St./College St, the majority of unsuccessful crossings (N=7, 87%) occurred on the inside/nearside track where a kerb runs alongside in close proximity (see Figure 6.7). Unsuccessful crossings at this location are likely due to the proximity of this kerb. All crossings in this location (including both unsuccessful and successful crossings) are far below the mean crossing angle seen across other locations. For successful crossing, crossing angles at this location were an average of 17° vs. 43° overall. Widening the roadway at this location to allow for safe crossing angles would likely have a significant relative effect on the fall rates.

Physical separation of cyclists from tram tracks is recommended, and at locations where cyclists are expected to cross tracks, sufficient space should be available for a safe approach an-

gle. Furthermore, by visual inspection, most ($N=12$, 92%) unsuccessful crossings at other locations involve obstacles that limit crossing angle, i.e., kerbs or nearby/passing vehicles/other cyclists (Table D.1). The Safe System approach calls for prioritisation of system-level redesign over attempts to influence individual behaviour [5], therefore, it is recommended that engineering interventions be prioritised over educational/media campaigns to allow for safe crossing angles. Furthermore, many cases involve passing/nearby motorised vehicles ($N=4$, 31%), and indeed, international literature also indicates that traffic pressure contributes to the majority of falls on tram tracks [228]. Therefore, efforts to increase priority for cyclists at crossings, and provision of segregated lanes are recommended where possible.

Descriptive statistics (Figure 6.8) show that while mean crossing velocities are similar across successful and unsuccessful crossings (4.8m/s vs. 4.7m/s), mean crossing angles were not (43° vs. 10°). Therefore, as expected, from multivariable modelling, crossing angle was found to be a strong predictor of crossing success. Though crossing velocity was not a significant predictor (Table D.2), similar to findings from Ling et al. (2017) [55], it is possible that velocity could factor into a multiclass predictive model. With this in mind, a multinomial regression was performed with crossing categories, i.e., a dependent variable with 4 levels (SC, UC-Cat. 1, UC-Cat. 2, UC-Cat. 3), however, the model was not statistically significant and had low discrimination. With a greater sample size, such a model may reveal predictive effects. As described in section 6.4.4, of the two predictive models (b and c), there are slight differences in risk curves. Specifically, while both models indicate that the boundary for the definition of a minimum ‘safe’ crossing angle is in the region of 30° , probabilities of successful crossings vary below this. These differences are tested in the context of a potential SMoS for the prediction of unsuccessful crossing numbers (N_{UC}) in section 6.4.5, showing that both models predict similar numbers in application, though model (c) generally predicts slightly higher. Furthermore, model (c) allows for approximate risk estimates for crossings on tracks

with different groove gap widths, which may be useful for other locations with different track types. Most track types included in this study could be assigned a minimum 'safe' angle of roughly 30° (track gaps ranging from 35.94mm to 42.36mm), however, track gaps wider than these should be given larger safety margins. For example, the 60R2_R160_R13 track with a gap of 55.83mm should be designed to allow for crossing angles of at least 45° (Figure 6.11).

Infrastructural planners in Dublin/Ireland should plan for road designs that allow for and encourage crossing angles of 30° or more. However, for site-specific infrastructural planning, it may be difficult to account for all common cyclist trajectories, highlighting the potential utility of this SMOs framework. Proof-of-concept is provided that further training on a relatively small sample of domain-specific data can achieve substantial accuracy improvements for cyclist detection in traffic camera footage. The accuracy of the native YOLOv5x model applied to DCC data for bicycle detection was $0.31AP_{0.5}$, i.e., with an IoU threshold of 0.5, after training this rose dramatically to $0.98AP_{0.5}$ (Figure 6.13). These improvements are also observed qualitatively between the models (Figure 6.14). Furthermore in application, automatically inferring trajectories using the YOLOv5xDCC model with tracking yields very similar crossing angles to manual tracking (Figure 6.14, and Table 6.3). Further accuracy may be achieved by instead retraining on a higher accuracy (but slower) model such as DINO [229], however, we demonstrate that YOLO can achieve sufficient accuracy for tracking cyclists after retraining. The critical number of cases required for retraining YOLO is also investigated for domain adaptation, and based on this analysis, it is recommended that at least 100 images are used. Future work will incorporate automatic cyclist trajectory detection into the SMOs framework, which after ground-plane calibration, i.e., T-Calibrate [60], could allow for semi-automatic prediction of unsuccessful crossings. Further work is required to overcome the flatness problem associated with relating detections in 2D space to 3D space as described by Laureshyn et al. (2010) [230], i.e., a problem which arises because the 2D

projections of a 3D object/road user can vary widely depending on its orientation relative to the camera. One common approach to addressing the flatness problem is to use multiple cameras or sensors that capture different views of the same object, however, this complicates the data collection process. Another approach which may allow for monocular collection is to incorporate additional information about the object/road user, such as its size, shape, or motion characteristics to help constrain its possible 3D configuration (e.g., Ahrnbom et al. (2022) [231]). Further work is also required into other causes of single cyclist collisions such as slippery roads, sharp bends/downhill sections, and infrastructural causes such as kerbs, manholes, potholes etc., and this study demonstrates the potential of computer vision-based approaches

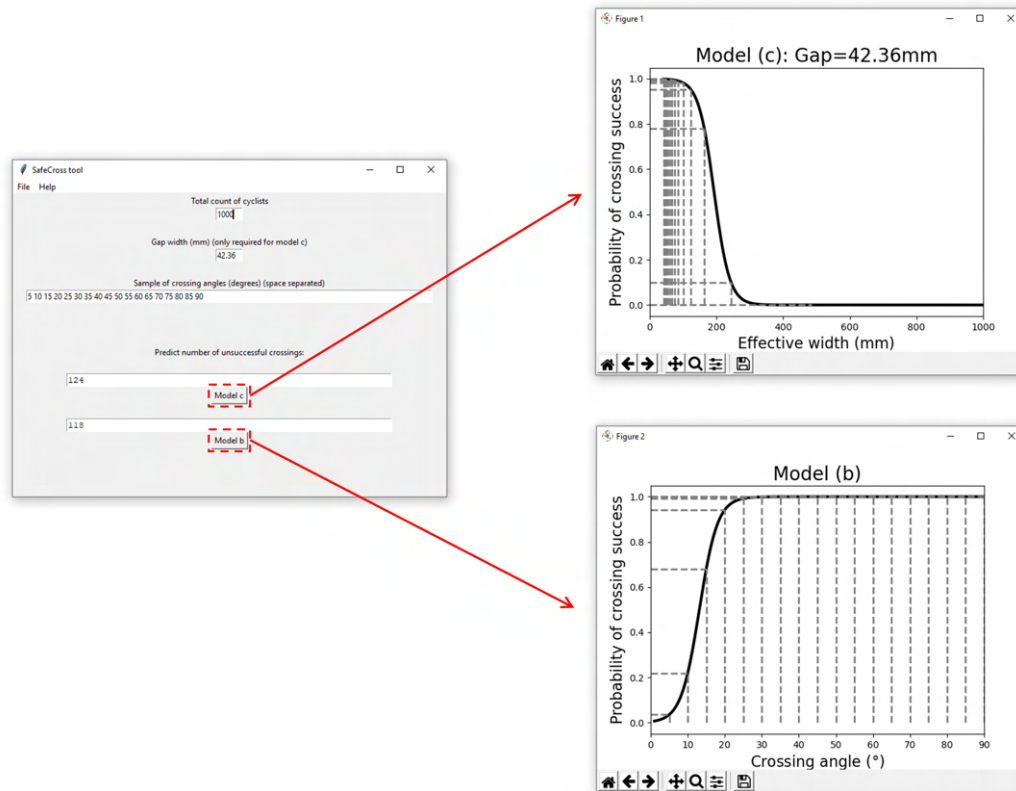


Figure 6.16: SafeCross tool for prediction of unsuccessful crossing numbers in wet road conditions given 1) a representative random sample of crossing angels, 2) a cyclist traffic count, and 3) the track gap width.

6.6 Conclusions

This study presents the first video-based trajectory and fall analysis for cyclist interactions with light rail tram-tracks. The analysis focuses on wet road conditions as a common and safety-critical edge case. Actionable site-specific safety issues at locations in Dublin city centre are highlighted, and the risk of unsuccessful crossing occurrence by crossing angle is modelled. As evident by the prevalence of external factors limiting crossing angle (e.g., kerbs, other road users), personal responsibility/educational campaigns targeted towards cyclists are unlikely to address the majority of falls on tracks. In the context of the Safe System approach, i.e., to proactively target and treat risk, these findings imply the need for bolstered data collection regimes in urban environments, and engineering interventions to facilitate safe crossing angles. The use of the SMoS algorithm developed in this study can help achieve these goals, and an open-source tool is provided for this purpose (SafeCross⁴).

⁴<https://kevgildea.github.io/SafeCross/>

CRedit authorship contribution statement [210]

Kevin Gildea: Conceptualisation, Data curation, Formal analysis, Software, Investigation, Methodology, Resources, Validation, Visualisation, Writing - original draft, Writing - review & editing, Project administration. **Daniel Hall:** Visualisation, Writing - review & editing. **Clara Mercadal-Baudart:** Conceptualisation. **Brian Caulfield:** Resources, Writing - review & editing. **Ciaran Simms:** Supervision, Conceptualisation, Funding acquisition, Methodology, Project administration, Resources, Writing - review & editing.

Chapter 7

Study E: KinePose: a novel inverse kinematics algorithm for automatic configuration of biomechanical models from video

Related publication:

- KinePose: A temporally optimised inverse kinematics technique for 6DOF human pose estimation with biomechanical constraints,
K. Gildea, C. Mercadal-Baudart, R. Blythman, A. Smolic, C. Simms,
Irish Machine Vision & Image Processing Conference (IMVIP) (2022)

7.1 Introduction

Human motion capture technologies are widely used for animation, physiotherapy, sports biomechanics, ergonomics, robotics, and augmented/virtual reality. However, many of these systems currently involve the use of calibrated multi-sensor setups, making them prohibitively expensive and unsuitable for potential in-the-wild applications. In recent years, a wide variety of computer vision based 3D pose estimation methods have been developed, which present opportunities for a form of free/low-cost markerless motion-capture for use on in-the-wild video footage, e.g., Pavllo et al. (2018) [172], Liu et al. (2020) [171], Dinesh Reddy et al. (2021) [164]. As detailed in section 2.8, state-of-the-art position-based 3D pose estimators are capable of inferring root-relative joint positions with remarkable accuracy, however, joint/link orientations are often not included, limiting their practical uses. Furthermore, approaches that indirectly regress for joint positions through applying joint orientations within a kinematic chain currently have sub-par performance, and do not allow for user definition of chain properties, i.e., limb lengths and joint ranges of motion (ROMs).

7.2 Study aims

Therefore, a temporal optimisation technique is proposed for mapping/retargeting the motion of an ordered set of 3D joint positions obtained from a pose estimator, to a user-defined open kinematic chain. The kinematic solution space (see section 7.3.2) is constrained using joint degrees of freedom (DOFs) and ROMs and limiting joint orientation changes between adjacent frames for temporal consistency (see section 7.3.3). The proposed approach can be applied as a post-processing technique for position-based 3D pose estimates (particularly useful for monocular pose estimators), allowing for the refinement of 3D poses for a subject-specific biomechanical model. See Figure 7.1 for a demonstration. A visualisation is also available [here](#)¹.

¹<https://kevgildea.github.io/assets/Thesis/7.2-KinePose.gif>

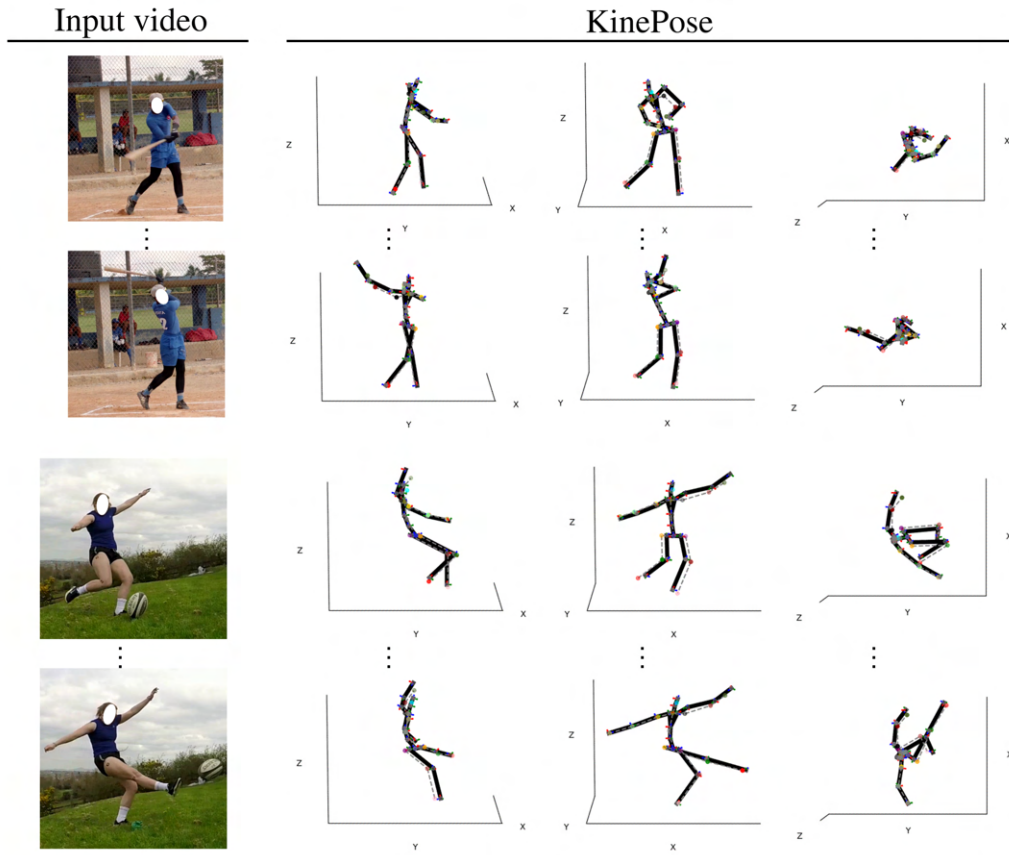


Figure 7.1: KinePose applied to an example cases, with 3D poses from Liu et al. (2020) [171] (multicolor keypoints and gray dashed lines).

7.3 Methods

In this section, an overview of the IK approach for mapping kinematic chains is provided, i.e., kinematic retargeting. In section 7.3.1 the process of FK is described, which is used in parameterisation of the biomechanical model. In section 7.3.2, the 3D rotation group and vector mapping are introduced, and the indeterminate nature of the kinematic chain mapping problem is described. In section 7.3.3, the proposed IK optimisation procedure is detailed, with incorporation of chain DOFs, ROMs, and kinematic loss terms.

7.3.1 Forward kinematics

Kinematic chains can be described as a hierarchical system of links and joints. They are represented by: 1) the locations and orientations of each of the joints, and 2) the hierarchy of the joints in the system. The Denavit-Hartenberg (DH) FK convention allows for compact representation and convenient manipulation of kinematic chains as a series multiplication of 4x4 transformation matrices along the path to the joint [232]. DH-FK uses a parent-child convention, whereby positions and orientations of child joints are expressed in the parent coordinate systems, i.e., the position of an arbitrary joint (j) is expressed as a vector in the coordinate system of its parent joint/body (j_{parent}), i.e., $\{\vec{r}\}_{j,j_{parent}}^{j_{parent}}$, and the orientation of the joint is expressed as a 3x3 rotation matrix which specifies the orientation with respect to the parent, i.e., $[R^{j,j_{parent}}]$. For each joint, the parent-child transformation matrix is then defined in Equation 7.1. The set of these for an N-joint chain C (with ‘0’ denoting the global coordinate system) is expressed in Equation 7.2.

$$\{T_j\}_{j,j_{parent}} = \begin{bmatrix} [R^{j,j_{parent}}] & \{\vec{r}\}_{j,j_{parent}}^{j_{parent}} \\ 0 & 0 & 0 & 1 \end{bmatrix}. \quad (7.1)$$

$$C = \left\{ \{T_1\}^{1,0}, \dots, \{T_N\}^{N,N_{parent}} \right\}. \quad (7.2)$$

To perform kinematic operations on an open chain with branching (e.g., the human body) a directed graph (G) is also required to specify its hierarchical structure. FK can then be performed to express joint/body positions and orientations in the global coordinate system (Equation 7.3).

$$\begin{aligned} \{T_j\}^{j,0} &= \prod_{i=j}^1 \{T_i\}^{i,i_{parent}} \\ \text{for } i \text{ on path to root} &= \mathbf{FK}(C, G). \end{aligned} \quad (7.3)$$

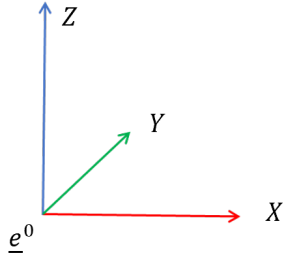
The utility of defining a kinematic chain in this manner can be demonstrated if we would like to edit or reorient a kinematic chain. It makes physical sense to apply the rotation in the local coordinate system, e.g., a rotation of the knee is kinematically constrained (due to its DOFs) to occur about a fixed axis defined in the local coordinate system (usually chosen to be a cardinal axis). Furthermore, performing FK with the inclusion of a reorientating transformation matrix $\{T_{j\Delta R}\}^{j,j_{parent}}$ will automatically reorient and reposition all down-chain joints (Equation 7.4). The kinematic chain is parameterised in this way.

$$\begin{aligned} \{T_j\}^{j,0} &= \prod_{i=j}^1 \{T_i\}^{i,i_{parent}} \{T_{j\Delta R}\}^{j,j_{parent}} \\ \text{for } i \text{ on path to root} &= \mathbf{FK}(C, G, \{T_{j\Delta R}\}^{j,j_{parent}}). \end{aligned} \quad (7.4)$$

7.3.2 Kinematic indeterminacy

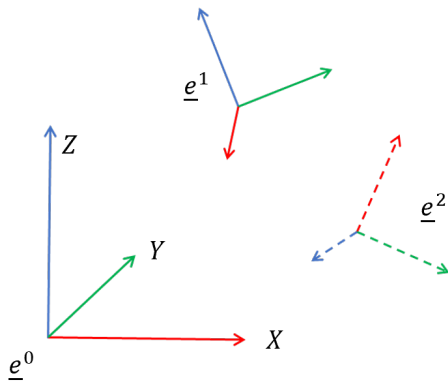
The 3D rotation group and vector mapping

Basis vectors are used to define the directions of the cardinal axes of an object's local coordinate system. For example, object '0' is aligned with the global coordinate system, so the basis vector system can be expressed as a 3×3 identity matrix (I), with each of the basis vectors $\{\vec{e}_1\}^0$, $\{\vec{e}_2\}^0$, and $\{\vec{e}_3\}^0$ extending 1 unit from the origin along each of the cardinal axes:



$$\underline{e}^0 = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \quad \text{or, } \{\vec{e}_1\}^0 = \begin{Bmatrix} 1 \\ 0 \\ 0 \end{Bmatrix}, \{\vec{e}_2\}^0 = \begin{Bmatrix} 0 \\ 1 \\ 0 \end{Bmatrix}, \{\vec{e}_3\}^0 = \begin{Bmatrix} 0 \\ 0 \\ 1 \end{Bmatrix}$$

Furthermore, one coordinate system defined using basis vector system $\underline{e}^2$ can be represented with respect to another coordinate system $\underline{e}^1$ by multiplying the latter by the 3×3 rotation matrix $[R^{2,1}]$. If the orientations of both of these coordinate systems with respect to a 3^{rd} coordinate system $\underline{e}^0$ are known, i.e., the global coordinate system, then $[R^{2,1}]$ can be found:



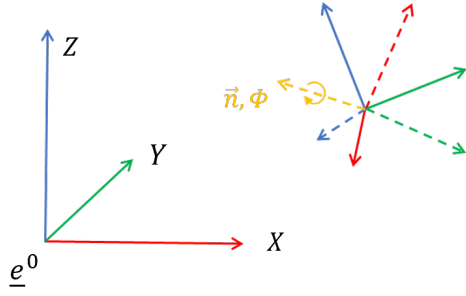
$$\underline{e}^2 = [R^{2,1}] \underline{e}^1$$

$$\text{similarly, } \underline{e}^1 = [R^{1,0}] \underline{e}^0, \text{ and } \underline{e}^2 = [R^{2,0}] \underline{e}^0$$

$$\text{giving, } \underline{e}^2 = [R^{2,0}] [R^{1,0}]^T \underline{e}^1$$

$$\begin{Bmatrix} \vec{e}_1^2 \\ \vec{e}_2^2 \\ \vec{e}_3^2 \end{Bmatrix} = \begin{bmatrix} r_{11}^{20} & r_{12}^{20} & r_{13}^{20} \\ r_{21}^{20} & r_{22}^{20} & r_{23}^{20} \\ r_{31}^{20} & r_{32}^{20} & r_{33}^{20} \end{bmatrix} \begin{bmatrix} r_{11}^{10} & r_{12}^{10} & r_{13}^{10} \\ r_{21}^{10} & r_{22}^{10} & r_{23}^{10} \\ r_{31}^{10} & r_{32}^{10} & r_{33}^{10} \end{bmatrix}^T \begin{Bmatrix} \vec{e}_1^1 \\ \vec{e}_2^1 \\ \vec{e}_3^1 \end{Bmatrix}$$

Euler's rotation theorem [233] states that, in 3D space, displacement from an initial orientation $\underline{e}^1$ to final orientation $\underline{e}^2$ is achieved by rotation through an angle about an axis with same coordinate matrix in both bases. This axis is called the Euler axis, or the Screw axis, $\vec{n}$, and has an associated angle Φ to achieve a rotation:



$$\begin{pmatrix} \vec{e}_1^2 \\ \vec{e}_2^2 \\ \vec{e}_3^2 \end{pmatrix} = \begin{bmatrix} r_{11}^{21} & r_{12}^{21} & r_{13}^{21} \\ r_{21}^{21} & r_{22}^{21} & r_{23}^{21} \\ r_{31}^{21} & r_{32}^{21} & r_{33}^{21} \end{bmatrix} \begin{pmatrix} \vec{e}_1^1 \\ \vec{e}_2^1 \\ \vec{e}_3^1 \end{pmatrix}$$

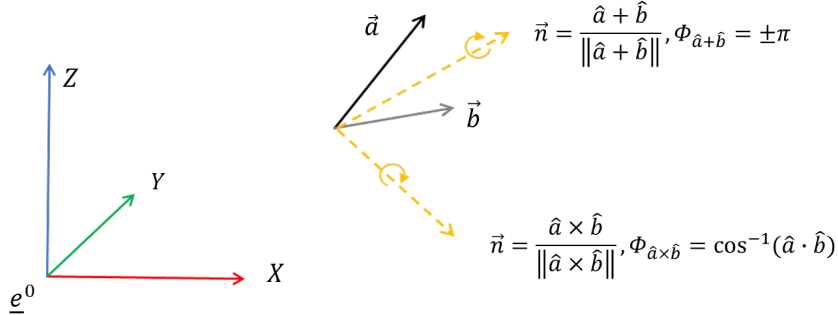
where, $([R^{2,1}] - I)\vec{n} = 0$

The Euler/Screw angle, and axis can be found using,

$$\Phi = \cos^{-1} \left[\frac{\text{trace}[R^{2,1}] - 1}{2} \right]$$

$$n_i = \frac{a_{jk} - a_{kj}}{2 \sin \Phi} \text{ where } i, j, k = 1, 2, 3 \text{ cyclically}$$

Consider the case where instead of having two complete coordinate systems represented by basis vectors, only have two vectors $\vec{a}$ and $\vec{b}$ are available, which represent a rotation between the two coordinate systems. There will not be a unique solution to this problem, so we need to define the Screw axis about which a rotation is applied. Two obvious candidate axes that can be chosen for this are: 1) the cross product of the vectors, which will be mutually perpendicular to both $\vec{a}$ and $\vec{b}$, or 2) the sum of the normalised vectors $\hat{a}$ and $\hat{b}$, which symmetrically bisects $\vec{a}$ and $\vec{b}$.



The Euler axis-angle combination can then be related to the direction cosines of a rotation matrix using:

$$[R^{\hat{a} \rightarrow \hat{b}}] = \begin{bmatrix} n_1^2 + (n_2^2 + n_3^2)\cos(\Phi) & n_1n_2(1 - \cos(\Phi)) - n_3\sin(\Phi) & n_1n_3(1 - \cos(\Phi)) + n_2\sin(\Phi) \\ n_1n_2(1 - \cos(\Phi)) + n_3\sin(\Phi) & n_2^2 + (n_1^2 + n_3^2)\cos(\Phi) & n_2n_3(1 - \cos(\Phi)) - n_1\sin(\Phi) \\ n_1n_3(1 - \cos(\Phi)) - n_2\sin(\Phi) & n_2n_3(1 - \cos(\Phi)) + n_1\sin(\Phi) & n_3^2 + (n_1^2 + n_2^2)\cos(\Phi) \end{bmatrix}$$

It is known that the two points are on the Euler axis solution space, so along with the origin, these can be used to define the plane that contains all possible rotation axes:

$$p_1 = \begin{Bmatrix} 0 & 0 & 0 \end{Bmatrix}, p_2 = \frac{\hat{a} + \hat{b}}{\|\hat{a} + \hat{b}\|}, p_3 = \frac{\hat{a} \times \hat{b}}{\|\hat{a} \times \hat{b}\|}.$$

The Euler axis solution space can be defined as all unit vectors on the plane, for $\alpha : [-\pi, \pi]$:

$$\vec{n}_\alpha = \begin{Bmatrix} p_{1,1} + \cos(\alpha)(p_{2,1} - p_{1,1}) + \sin(\alpha)(p_{3,1} - p_{1,1}) \\ p_{1,2} + \cos(\alpha)(p_{2,1} - p_{1,1}) + \sin(\alpha)(p_{3,1} - p_{1,1}) \\ p_{1,3} + \cos(\alpha)(p_{2,1} - p_{1,1}) + \sin(\alpha)(p_{3,1} - p_{1,1}) \end{Bmatrix}.$$

Projecting vectors $\hat{a}$ and $\hat{b}$ to lay on the base of a cone with the Euler axis as the cone's axis, the associated Euler/screw angles can be determined (Φ), i.e., the azimuth angle:

$$\hat{a}_\alpha = \frac{\hat{a} \times \vec{n}_\alpha}{\|\hat{a} \times \vec{n}_\alpha\|}, \hat{b}_\alpha = \frac{\hat{b} \times \vec{n}_\alpha}{\|\hat{b} \times \vec{n}_\alpha\|},$$

$$\Phi_\alpha = \cos^{-1}(\hat{a}_\alpha \cdot \hat{b}_\alpha).$$

Now, all possible rotation matrices representing all possible Euler axis-angle combinations can be formulated, i.e., the Euler axis-angle solution space (EAS):

$$\begin{aligned} & \left[\mathbf{R}^{\hat{\mathbf{a}} \rightarrow \hat{\mathbf{b}}} \right]^{EAS} = \\ & \begin{bmatrix} n_{\alpha,x}^2 + (n_{\alpha,y}^2 + n_{\alpha,z}^2)\cos(\Phi_\alpha) & n_{\alpha,x}n_{\alpha,y}(1 - \cos(\Phi_\alpha)) - n_{\alpha,z}\sin(\Phi_\alpha) & n_{\alpha,x}n_{\alpha,z}(1 - \cos(\Phi_\alpha)) + n_{\alpha,y}\sin(\Phi_\alpha) \\ n_{\alpha,x}n_{\alpha,y}(1 - \cos(\Phi_\alpha)) + n_{\alpha,z}\sin(\Phi_\alpha) & n_{\alpha,y}^2 + (n_{\alpha,x}^2 + n_{\alpha,z}^2)\cos(\Phi_\alpha) & n_{\alpha,y}n_{\alpha,z}(1 - \cos(\Phi_\alpha)) - n_{\alpha,x}\sin(\Phi_\alpha) \\ n_{\alpha,x}n_{\alpha,z}(1 - \cos(\Phi_\alpha)) - n_{\alpha,y}\sin(\Phi_\alpha) & n_{\alpha,y}n_{\alpha,z}(1 - \cos(\Phi_\alpha)) + n_{\alpha,x}\sin(\Phi_\alpha) & n_{\alpha,z}^2 + (n_{\alpha,x}^2 + n_{\alpha,y}^2)\cos(\Phi_\alpha) \end{bmatrix}. \end{aligned} \quad (7.5)$$

Where $\vec{n}_\alpha$ and Φ_α represent the Euler axis-angle solution space (EAS), and α is a continuous angular value spanning $-\pi$ to π used to define unit vectors on the plane symmetrically bisecting the vectors, i.e., candidate Euler axes for which corresponding Euler angles can be computed.

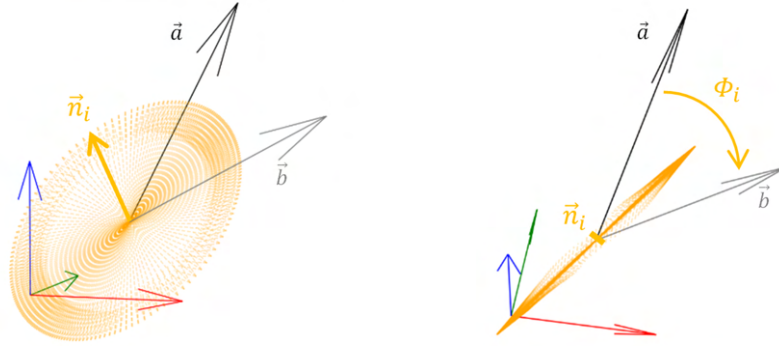


Figure 7.2: The Euler axis-angle solution space (EAS) for mapping/retargeting incongruent vectors.

Therefore, with a lack of complete basis vector representation for the two coordinate systems, there are infinite axis-angle combinations that can be applied to achieve a desired vector mapping/retargeting. However, candidate Euler/Screw axes are constrained to be on the plane that symmetrically bisects the vectors (Figure 7.2). A visualisation is also available [here](https://kevgildea.github.io/assets/Thesis/7.3.2-vector-mapping.gif)².

²<https://kevgildea.github.io/assets/Thesis/7.3.2-vector-mapping.gif>

Mapping kinematic chains

Equation 7.5 can be used to analytically define the solution space for retargeting/mapping one kinematic chain (C) to an ordered set of 3D positions (P). The Euler axis-angle solution spaces for all joints in the chain are computed by combining Equations 7.4, and 7.5. This is visualised in Figure 7.3 for a 3-joint serial chain. The problem has an indeterminate solution (infinite solution space), therefore, optimisation is needed. Specifically, the indeterminacy of this problem is due to the ambiguous ‘twist’ angle. The solution space can be somewhat constrained by specifying anatomical joint DOFs and ROMs (see section 7.3.3). The problem is complicated in a chain such as the human body with branching, i.e., the mapping process used to generate the solution space is faced with a dilemma when reorienting branching joints. Therefore, the proposed approach involves IK optimisation, with parameterisation of the reorientation transformation matrix in Equation 7.4 (i.e., $\{T_{j\Delta R}\}^{j,j_{parent}}$). In general terms, since motion sequences involve kinematic indeterminacy the hypothesis is that two metrics can be used to converge to an optimal solution: 1) a frame-based pose loss term, and 2) a temporal consistency loss term (see section 7.3.3).

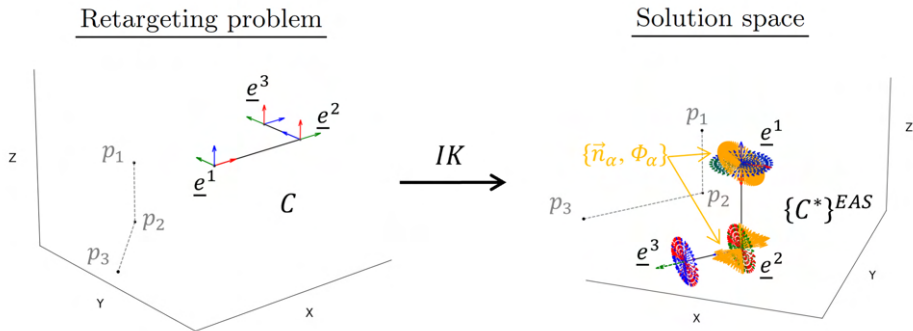


Figure 7.3: Solution space for mapping/retargeting a kinematic chain to an incongruent hierarchical set of 3D positions.

7.3.3 Inverse kinematics optimisation

Kinematic chain

Many position-based 3D pose estimators employ a similar chain configuration. A kinematic chain is defined based on this, using common characteristics to optimise for joint orientations. Joints/bodies are defined to correspond to keypoints, i.e., the mid pelvis (defined as the root), hips, knees, ankles, mid spine, neck, head, shoulders, elbows, and ankles. Additional joints are also defined for greater biomechanical fidelity, i.e., the lower spine, and clavicles (see Figure 7.4). The chain has 14 joints for reorientation, and a total of 28 rotational DOFs. Initially, the kinematic chain is defined in a rest/quiet standing pose, i.e., a set of transformation matrices are defined (see Equations 7.2, and 7.3) to represent a human in a relaxed standing pose with their arms by their sides. Limb/link lengths in the chain are constant and may be user defined. Changes in pose from rest are implemented using FK and an additional transformation matrix (see Equation 7.4). Joint ROMs may be specified in the local coordinate system as allowable angle ranges about each cardinal axis of the joint coordinate system, where θ_j , ϕ_j , and ψ_j correspond to sequential rotations about the local X, Y, and Z axes respectively (see Figure 7.4). For assessment, generalised ROM limits are used, however, they can be further customised. Since there is no 3D keypoint that can be used to directly target the lower spine joint, the lower and mid spine joints are assigned equally proportioned ROMs which add to the overall ROM of that area of the spine. Though not without limitations [234], Cardan/Euler angles present a convenient and intuitive approach for parameterising the optimisation weights associated with joint rotations within the kinematic chain, whilst also allowing for specification of joint ROMs using bounds to constrain the solution space.

Gimbal lock singularities limit the use of Cardan/Euler angles for parameterisation of human pose, i.e., for Cardan rotation order X (θ) $\rightarrow$ Y (ϕ) $\rightarrow$ Z (ψ) a rotation matrix $[R^{2,1}]$ is defined:

$$[R^{2,1}] = \begin{bmatrix} 1 & 0 & 0 \\ 0 & \cos(\theta) & -\sin(\theta) \\ 0 & \sin(\theta) & \cos(\theta) \end{bmatrix} \begin{bmatrix} \cos(\phi) & 0 & \sin(\phi) \\ 0 & 1 & 0 \\ -\sin(\phi) & 0 & \cos(\phi) \end{bmatrix} \begin{bmatrix} \cos(\psi) & -\sin(\psi) & 0 \\ \sin(\psi) & \cos(\psi) & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

When $\phi = \frac{\pi}{2} + n\pi$:

$$= \begin{bmatrix} 1 & 0 & 0 \\ 0 & \cos(\theta) & -\sin(\theta) \\ 0 & \sin(\theta) & \cos(\theta) \end{bmatrix} \begin{bmatrix} 0 & 0 & 1 \\ 0 & 1 & 0 \\ 1 & 0 & 0 \end{bmatrix} \begin{bmatrix} \cos(\psi) & -\sin(\psi) & 0 \\ \sin(\psi) & \cos(\psi) & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

Then, by trigonometry:

$$= \begin{bmatrix} 0 & 0 & 1 \\ \cos(\theta + \psi) & \cos(\theta + \psi) & 0 \\ -\cos(\theta + \psi) & \sin(\theta + \psi) & 0 \end{bmatrix}$$

Relating the coefficients to direction cosines, i.e., $r_{i,j}^{2,1} = \vec{e}_i^2 \cdot \vec{e}_j^1$, it is noted that the direction of the x axis of the coordinate system post-rotation will always align with the z axis pre-rotation, i.e., since $\angle(\vec{e}_i^2, \vec{e}_j^1) = \cos^{-1}(\vec{e}_i^2 \cdot \vec{e}_j^1)$, then $\angle(\vec{e}_1^2, \vec{e}_3^1) = 0$, and $\angle(\vec{e}_1^2, \vec{e}_1^1)$, $\angle(\vec{e}_1^2, \vec{e}_2^1)$, $\angle(\vec{e}_2^2, \vec{e}_3^1)$, $\angle(\vec{e}_3^2, \vec{e}_3^1) = \frac{\pi}{2}$. However, the application of anatomical joint DOFs and ROMs in the form of Cardan/Euler angle ranges naturally avoids singularities in this formulation by limiting $-\frac{\pi}{2} < \phi_j < \frac{\pi}{2}$.

However, since the root joint retains a full ROM, the root orientation with respect to the global coordinate system is parameterised using the Euler/Screw axis-angle convention ($\vec{n} = \{n_x, n_y, n_z\}, \Phi$). Using ROMs throughout the chain and bounding the Screw angle in the root joint also overcomes rotation periodicity, i.e., $\sin x = \sin(x + 2\pi)$, and $\cos x = \cos(x + 2\pi)$.

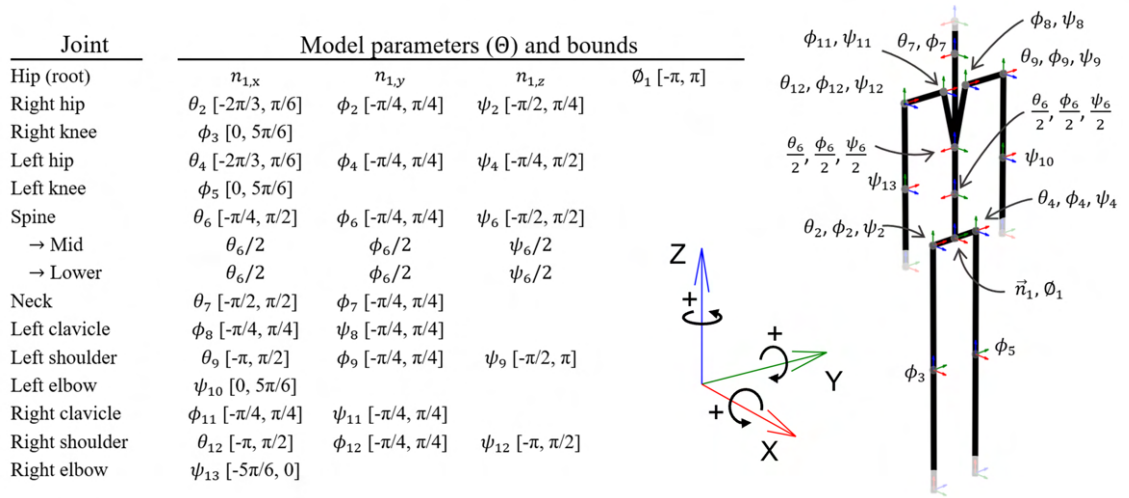


Figure 7.4: Kinematic chain parameters and bounds used in IK optimisation.

Losses

Two frame-based pose error terms are defined, which both minimise the angular difference in vectors between the 3D pose and the reoriented kinematic chain. A local pose error term is applied (Equation 7.6) which penalises angular difference in link vector directions (shown in green in Figure 7.5), where $\{\hat{\mathbf{r}}\}_{j,j_{parent}}^0$ is the normalised vector in the kinematic chain linking joint j to its parent in the global coordinate system (denoted by superscript ‘0’) and $\{\hat{\mathbf{p}}\}_{j,j_{parent}}^0$ is the corresponding normalised vector on the 3D pose skeleton. Since the kinematic chain includes clavicles which do not correspond to 3D pose keypoints, and there is no appropriate local pose vector to use to constrain the orientations of these joints, a global pose error term is also included (Equation 7.7) which considers angular difference in global vectors in the arms of the kinematic chain $\{\hat{\mathbf{r}}\}_{j,1}^0$, i.e., stemming from the root joint (shown in orange in Figure 7.5).

$$E_{\angle(\vec{r}, \vec{p})_{local}} = \frac{1}{N} \sum_{j=1}^N \left\| \cos^{-1}(\{\hat{\mathbf{r}}\}_{j,j_{parent}}^0 \cdot \{\hat{\mathbf{p}}\}_{j,j_{parent}}^0) \right\|. \quad (7.6)$$

$$E_{\angle(\vec{r}, \vec{p})_{global}} = \frac{1}{A} \sum_{j=1}^A \left\| \cos^{-1}(\{\hat{\mathbf{r}}\}_{j,1}^0 \cdot \{\hat{\mathbf{p}}\}_{j,1}^0) \right\|. \quad (7.7)$$

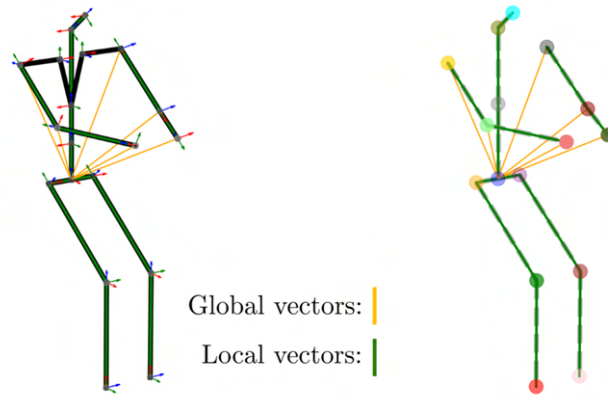


Figure 7.5: Global and local vectors used to formulate the pose loss terms.

In cases where there are co-linear sequential links, i.e., when there are fully extended limbs (knees or elbows), there will be kinematic indeterminacy. The hypothesis is that appropriately weighted minimisation of joint orientation changes between frames ($\Delta\Theta_j$) can constrain the solution space toward an optimal solution with temporal consistency, i.e., optimising poses across frames with extended and bent limbs (Equation 7.8) (for a sequence of poses M frames long).

$$E_{\Delta\Theta} = \frac{1}{M} \sum_{m=1}^M \left\{ \sum_{j=1}^N \|\Delta\Theta_j\| \right\}_m, \text{ where, } \Delta\Theta_j = \begin{cases} \Theta_j^{m+1} - \Theta_j^m, & \text{for } m = 1, \\ (\Theta_j^{m+1} - \Theta_j^{m-1})/2 & \text{for } 1 < m < M, \\ \Theta_j^m - \Theta_j^{m-1} & \text{for } m = M. \end{cases} \quad (7.8)$$

A loss function L_{frame} for frame-by-frame IK (Equation 7.9) is defined, and combining Equations 7.6, 7.7, and 7.8 with scalar weighting for the temporal term which competes with the pose error terms, $L_{temporal}$ for temporal IK is defined (Equation 7.10).

$$L_{frame} = E_{\angle(\vec{r}, \vec{p})_{local}} + E_{\angle(\vec{r}, \vec{p})_{global}}, \quad (7.9)$$

$$L_{temporal} = \frac{1}{M} \sum_{m=1}^M L_{frame=m} + \lambda E_{\Delta\Theta}. \quad (7.10)$$

Algorithms

A sequential least squares programming procedure is used to solve the minimisation problem [235]. This procedure is commonly used for robust nonlinear programming solutions to kinematic retargeting and IK. All algorithms take the kinematic chain C in its rest/quiet pose, and a sequence of 3D poses for F frames as inputs (P). The algorithms output optimised model parameters or joint DOFs (Θ^*) using IK (Equation 7.11). These can then be used to specify a sequence of retargeted chains $\{C_1^*, \dots, C_F^*\}$ using Equation 7.4.

$$\Theta^* = \mathbf{IK}(C, G, P, \Theta_0) \text{ subject to } \arg \min_{\Theta}(L). \quad (7.11)$$

Since convergence of local optimisation methods depends on the initial guess (Θ_0), a relatively computationally inexpensive frame-by-frame pre-optimisation is performed as input to the temporal optimisation, using L_{frame} (Equation 7.9) as the objective function (Algorithm 1). This addition also speeds up the optimisation time significantly.

Algorithm 1: Frame-based retargeting

Data: C, G, P

Result: $\{\Theta_1^*, \dots, \Theta_F^*\}$

for $f = 1, \dots, F$ **do**

if $f = 1$ **then**

$\Theta_f^* = \mathbf{IK}(C, G, P, \Theta_0) \rightarrow \text{Subject to } \arg \min_{\Theta}(L_{frame})$

 Where Θ_0 corresponds to the chain in its rest pose.

else

$\Theta_f^* = \mathbf{IK}(C, G, P, \Theta_{f-1}^*) \rightarrow \text{Subject to } \arg \min_{\Theta}(L_{frame})$

end

end

The temporal algorithm (Algorithm 2) involves blocks, or patches of M frames (out of a total of F frames) in which sequences of poses are retargeted in tandem with the inclusion of both pose and temporal error terms (Equation 7.10). Patches are temporally linked or ‘stitched’ with an additional temporal error term, i.e., the difference in model parameters ($E_{\Delta\Theta}$) between the final frame of patch $i - 1$ and the first frame of patch i are used in the loss function for patch i (Figure 7.6).

Algorithm 2: Temporal retargeting

Data: $C, G, P, \{\Theta_1, \dots, \Theta_F\}$

$\rightarrow \Theta_F$ obtained from Algorithm 1

Result: $\{C_1^*, \dots, C_F^*\}$

Reshape $\{\Theta_1, \dots, \Theta_F\}$ into $\{\Theta_1, \dots, \Theta_{\frac{F}{M}}\}$

for $i = 1, \dots, \frac{F}{M}$ **do**

$\Theta_i^* = \mathbf{IK}(C, G, P, \Theta_i) \rightarrow \text{Subject to } \arg \min_{\Theta} (L_{temporal})$

end

Reshape $\{\Theta_1^*, \dots, \Theta_{\frac{F}{M}}^*\}$ into $\{\Theta_1^*, \dots, \Theta_F^*\}$

for $f = 1, \dots, F$ **do**

for $j = 1, \dots, N$ **do**

 Express $\Theta_{f,j}^*$ as $\{T_{j\Delta R}\}_{f,j}^{j, j_{parent}}$

end

$C_f^* = \left\{ \{T_1\}_1^{1,0} \{T_{1\Delta R}\}_{f,1}^{1,0}, \dots, \{T_N\}_N^{N, N_{parent}} \{T_{N\Delta R}\}_{f,N}^{N, N_{parent}} \right\}$

end

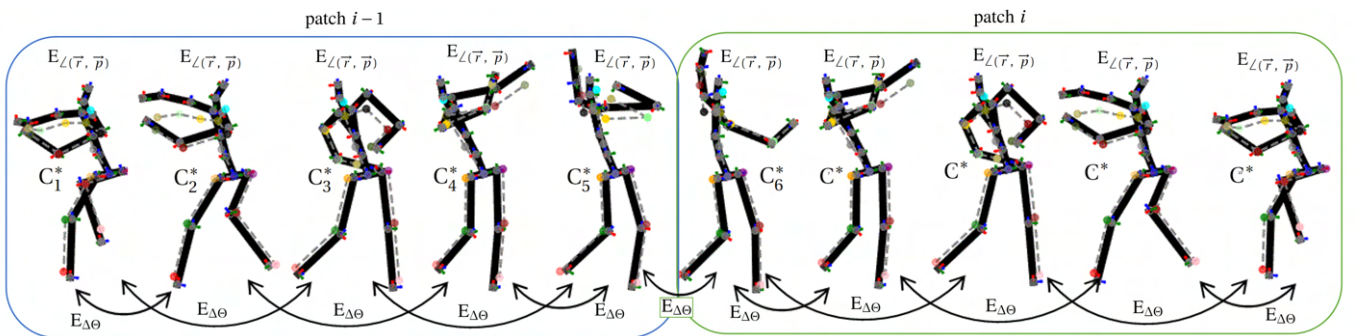


Figure 7.6: Overview of the proposed IK approach (patch length $M=5$).

Assessment

For algorithmic assessment of the IK approaches, twenty-four 30-frame long motion sequences are generated within joint ROMs for the kinematic chain, with three levels of motion speed, with maximum cardan angle changes between frames of a) $\frac{\pi}{500}$, b) $\frac{\pi}{200}$, and c) $\frac{\pi}{70}$. The latter corresponding approximately to full movement within ROMs. Half of the sequences consist of only bent limbs, and the other half have a combination of prescribed phases of either bent or extended limbs. The motion sequences have been defined such that each sequence with bent limbs has a corresponding sequence with phases of bent limbs and extended limbs, where motion in the rest of the skeleton is identical. These phases are: 1) 3 frames extended, 2) 9 frames bent, 3) 6 frames extended, 4) 9 frames bent, 5) 3 frames extended. Generation of motion in this manner allows for analysis of the effect on accuracy of extended limbs (which results in ambiguity in twist angle) for various IK implementations.

A series of IK algorithms are applied to the resulting joint pose sequences, i.e., with ground truth joint orientations hidden. Algorithm 1 with and without feeding of optimised model parameters from previous frames (1_a and 1_b respectively), and Algorithm 2 with different patch sizes are compared, i.e., 2_3 (M=3) and 2_5 (M=5). Computation time on an Intel[®] Core[™] i7-9700 processor is recorded for each implementation. Overall agreement was assessed using Mean Per Joint Angular Separation ($MPJAS_N$) for all joints that are reoriented (N=14) across frames, i.e., the average angular difference about the Screw axis between inferred and ground truth (GT) joint orientations $\{\Phi_j\}_{pred,GT}$ (Equation 7.12). For comparison, $MPJAS$ are also calculated for each individual joint.

$$MPJAS_N = \frac{1}{F} \sum_{f=1}^F \left\{ \frac{1}{N} \sum_{j=i}^N \left\| \{\Phi_j\}_{pred,GT} \right\| \right\}_f. \quad (7.12)$$

An ablation study was performed on a sample of 12 additional motion sequences to determine the optimal scalar weight for the temporal model (λ) for different motion speeds ($\lambda = 0.3$ for speed c, $\lambda = 0.5$ for speed b, and $\lambda = 0.7$ for speed a).

7.4 Results

7.4.1 General accuracy

Table 7.1 shows a comparison of average angular errors and optimisation times for Algorithm 1 with feeding of weights between frames for initialisation (1_b), or no feeding (1_a), and Algorithm 2 with patches of length 3 (2_3) or 5 (2_5) for three levels of motion speed.

Table 7.1: Accuracy of IK Algorithms 1 and 2. MPJAS₁₄ per frame for three levels of motion speed (fps: Optimisation frames per second, E: 14-joint Mean Per Joint Angular Separation (rad/joint)).

Algorithm	Speed a		Speed b		Speed c		Average	
	fps	E	fps	E	fps	E	fps	E
1_a	7.44×10^{-2}	9.45×10^{-2}	6.96×10^{-2}	9.13×10^{-2}	7.48×10^{-2}	8.12×10^{-2}	7.29×10^{-2}	8.90×10^{-2}
1_b	9.63×10^{-2}	7.65×10^{-2}	9.28×10^{-2}	7.45×10^{-2}	8.61×10^{-2}	5.68×10^{-2}	9.15×10^{-2}	6.93×10^{-2}
2_3	2.03×10^{-2}	8.28×10^{-2}	2.33×10^{-2}	7.69×10^{-2}	5.74×10^{-2}	5.07×10^{-2}	2.74×10^{-2}	7.01×10^{-2}
2_5	8.94×10^{-3}	7.07×10^{-2}	1.32×10^{-3}	7.40×10^{-2}	3.90×10^{-2}	5.13×10^{-2}	1.41×10^{-2}	6.53×10^{-2}

Table 7.2 shows a comparison of average angular errors for motions with 1) bent limbs only, or 2) a combination of bent and extended limbs. Motion sequences with only bent limbs have low errors for all algorithms, and for sequences with phases of extended limbs algorithm 1_b and both temporal algorithms have lower errors.

Table 7.2: MPJAS₁₄ per frame for motion sequences with 1) only bent limbs, or 2) phases of extended limbs.

Algorithm	Bent limbs only	Extended & bent limbs
1_a	5.84×10^{-2}	1.20×10^{-1}
1_b	6.05×10^{-2}	7.80×10^{-2}
2_3	5.39×10^{-2}	8.64×10^{-2}
2_5	5.64×10^{-2}	7.43×10^{-2}

7.4.2 Overcoming twist angle ambiguity

Figure 7.7 shows a comparison of average average angular errors for parameterised joints in the chain for motion sequences with phases of bent and extended limbs. Algorithm 1_a produces higher errors in the clavicles (due to a lack of corresponding keypoints), and shoulders and hips (associated with ambiguity in twist angles).

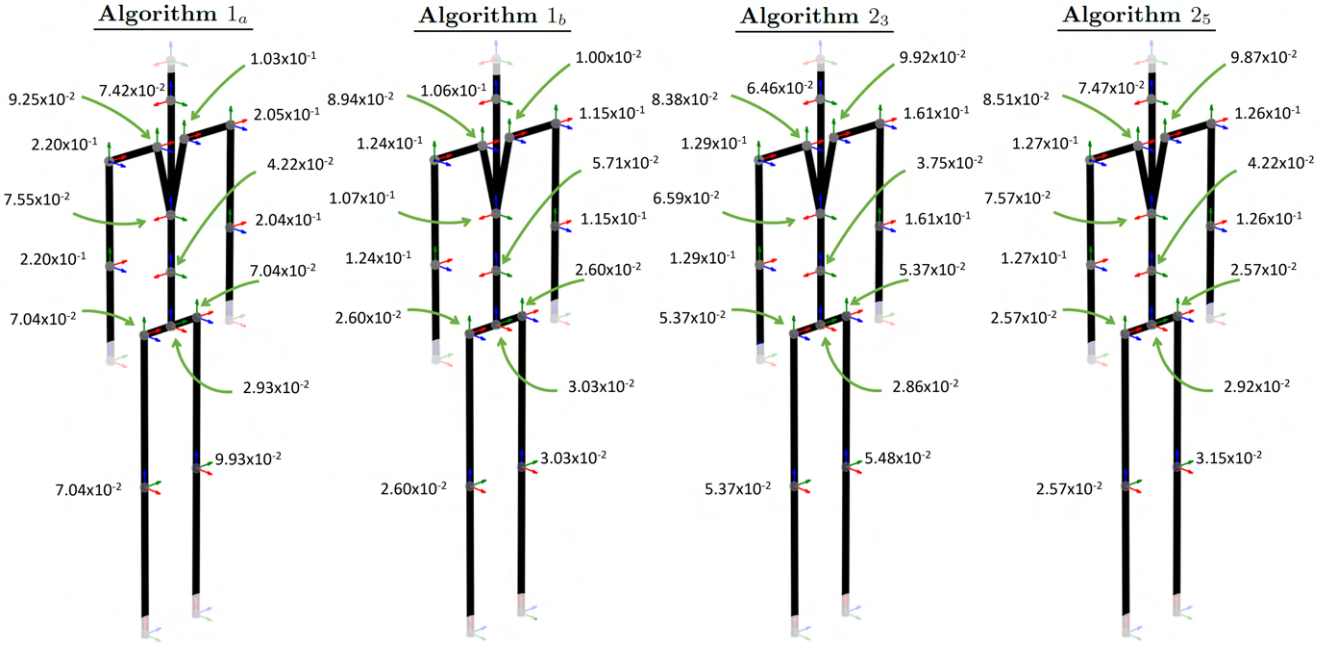


Figure 7.7: MPJAS₁ by joint and algorithm, for motion sequences with phases of bent and extended limbs.

Figure 7.8 shows a comparison of average average angular errors for parameterised joints in the chain for motion sequences involving motion with bent limbs throughout. In comparison to the results for motion sequences involving phases of both bent and extended limbs (Figure 7.7) the results are similar across all algorithms, demonstrating that twist angle ambiguity is not as problematic for this kind of motion. In Appendix E the relationship between phases of extended/bent limbs are investigated further for boundary cases. A visualisation of how algorithm 1_b and both temporal algorithms overcome twist angle ambiguity is also available

here³.

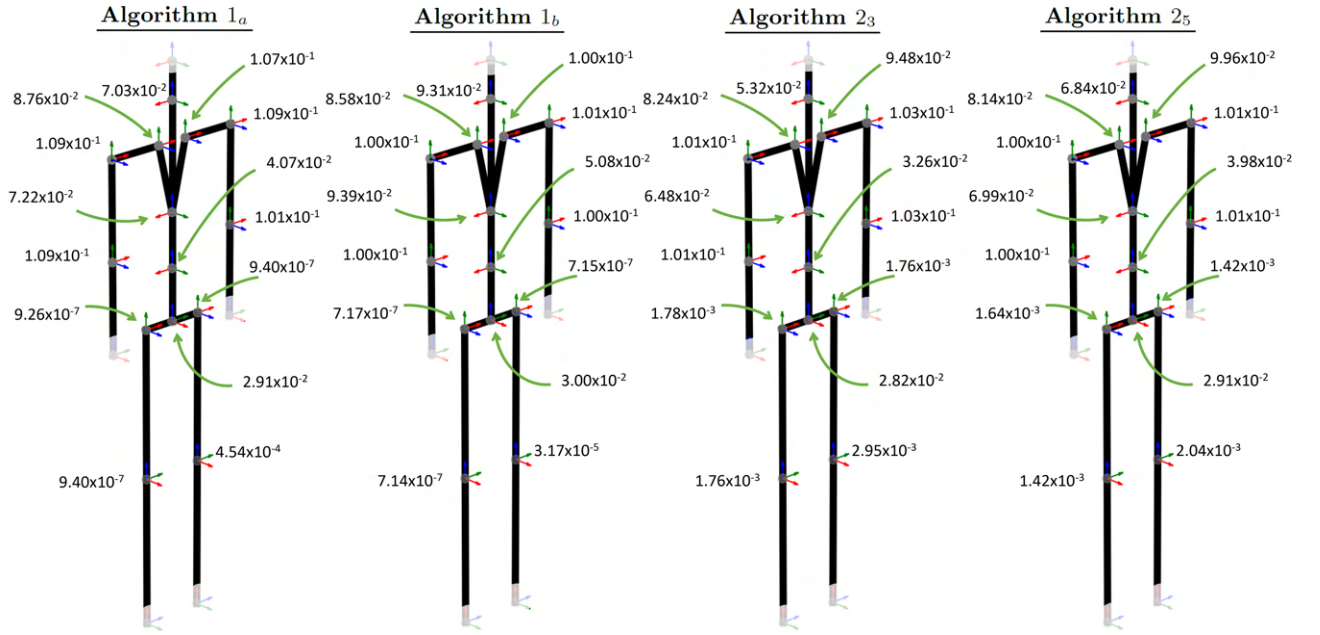


Figure 7.8: MPJAS₁ by joint and algorithm, for motion sequences with bent limbs only.

7.5 Discussion

MPJAS₁₄ errors are low for all algorithms and motion speeds, ranging from average errors of 8.90×10^{-2} rad/joint for algorithm 1_a (5.1°), to 6.53×10^{-2} rad/joint for algorithm 2₅ (3.7°) (Table 7.1). Differences observed between algorithm 1_a and 1_b highlight the importance of the initialisation guess for weights, i.e., feeding weights from previous frames for initialisation in a frame-by-frame optimisation reduces time to convergence (Table 7.1), and adds a degree of temporal consistency. The results provide a clear justification for the temporal model. While algorithm 1_b outperforms 2₃ on average, temporal algorithm 2₅ is the best performer across all indicators. The benefits of the temporal model relate to twist angle ambiguity (Table 7.2, and

³<https://kevgildea.github.io/assets/Thesis/7.4.2-twist-angle-ambiguity.gif>

Figure 7.7), and are of particular benefit for a specific boundary case involving an initial phase of extended limbs, followed by a phase of bent limbs (see Appendix E). Large fluctuations in twist angles are observed for algorithm 1_a , whereas, algorithm 1_b and both variations of the temporal algorithm result in lower errors both overall, and in boundary cases. Algorithm 2_5 achieves the highest accuracy for all motion speeds, and obtains particularly low errors for the lower limbs (hips and knees), i.e., 2.71×10^{-2} rad/joint (1.6°) for motion sequences involving phases of extended limbs (Figure 7.7), and 1.63×10^{-3} rad/joint (0.1°) for motion with only bent limbs (see Appendix E). Temporal implementations with sufficiently large patch sizes are effective for reducing ambiguity in twist angle, which is a key benefit. Nevertheless, algorithm 1_b is suitable for applications requiring faster processing. The temporal scalar weight should be tuned for both motion speed and video framerate. For fast motion or a low framerate, relative joint orientation changes between frames will naturally be higher, therefore requiring a lower weighting. Similarly, for slow motion or a high framerate a higher weighting is required.

Due to a lack of relevant keypoints, twist angles of the forearms and neck, and joint reorientations of the ankles and wrists are currently not included. However, an extension could include these for 3D pose inputs with more keypoints in the extremities. A large proportion of the errors are associated with those joints in the chain without corresponding keypoints, i.e., clavicles and lower spine. Parameterisation of the lower/mid spine with equally proportioned rotations in two joints may often not be biofidelic, indeed, this relationship is often the subject of analyses in biomechanics. These limitations are imposed by the fact that current 3D pose estimators do not include sufficient keypoints. Synthetic generation of motion, as per Beeson et al. (2015) [236], allows for a detailed assessment of the mathematical procedure including boundary cases of interest. However, for potential practical applications further testing should include GT activity-specific motion capture footage. Furthermore,

practical applications rely on the accuracy of the 3D pose estimator used; calibrated multi-camera pose estimators have higher accuracy, whereas monocular pose estimators are more practically useful. There are several potential sources of error associated with current 3D pose estimators. For example, all approaches (particularly monocular methods) are known to have errors associated with joint occlusion. There are other sources of error related to the training data, i.e., failure for rare poses, unbalanced 2D/3D datasets biasing predictions, and domain adaption issues. Furthermore, 2D pose datasets (e.g., COCO, MPII) suffer from systematic joint mislabeling by untrained annotators, particularly for the hip joints, resulting in 3D joint center positioning in a more lateral and inferior position compared to ground truth [237]. As opposed to a recent approach involving the use of the OpenSim IK tool (i.e., Pose2Sim) [185, 186], KinePose is applicable to either multi-camera, or monocular 3D pose estimators with incorrectly scaled skeletons and variable link lengths.

7.6 Conclusions

This chapter proposes KinePose, a convenient post-processing technique for position-based 3D human pose estimation methods, to infer joint orientations in a subject-specific biomechanical model. It is demonstrated that this technique allows for accurate prediction of joint orientations. This technique may be particularly useful for sports biomechanics, and telehealth applications. Though currently unsuited to real-time applications, many potential applications are envisaged as a post-processing technique for 3D pose estimators. Code is available through the project page⁴.

⁴<https://kevgildea.github.io/KinePose/>

CRedit authorship contribution statement [210]

Kevin Gildea: Conceptualisation, Data curation, Formal analysis, Software, Investigation, Methodology, Resources, Validation, Visualisation, Writing - original draft, Writing - review & editing, Project administration. **Clara Mercadal-Baudart:** Conceptualisation. **Richard Blythman:** Writing - review & editing. **Aljosa Smolic:** Writing - review & editing. **Ciaran Simms:** Supervision, Conceptualisation, Funding acquisition, Methodology, Project administration, Resources, Writing - review & editing.

Chapter 8

Study F: Towards computational modelling of cyclist falls with the inclusion of protective response

Related publication:

- Towards computational modelling of active response in cyclist falls from in-the-wild footage, **K. Gildea**, C. Simms, Congress of the European Society of Biomechanics (ESB) (2022)

8.1 Introduction

As detailed in section 2.7, the self-protective effects of active response in unplanned sideways falls is a well-established area of research. The general kinematic form initially involves the fall-side leg extending in an attempt to recover balance, followed by the arms extending to absorb impact energy and avoid head-ground contact (Figure 2.21). However, characteristics specific to single cyclist falls have not been well investigated. Chapter 3 [211] demonstrated that these falls are common, and chapter 4 [214] indicated that protective response may be of particular importance in these cases. In chapter 4 [214], a coding scheme with three common single cyclist fall types was devised. The majority were either 'skid-out' or 'topple-over' (N=126, 58%) the majority of which are likely sideways falls. Furthermore many 'pitch-over' falls are also likely sideways, i.e., not directly over the handlebars. In fact, all falls observed from in-the-wild footage (chapter 6, and the current chapter) were sideways falls.

In the field of traumatic injury biomechanics, injury prevention strategies are often investigated using instrumented dummies or physics-based computational models (detailed in section 2.5). Computational modelling approaches generally involve either multibody (MB), or finite element (FE) models. Dynamics solvers for these models implement the equations of motion as an initial value problem, i.e., initial conditions for the simulation are specified at a certain point in time. Understandably therefore, it has been demonstrated that resulting impact kinematics and dynamics from vehicle-cyclist/pedestrian collisions are influenced significantly by initial human posture and motion (see section 2.6.2). The effects of initial conditions for single cyclist falls have yet to be investigated in detail, however, due to the lower impact speeds, and longer reaction times, initial pose and motion are expected to have a larger relative effect. The potential effects of self-protective response have only recently been considered in a computational modelling study of workplace falls [238], using an imposed bracing pose with a single arm extended, with findings indicating that bracing poses

significantly reduce head impact speeds, and alter head impact angles. Moreover, findings for injury patterns from chapter 4 indicate that the upper extremities are used to absorb impact energy in single cyclist falls. Specifically, among serious injuries, single cyclist falls had high proportions of hand/wrist fractures compared to collisions with bonnet-type vehicles (29% vs. 13% - Table 4.5).

As detailed in section 2.7, the traditional approaches for computational modelling of falls involve setting up fictive cases, e.g., initialising a human body model with an initial velocity on a bicycle, and projecting them into an obstacle. Fictive reconstructions have been used to estimate head impact conditions and helmet effectiveness. However, the non-inclusion of protective response reduces reconstruction fidelity, as evident by the unrealistic ragdoll-type motion without protective limb movements (e.g., Figure 2.22). Therefore, overall effectiveness of injury prevention strategies are difficult to assess using this kind of approach, e.g., helmets, softer road surfaces, or other safety equipment.

8.2 Study aims

Protective response to a fall/perturbation can be decoupled into its kinematic and dynamic components. Here we aim to capture the kinematic response, which is described by 1) the Degrees of Freedom (DOFs) ($\underline{q}_0$ from section 2.5) i.e., linear position specified for the root of the model relative to its environment, and joint angular configurations throughout the body which specify pose at a certain point in time, and 2) 1st derivatives of these DOFs (d DOFs) ($\dot{\underline{q}}_0$ from section 2.5) specifying motion throughout the body, i.e., linear velocity of the root, and joint angular velocities throughout the body. A pipeline is created for calculating joint DOFs and d DOFs to represent the kinematic component of protective response in the MADYMO pedestrian multibody ellipsoid model using real-world footage. This pipeline, visualised in Figure 8.1, allows for greater reconstruction fidelity than previous approaches.

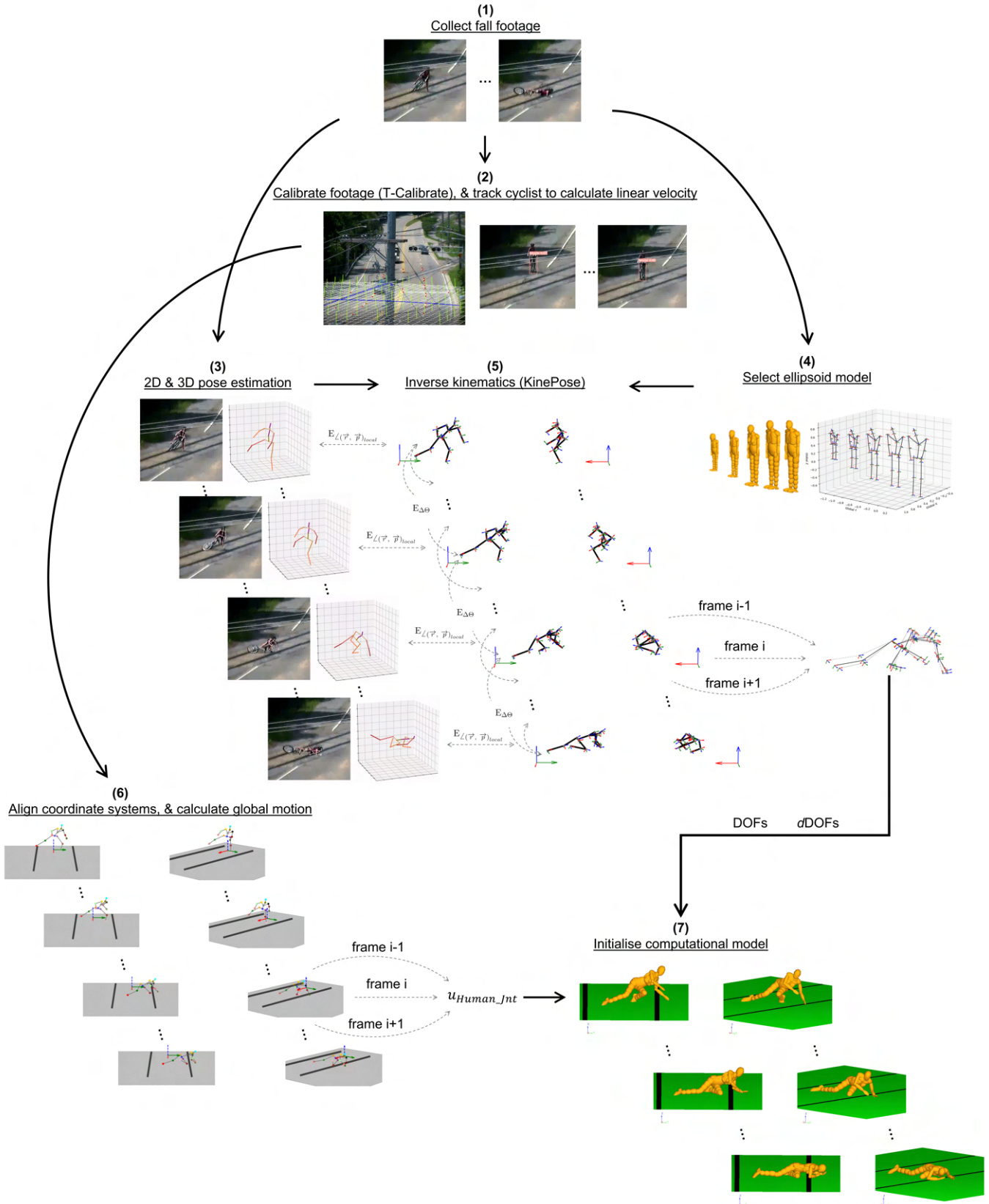


Figure 8.1: Pipeline for reconstruction of cyclist falls from monocular camera footage.

8.3 Methods

8.3.1 Data

The data used in this study were fall footage from a study involving cyclists crossing skewed railway tracks on Neyland Drive in Knoxville, Tennessee between August 2nd - October 3rd 2014 [55]. Since there is a good frontal view of the falling cyclists in this footage, with minimal self-occlusion, it is well suited for the purposes of reconstruction. Furthermore, this study involved continuous monitoring of a particular section of track, and the data can be considered representative of cyclist falls on railway/tram tracks. Of the 32 falls at this location, 2 were excluded due to 1) video failure, and 2) an obscured view of the fall.

8.3.2 Coding kinematic forms

Three general kinematic forms were coded based on the literature for sideways falls, 1) with trunk rotation, resulting in the cyclist impacting frontally with the ground with both arms outwards, 2) without trunk rotation, resulting in the cyclist impacting side-on with the ground, 3) partial fall, with incomplete loss of balance, 4) other fall, or 5) no fall. Fall types 1 and 2 are visualised in Figure 8.2. Furthermore, the incidence of impact to various body regions was coded in a similar fashion to Feldman et al. (2007) [145], i.e., the head, hips, hands, elbows, knees, or buttocks.

8.3.3 Case study for reconstruction

As a case study, a typical event is selected involving a middle-aged female involved in a sideways fall with trunk rotation, resulting in a frontal impact with the ground with both arms outwards (type 1 fall).

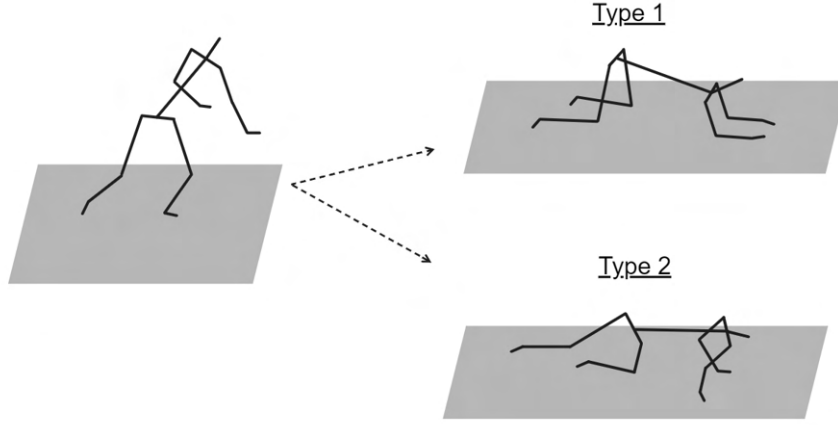


Figure 8.2: Two general kinematic form types common in sideways falls.

8.3.4 Human pose estimation

Deep learning-based 2D and 3D human pose estimation are used to extract human kinematics from the fall footage (step 3, Figure 8.1). 2D pose estimators are often used as a backbone for 3D pose estimation, e.g., HRNet [239], and OpenPose [162]. While 2D pose estimators may allow for an automatic pipeline, errors in 2D will propagate into 3D. Furthermore, for this example case automatic pose estimators performed poorly (Figure 8.3). Therefore, 2D poses were manually annotated¹.

GAST-Net was then applied to obtain 3D poses [171]². The resulting 3D pose sequence is given relative to a root joint ($\underline{P}^{xyz}$), i.e., one keypoint remains at a fixed position (mid-pelvis at 0,0,0), and body motion is defined around this point. Scene information is used to relate the coordinate systems (T-calibrate vs. 3D pose), i.e., noting that the bicycle wheels are in the track in a frame, and approximating the vertical rotation (about the Z-axis) (step 6,

¹<https://github.com/wkentaro/labelme/>

²<https://github.com/fabro66/GAST-Net-3DPoseEstimation/>

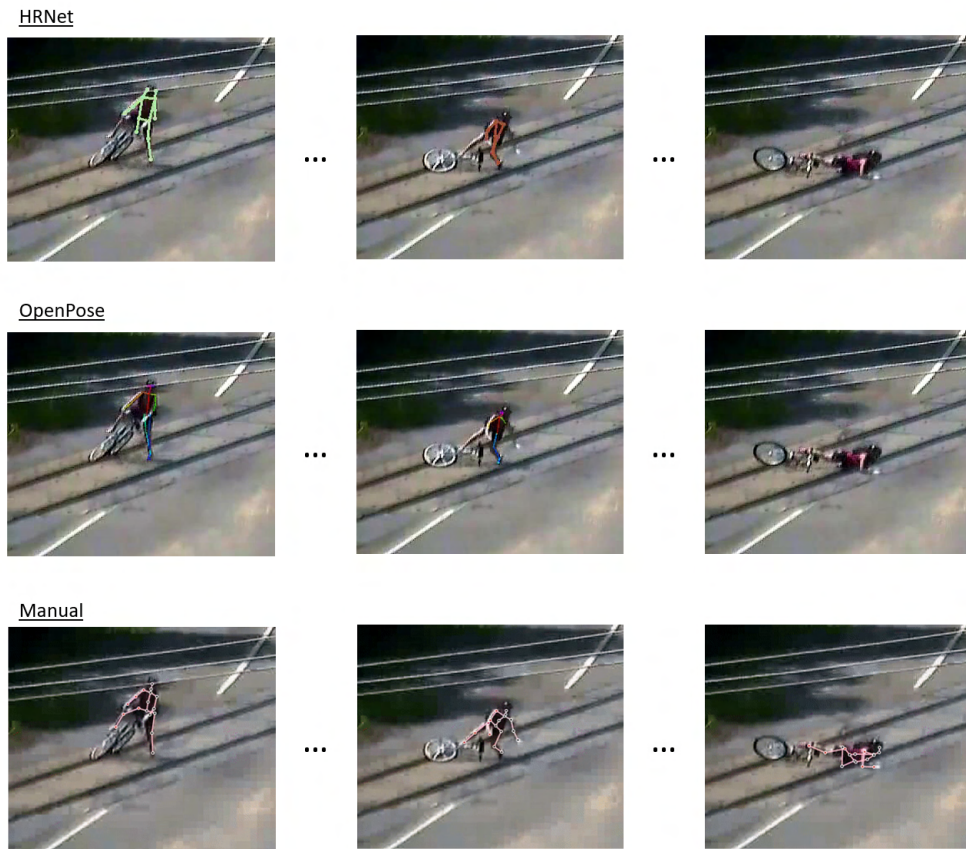


Figure 8.3: Automatic vs. manual 2D pose estimates.

Figure 8.1). To determine the initial velocity of the cyclist in the XY-plane at the instance before the fall, the footage was spatially calibrated with respect to the ground-plane using the approach from Tsai et al. (1987) [217], using T-calibrate [60], whereby scene points on the roadway are manually annotated in both camera footage and a satellite image of the recording location (obtained from Google Earth). The YOLOv5x object detector was used to track the position of the bicycle on approach to the track, the model was further trained on traffic camera footage of bicycles in a previous study for improved domain adaptation (step 2, Figure 8.1). Using the central difference method and camera framerate yields global velocity components on the ground plane (u_x , and u_y). During freefall, velocity components

in this plane can be assumed as constant, and therefore, positional time histories should vary in a linear fashion according to $s_x(t) = u_x t$, and $s_y(t) = u_y t$ (Figure 8.4). To bring the root-relative motion into the global coordinate system Algorithm 1 is applied. This relies on the motion involving two phases: 1) the cyclist in freefall, with the left ankle sliding on the ground plane, and 2) a static left knee on the ground plane (Figure 8.4).

Algorithm 3: Root-centric to global motion

Data: $\underline{P}^{xyz}, u_x, u_y$

Result: $\underline{P}^{XYZ}$

for $f = 1, \dots, 11$ **do**

$$\left| \begin{array}{l} \underline{P}_f^{XYZ} = \underline{P}_f^{xyz} + \left\{ \begin{array}{c} \{u_x t_f, u_y t_f, -p_{Ankle_L, 3}\} \\ \vdots \\ \{u_x t_f, u_y t_f, -p_{Ankle_L, 3}\} \end{array} \right\}_f \end{array} \right|$$

end

for $f = 12, \dots, 16$ **do**

$$\left| \begin{array}{l} \underline{P}_f^{XYZ} = \underline{P}_f^{xyz} + \left\{ \begin{array}{c} -p_{Knee_L} \\ \vdots \\ -p_{Knee_L} \end{array} \right\}_{f=11}^{XYZ} + \left\{ \begin{array}{c} -p_{Knee_L} \\ \vdots \\ -p_{Knee_L} \end{array} \right\}_f^{xyz} \end{array} \right|$$

end

8.3.5 Inverse kinematics & initialisation

A temporal inverse kinematics (IK) optimisation technique (KinePose) was developed to infer joint orientations in a user-customisable biomechanical model for 3D pose estimates (chapter 7) [240]. The approach is adapted for use with the MADYMO ellipsoid models using reorientable joints (see Figure 2.6). The adapted chains are shown in step 4, Figure 8.1. Since reorientable joints in MADYMO chain correspond directly to pose keypoints in many position-based 3D human pose estimators, including Gast-Net, only the local pose error term was applied ($E_{\angle(\vec{r}, \vec{p})_{local}}$ - Equation 7.6). All links were used for this, and therefore

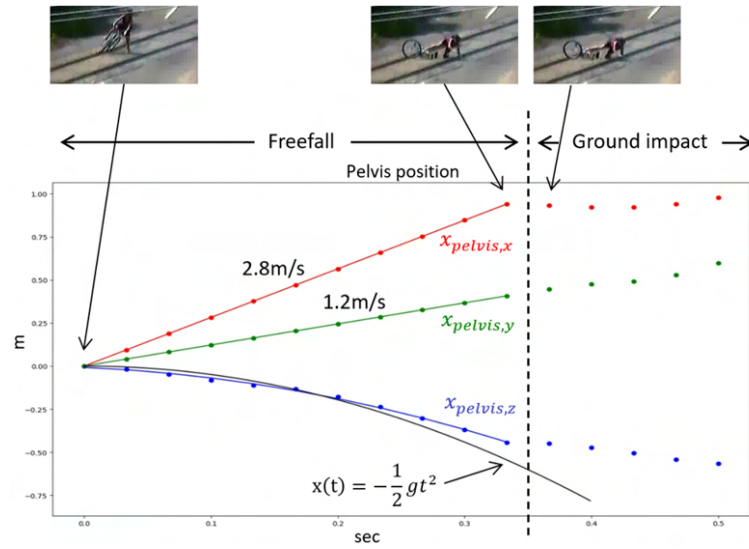


Figure 8.4: Definition of global motion for the cyclist.

link angular differences were also minimised for the links between the spine and the shoulders. Furthermore, since findings indicate that larger patch sizes improve accuracy (ibid.), poses were optimised across all frames in the motion sequence through a temporal error term ($E_{\Delta\theta}$ - Equation 7.8) (step 5, Figure 8.1). A visualisation of the output is shown in Figure 8.5.

The frame of interest for reconstruction in this case is frame 10 (frame i in Figure 8.1), i.e., at the end of freefall and the instance of first ground impact. Linear velocity of the root, and joint angular velocities are calculated at this frame using the central difference method, and output as .xml include files for interpretation by the MADYMO solver.

8.3.6 Computational modelling

As an approximation for the cyclist's size and shape, the MADYMO small female human pedestrian model was used. This is a biomechanical model consisting of rigid bodies linked by kinematic joints. The bodies are ellipsoid and are used to represent the outer surface of the human body, and the kinematic joints are used to constrain relative motion between bodies, with DOFs and ranges of motion (ROMs) which are representative of the human body. The small female model has a standing height of 1.53m, and a weight of 49,77kg. Since head-ground contact in a type 1 fall would involve an anterior region of the head, i.e., the nose and face, a contact stiffness was set at 97kN/m, as per Shang et al. (2021) [69].

8.3.7 Effect of initialisation

As an investigation into the effects of initialisation, we reconstruct four cases (Figure 8.6). One case includes all DOFs and d DOFs from our pipeline for the frame of interest for reconstruction (frame 10), another case includes only DOFs. Linear velocity of the pipeline cases are set using the approach described in Figure 8.4. The other two cases include manually configured DOFs by a second researcher through visual inspection of the video footage; one case at frame 0, and another at frame 10. Linear velocity for the former is defined using the ground-plane velocity estimate for the cyclist at frame 0, i.e., 0m/s in the z-direction. Whereas for the latter, the z component is calculated assuming freefall and acceleration due to gravity ($u_z(t) = gt$).

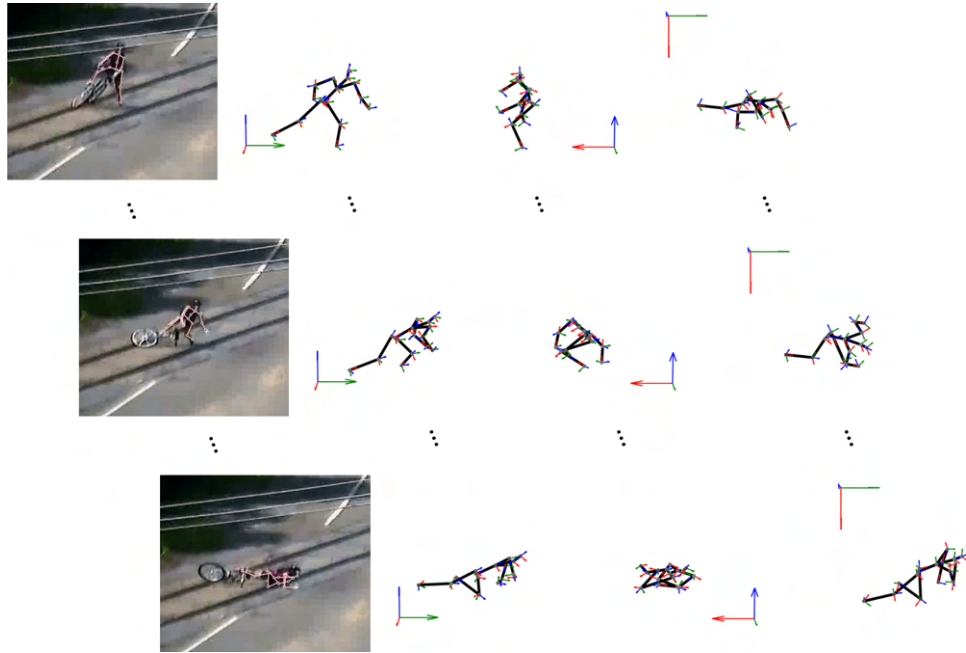


Figure 8.5: KinePose output given an input sequence of 3D poses.

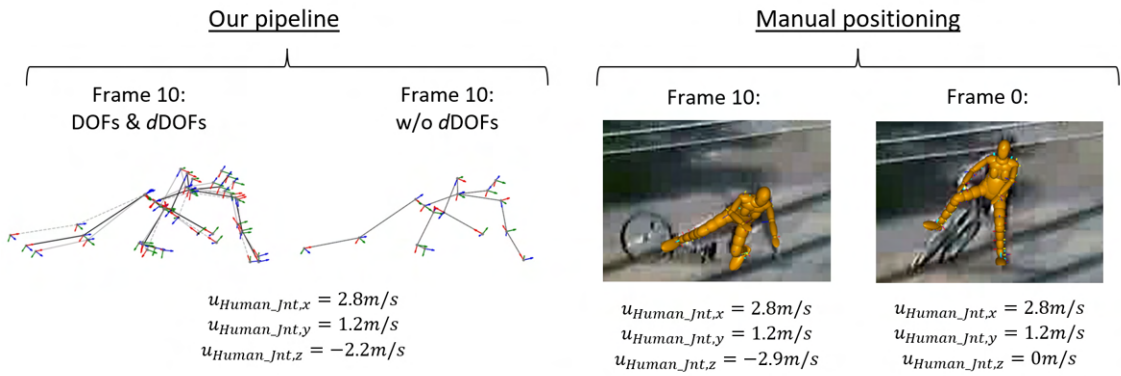


Figure 8.6: Four initialisation cases for comparison in computational modelling.

8.4 Results

8.4.1 Kinematic forms

Most cases were coded as either type 1 (N=10, 33%), or type 2 (N=10, 33%) (Figure 8.2). The remainder were comprised of type 5 (no fall) (N=7, 23%), type 3 (partial fall) (N=2, 7%), or type 4 (other fall) (N=1, 3%). A comparison of impacted body regions is shown for fall types 1 and 2 in Table 8.1. Overall, the left foot and left hand were the most commonly impacted body regions, impacted in N=23, 77%, and N=19, 63% cases respectively. The incidence of impact to the head was low overall (N=5, 17%), and was most commonly a result of type 2 falls (N=4).

Table 8.1: Frequency of ground-impact to various body regions for fall type 1, type 2, and overall.

Impacted body region	Type 1		Type 2		All types	
	N	%	N	%	N	%
Head	1	10%	4	40%	5	17%
Left foot	9	90%	4	40%	23	77%
Right foot	1	10%	1	10%	10	33%
Left hip	4	40%	7	70%	11	37%
Right hip	1	10%	1	10%	2	7%
Left hand	9	90%	8	80%	19	63%
Right hand	9	90%	2	20%	12	40%
Left elbow	3	30%	6	60%	9	30%
Right elbow	3	30%	1	10%	4	13%
Left knee	7	70%	4	40%	11	37%
Right knee	2	20%	1	10%	3	10%
Left shoulder	0	0%	7	70%	7	23%
Right shoulder	1	10%	1	10%	2	7%
Buttocks	0	0%	0	0%	2	7%
Thorax	4	40%	0	0%	4	13%

8.4.2 Case study

Acceleration time histories with 3ms peak accelerations annotated are shown in Figure 8.7 for the pipeline case (i.e., with DOFs and d DOFs). In Figure 8.8 kinematics during the ground impact phase are assessed, with matched video frames. Overall kinematics are similar, however, they diverge as the simulation progresses.

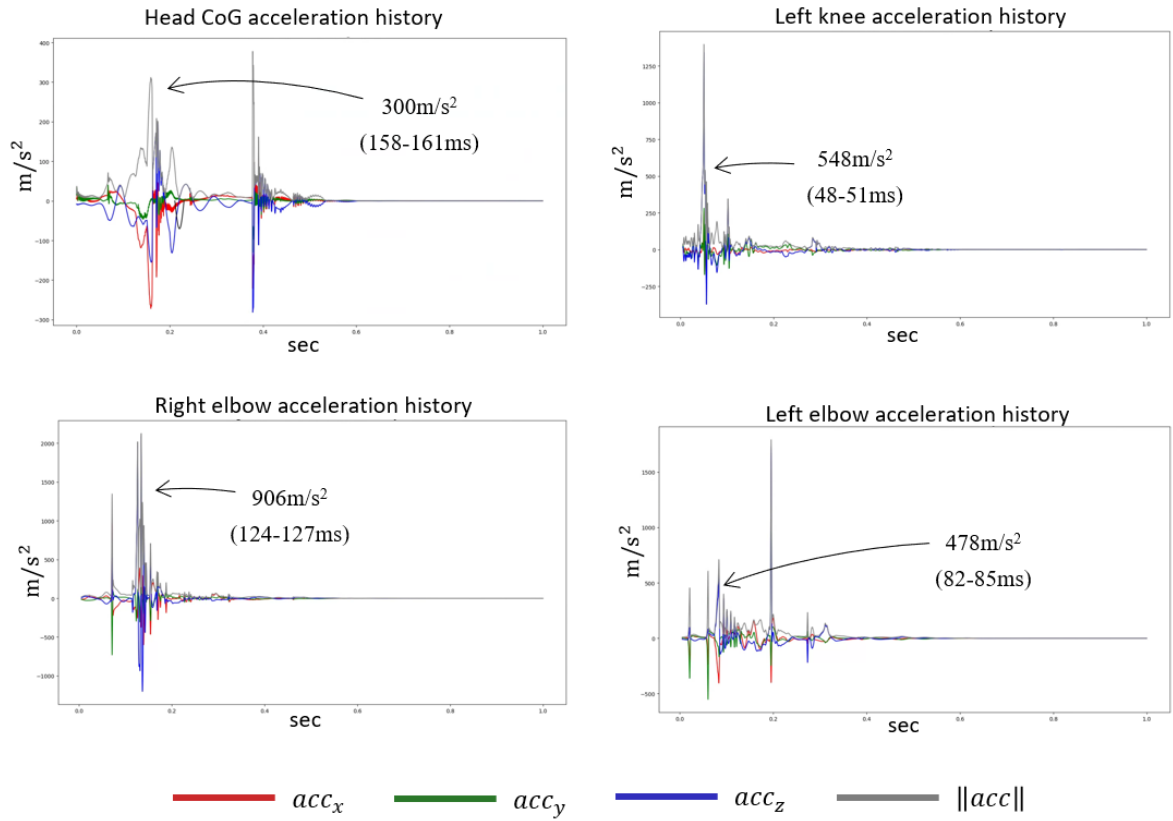


Figure 8.7: Acceleration time histories with 3ms peak accelerations for the pipeline case with DOFs and d DOFs.

8.4.3 Effect of initialisation

Overlaid visualisations of simulations for the four initialisation cases, with 3ms peak accelerations, are shown in Figure 8.9. Generally, this analysis demonstrates the effect of initialisation on resulting ground-impact kinematics. The pipeline case with DOFs and d DOFs has the lowest head impact acceleration ($300m/s^2$), though has the highest impact acceleration to the right elbow ($906m/s^2$).

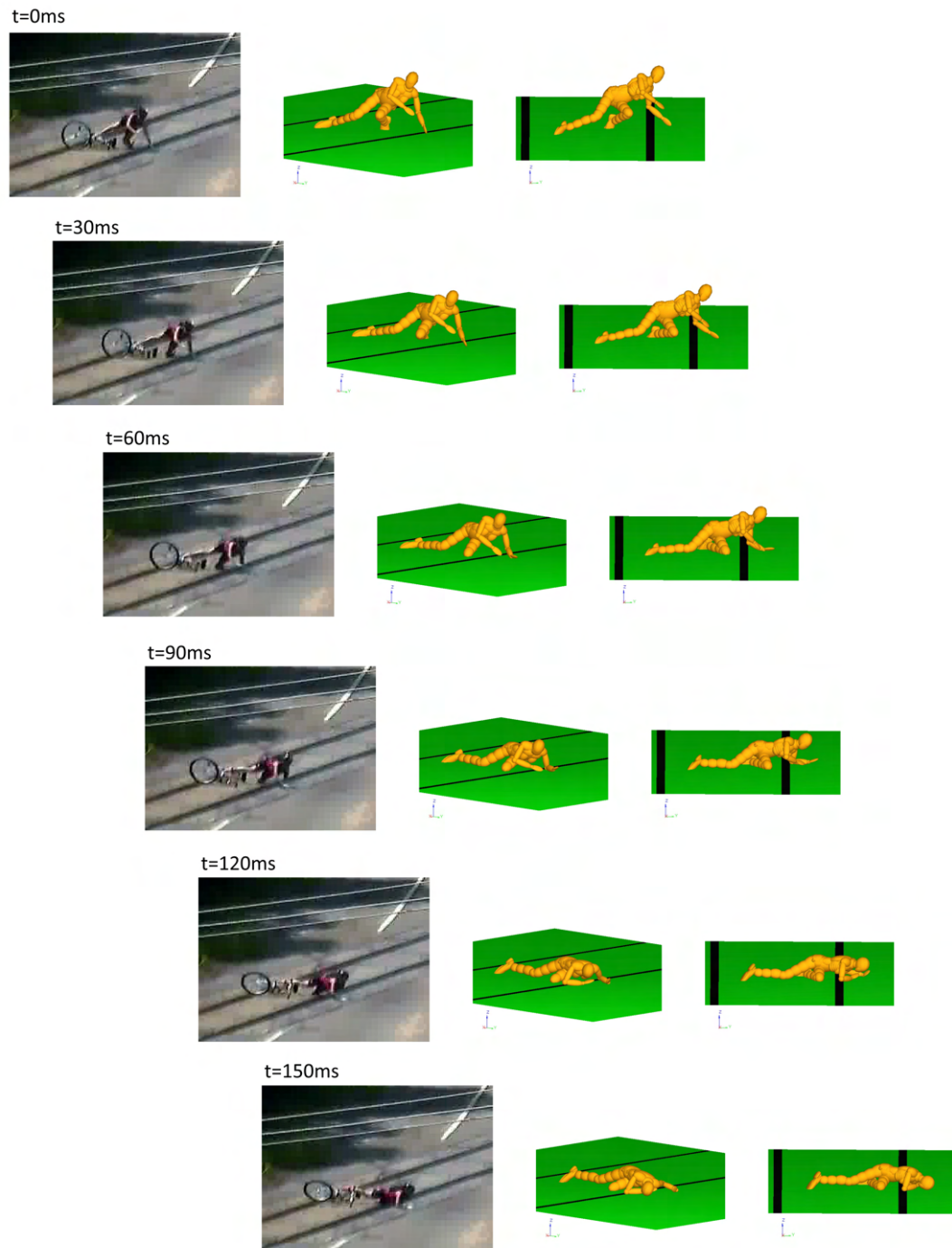


Figure 8.8: Qualitative comparison of kinematics in the ground impact phase for the pipeline case with DOFs and d DOFs.

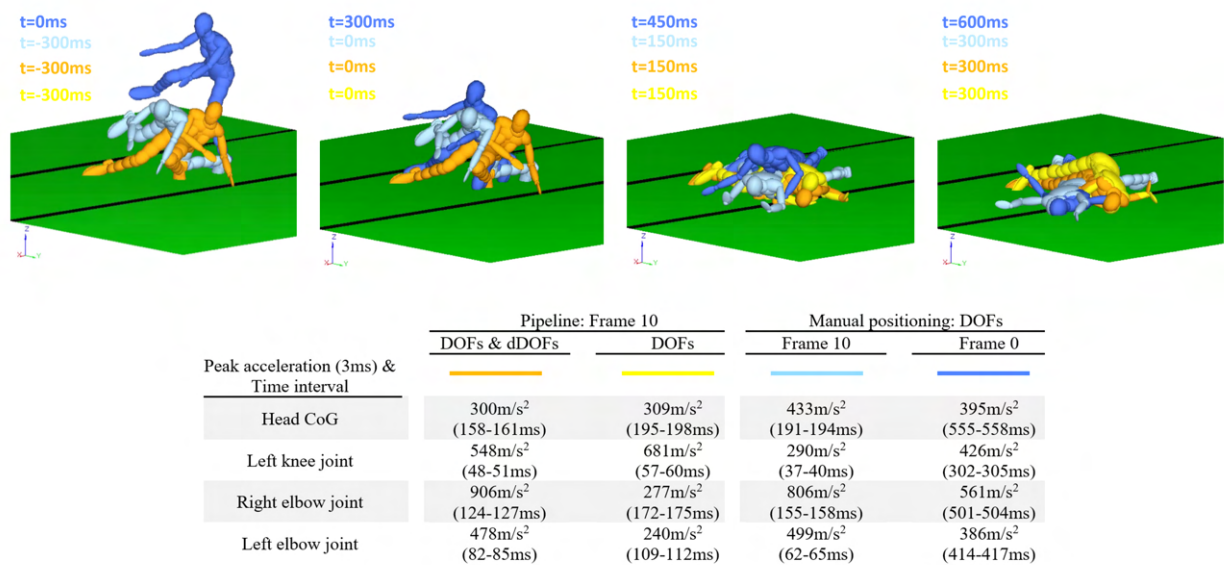


Figure 8.9: Overlaid visualisations, and comparisons of simulation results (3ms peak accelerations) for the four initialisations.

8.5 Discussion

Here we categorise two common sideways fall types based on real-world footage: 1) with trunk rotation, resulting in the cyclist impacting frontally with the ground with both arms outwards, 2) without trunk rotation, resulting in the cyclist impacting side-on with the ground (Figure 8.2). Findings indicate that each type comprises an equal proportion of falls of tracks. Due to the road configuration, all of the falls were to the cyclist's left sides, and accordingly, the most commonly ground-impacted body regions were the left foot (N=23, 77%), and the left hand (N=19, 63%), with the left leg initially extending in an attempt to regain balance, and the left hand extending to break the fall once balance is lost. Furthermore, overall incidence of head impact was low (N=5, 17%), and was primarily a consequent of fall type 2 (N=4). However, all fictive reconstructions from the literature result in head impact, and high linear and angular accelerations on impact. Findings from this study indicate that the limbs are used to prevent falls, absorb impact energy and protect the head in the case of single cyclist falls.

Due to methodological constraints, previous attempts at reconstructing falls, e.g., single cyclist falls [146, 148, 149, 147, 73], or electric scooter falls [154, 155], have been confined to fictive initialisations for pose and velocity. For example, Wang et al. (2022) [73] simulated a cyclist fall after 1) impact with a kerb and 2) a skid out. In both scenarios, a cyclist model was positioned on a bicycle, and both were set at a plausible initial velocity of 5.5m/s. While the initial pose and motion of the cyclist on the bicycle may be representative of a real-world scenario, the time taken to fall to the ground in single cyclist and electric scooter falls (300ms in this case) leaves a large temporal window for protective responses. Through capturing kinematics from in-the-wild footage and initialising at the instant before ground impact, the proposed reconstruction pipeline accounts for the kinematic component

of protective response during the fall. While traditional computational modelling approaches may allow for modelling of worst-case head impact conditions, the proposed pipeline allows for more plausible estimates, which may be useful in developing helmet designs and more comprehensive type-testing protocols. Furthermore, other injury prevention strategies, such as softer road surfaces, or the presence/absence of road furniture at the fall location (e.g., a kerb, or a bollard) may be more accurately assessed.

While the ellipsoid model used in this study was originally developed and validated for vehicle-pedestrian impact modelling [241], it has been validated for a variety of blunt impacts. The model has also been validated for ground impact, however, the model has not been explicitly validated for falls. There are simplifications in the model, particularly relating to surface and contact representations. Though recently, an updated version of the model has been created, with improved biofidelity [242]. Due to the easy specification of initial pose and motion, MADYMO ellipsoid multibody models are well suited to the pipeline. Similarly, facet models, and combined multibody body finite element head models may be suitable. The use of finite element models in this pipeline is possible, however, setting DOFs and d DOFs is currently a challenge [71].

This study includes sideways falls, which is the most common fall type, and the only observed fall type resulting from interactions with tram/train tracks, i.e., chapters 6, and 8 [55]. However, findings from chapter 4 [214] indicate that a large proportion ($N = 30$, 45%) of pitch-over falls result in head injury, compared to 31% for skid-out and topple-over falls. Pitch-over falls were also the single cyclist fall type with the highest levels of head injury (45%) and direct head impact (52%), and also had the highest levels of upper/lower extremity and torso injury. Therefore, future work should include a kinematic/dynamic analysis of forward falls.

Frame-matched comparisons to the footage show the further effect of the active component on protective response during the ground impact phase of the fall, i.e., muscle activation, which currently is not accounted for (Figure 8.8). Since the proposed pipeline accounts for the kinematic component of protective response, to account for the dynamic component, future work should include an optimisation procedure for active (dynamic) response in the ground impact phase.

8.6 Conclusions

Here a novel pipeline is presented for the reconstruction of cyclist falls from monocular footage with the inclusion of the kinematic components of protective response. This approach can be applied to a variety of impact biomechanics tasks not limited to cyclist falls. Furthermore, common kinematic forms for sideways cyclist falls are characterised. Findings from this study indicate that the limbs are used to prevent falls, absorb impact energy, and protect the head. The kinematic forms characterised in this study can be used to inform initial conditions for computational modelling and injury estimation in single cyclist falls.

CRedit authorship contribution statement [210]

Kevin Gildea: Conceptualisation, Data curation, Formal analysis, Software, Investigation, Methodology, Resources, Validation, Visualisation, Writing - original draft, Writing - review & editing, Project administration. **Daniel Hall:** Validation. **Clara Mercadal-Baudart:** Conceptualisation. **Christopher Cherry:** Resources. **Ciaran Simms:** Supervision, Conceptualisation, Funding acquisition, Methodology, Project administration, Resources, Writing - review & editing.

Chapter 9

Discussion

In this chapter, the practical implications of findings from chapters 3, 4, and 5 are discussed, with a focus on the Irish national context. Specifically, implications for strategies to target and treat cyclist road safety risks are discussed in section 9.1, and prevention strategies for cyclist-motorised vehicle collisions and single cyclist collisions are discussed in sections 9.2, and 9.3, respectively. While this discussion is not exhaustive, it highlights some of the key areas where action is required to improve cyclist safety in Ireland.

Since much of the work presented in chapters 6, 7, and 8 contain methodological elements with broader scope, i.e., Computer Vision (CV) and Artificial Intelligence (AI) algorithms for cyclist tracking and reconstruction of fall dynamics, they are further discussed in a more general context in section 9.4.

9.1 Targeting & treating risk

The Safe System approach to road safety (detailed in section 2.2) has recently been adopted in Ireland [4]. This is a holistic approach to road safety, which aims to eliminate serious injuries and fatalities on the road network. Since Vulnerable Road Users (VRUs), i.e., pedestrians, cyclists, and motorcyclists are more susceptible to severe harm in a collision, they are prioritised under this paradigm. This prioritisation is primarily due to their lack of protection as compared to vehicle occupants. Therefore, to ensure VRU safety in a Safe System, road infrastructure, vehicles, and speed limits must be designed in a manner that mitigates the risk of collisions and reduces the severity of injuries.

As detailed in section 2.3, while significant fatality reductions have been achieved across Europe for most road users, cyclist fatality numbers have remained at similar levels (see Figure 2.1). Furthermore, the frequency and share of cyclist injuries are increasing in Ireland (Figures 2.2, and 2.3). While these trends are likely strongly influenced by the reflected increase in cycling popularity and modal share, they place an added onus on road safety stakeholders to improve the road safety environment for cyclists.

Bedford et al. (2011) [32], Short et al. (2014) [26], and Foley et al. (2016) [33] previously presented analyses of police and hospital data, demonstrating underreporting in Ireland, and findings from chapters 3, and 4 provide further evidence through the addition of survey-based data. Findings indicate that roughly three-quarters of cases are not reported to the police. By comparison, international findings show reporting rates to range between 0% (Israel) and 35% (Germany) [30]. Furthermore, Short et al. (2016) [243] found that cyclist injuries are the least likely collision type to be reported to the police in Ireland. In project findings, 39% of self-reported collisions involving injuries were either reported to the police or resulted in a hospital attendance (or both) (see Figure 3.3). Improvements in road safety

can only be achieved through a combination of targeting and treating road safety risks. The significant shortcomings in data coverage imposed by underreporting is a critical issue that should be addressed. The International Transport Forum recently recommended that cyclist injuries be monitored using a combination of police, hospital, and insurance data [200]. As demonstrated by Short and Caulfield (2014, 2016, 2018) [26, 243, 244], linking data from different sources gives a clearer picture. Results from chapter 3 indicate that the combined monitoring of police and hospital data may be effective for monitoring serious injury collisions (as suggested by Foley et al. (2016) [33]). For example, road traffic collisions in hospital and police data are systematically linked in Sweden, i.e., the Swedish Traffic Accident Data Acquisition (STRADA). Adopting a similarly comprehensive approach in Ireland would be in line with our Vision Zero strategy to target and treat all serious and fatal cases [4].

However, findings from chapter 3 also highlight the need for alternative data sources for capturing details on less severe cases. Forty-two percent of serious injuries reported to the police compared to 15% for minor injuries, and the odds of police reporting for serious injury cases are 7 times greater than minor injury collisions (Figure 3.4). These findings indicate that the effects of minor injuries are particularly underestimated, and warrant further consideration. Collision surveys are crucial for capturing information on these cases. While Vision Zero emphasises the need to eliminate fatal and serious injuries, it also recognises the importance of addressing minor injuries. Though less severe, they can still have a significant impact. Minor injuries can cause pain, suffering, and inconvenience for those involved, as well as result in lost productivity and economic costs [36]. Additionally, minor injuries can be used as an early warning sign of more serious road safety problems, and addressing them can help prevent more severe injuries from occurring in the future. In a similar way, studying traffic conflicts and near-misses can provide valuable safety insights by identifying potential safety issues and patterns, i.e., at the base of Hydén's safety pyramid (Figure 2.4), there are

many near-misses and conflict events, while at the top, there are far fewer collisions involving injuries or fatalities. Furthermore, given the particular issue of underreporting for single cyclist collisions, obtaining data on surrogate measures of safety for these cases using near misses and conflict events becomes even more important (discussed further in section 9.4.1).

9.2 Priorities for cyclist-motorised vehicle collisions

Representative pre-crash scenarios and collision factors have been identified both for non-fatal cyclist-motorised vehicle collisions from chapter 4, and more serious and fatal cases from chapter 5 (Table 9.1). Collisions with bonnet-type vehicles dominate in both datasets (94% in chapter 4, and 72% in chapter 5), i.e., sedans/hatchbacks, Sports Utility Vehicles (SUVs), and vans. In both cases, sedans/hatchbacks are most common. However, the reason why bonnet-type vehicles are more dominant in chapter 4 is that fatal cases in chapter 5 are commonly a result of impact with a Heavy Goods Vehicle (HGV) (31%) (discussed further in section 9.2.1). Sports utility vehicles (SUVs) comprise a relatively small proportion of cases (N=35, 6% of self-reported cases, and N=6, 10% of fatal cases). However, in recent years there has been a trend towards increased vehicle sizes and weights, and an increase in the popularity of SUVs [245, 246]. This raises concerns since larger bonnet leading edge heights, and SUVs have been shown to increase injury/fatality risk for cyclists through analysis of historical crash records [247]. This is considered to pose a particular risk to children. Increases in vehicle sizes are in part due to efforts to improve occupant safety, i.e., increased crumple zones/safety cells, airbags etc. However, these improvements should not come at the detriment of VRU passive safety.

Table 9.1: Representative cases for cyclist-motorised vehicle collisions in Ireland.

Fatal and serious cases

OT/SD:

Cyclist and vehicle initially travelling in the same direction, with a collision resulting from the vehicle attempting to overtake the cyclist.



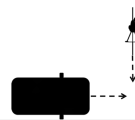
LT/SD:

Cyclist and HGV initially travelling in the same direction, with a collision resulting from the vehicle taking a left turn across the cyclist's path.



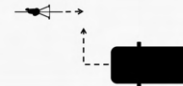
SCP/LD:

Collision resulting from a bonnet-type vehicle travelling straight ahead, and cyclist approaching from the vehicle driver's left direction.



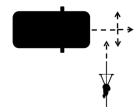
RT/OD:

Cyclist and vehicle initially travelling in opposite directions, with a collision resulting from the vehicle taking a right turn across the cyclist's path.

**Lower severity cases**

LT/RD & SCP/RD & RT/RD:

Collision resulting from a bonnet-type vehicle taking a left turn, a right turn or travelling straight ahead, and cyclist approaching from the vehicle driver's right direction.



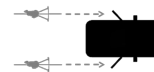
LT/SD:

Cyclist and bonnet-type vehicle initially travelling in the same direction, with a collision resulting from the vehicle taking a left turn across the cyclist's path.



D:

Collision resulting from a bonnet-type vehicle occupant opening their door, with the cyclist approaching from behind.



CL/SD:

Cyclist and bonnet-type vehicle initially travelling in the same direction, with a collision resulting from the vehicle changing lanes.



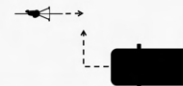
OT/SD:

Cyclist and bonnet-type vehicle initially travelling in the same direction, with a collision resulting from the vehicle attempting to overtake the cyclist.



RT/OD:

Cyclist and bonnet-type vehicle initially travelling in opposite directions, with a collision resulting from the vehicle taking a right turn across the cyclist's path.



9.2.1 Longitudinal/same directions of travel

The largest share (51% - Table 4.1, rank 1) of collisions with bonnet-type vehicles were preceded by the vehicle and cyclist travelling in the same direction. These collisions comprise a large share of fatalities internationally [76], and in Ireland (57% - Table 5.1). These findings supplement existing knowledge, further emphasising the importance of this traffic environment in Ireland across the injury spectrum. The prevalence of these collision types is generally symptomatic of a road environment with inadequate cycling infrastructure. Physical separation of cyclists and vehicles on roadways (not at intersections) could plausibly eliminate roughly half (i.e., cases involving same directions of travel that were not at intersections, Table 4.1, rank 1). Provision of segregated infrastructure both reduces collision risk for cyclists [248], and increases perceived safety and popularity [249, 250] likely further reducing collision risk via the safety-in-numbers effect [39]. Therefore, the Irish road safety strategy for the years 2021-2030 includes a Safety Performance Indicator (SPI) on the proportion of extra cycle and pedestrian infrastructure developed [4]. Though no data exists on the proportion of roads with segregated lanes in Ireland, it is likely low as only 2% of self-reported collisions without motorised vehicles were associated with segregated cycle lanes (chapter 4). Furthermore, a low proportion of fatal and serious cases in police investigation files were on segregated lanes (3% - Table 5.4 for collisions with bonnet-type vehicles, and 6% - Table 5.7 for collisions with HGVs). Since most self-reported collisions with bonnet-type vehicles were preceded by the cyclist and vehicle travelling in the same direction occurred in urban environments (94%), segregated lanes should be prioritised in urban environments. Indeed, 93% of all self-reported collisions with motorised vehicles occurred in an urban environment (Figure 3.2). Along with infrastructural interventions, reductions to motor vehicle volumes and speed limits in urban environments are known to reduce collision risk [251], and injury risk [96] (detailed in section 2.6). Speed is a critical factor for the occurrence and severity

of collisions, and efforts should be made to reduce speeds to levels that are safe for VRUs. The potential of lowering speed limits in urban environments has received a lot of attention in recent years, with 30km/h speed limits in urban environments now targeted in our road safety strategy [4].

While collisions in urban environments are common for self-reported and lower severity cases, rural environments are common for fatal and serious collisions with bonnet-type vehicles. Specifically, cases involving a bonnet-type vehicle attempting to overtake/pass a cyclist (OT/SD): 70% of OT/SD cases are in rural environments, and 54% cases in rural environments are OT/SD (Table 5.4). Overtaking collisions are also the most common collision type in rural environments for self-reported cases (Table 4.2, rank 4). Furthermore internationally, fatalities from same direction of travel collisions are commonly in rural environments [76, 75]. Overtaking collisions on rural roads should be mitigated through a combination of education, engineering, and enforcement (the three E's). In Ireland, there have been significant education and awareness campaigns toward educating road users on the dangers of overtaking cyclists too closely. Furthermore, legislative interventions are being implemented in Ireland and Internationally (e.g., cyclist-specific overtaking legislation), however, their effectiveness is uncertain [252]. Furthermore, findings from chapter 5 indicate that OT/SD cases that result in a fatality or a serious injury often involve low visibility, i.e., occurring in the dark/dusk, or in light conditions involving glare (low sun ahead of the driver/cyclist). Therefore, under the Safe System paradigm, other engineering and enforcement strategies should now be a focus. While current Autonomous Emergency Braking (AEB) systems may be effective in reducing cyclist rear impacts during vehicle overtaking manoeuvres [253, 254] (common for fatal and serious cases), most overtaking manoeuvres among self-reported cases result in Side-Side impacts (Table 4.2), for which AEB, Autonomous Emergency Steering (AES), and Forward Collision Warning (FCW) effectiveness is unclear. Therefore, findings indicate that

all phases of the overtaking manoeuvre must be addressed, i.e., including the passing and returning phases, as described by Dozza et al. (2016) [255], and Rasch et al. (2020) [256]. Of course, road design measures such as wider shoulders, and segregated cycling infrastructure in rural environments would also improve cyclist safety, however, this may not be viable on many rural roads, therefore, lowering speed limits should also be considered as an effective strategy for these cases. Lower speed limits encourage drivers to slow down and be more aware of their surroundings, which can reduce the likelihood of collisions and mitigate the severity of injuries if a collision occurs (detailed in section 2.6.2). As previously discussed, 30km/h speed limits in urban environments are now targeted in our road safety strategy [4]. Furthermore, the strategy includes an SPI for measuring the safety and credibility of speed limits, i.e., the degree to which drivers perceive the speed limit as reasonable and obey it, for both urban and rural roads. Current speed limit guidelines allow for safety-based reductions based on collision data, i.e., identification of at-risk locations is used to identify areas to set special (lower) speed limits [257]. While this approach can be effective in urban areas, its application in rural environments is limited by several factors. One primary challenge is the more dispersed nature of collisions in rural areas, resulting in fewer instances of significant concentrations of collisions. This, in turn, can make it difficult to identify hot-spots. Furthermore, under the Safe System paradigm, a proactive approach is preferred to reactive analysis of historical collision data, i.e., to target and treat collision risk before any occur. It is known that a significant proportion of road fatalities occur on rural roads for both cyclists (chapter 5), and more generally for other road users [258], and many rural roads in Ireland have inappropriately high speed limits [259]. Notwithstanding potential issues around speed limit consistency, these statistics imply the need for a straightforward and proactive mechanism for lowering speed limits on rural roads, and potentially the reductions in default speed limit levels, which are currently set at 100 km/h for National roads, and 80 km/h for Regional

and Local roads [257]. Lubbe et al. (2022) [99] recently highlighted that injury/fatality risk curves suggest that 30 km/h speed limits are generally safe in urban settings, but that current practices of allowing much higher speed limits on rural roads are considerably unsafe for VRUs, and warrant greater attention. According to Nilsson's Power model, collision reduction effects that may accompany speed limit reductions on rural roads would be significant [260]. Rural roads also often have low traffic volume, which leads drivers to become complacent and drive at higher speeds. In free-speed conditions, i.e., unconstrained by road geometry, weather conditions, or traffic conditions, 27% of drivers on rural roads in Ireland travel over the speed limit [261]. Therefore, effective enforcement is also important to include with any speed limit reductions. An ongoing study in the UK has found that while speed limit reductions on rural roads achieve the intended effect of reducing collision rates, speed choice is also influenced by the road environment [262]. Therefore, speed management measures should also be considered in rural environments alongside speed limit reductions, e.g., geometric changes such as chicanes are considered a particularly useful measure because they force drivers to slow down and pay closer attention to their surroundings.

Nearside-hook collisions (LT/SD) comprise the largest proportion of self-reported collisions with bonnet-type vehicles (19% of collisions - Table 4.2, rank 1). This is far higher than their proportion of slight, serious, or fatal collisions in GIDAS (Germany) (5.6%) [74], or V_CAD (Sweden) (<5%) [83]. Understandably therefore, resulting nearside-hook injuries have the lowest police reporting level of all pre-crash scenarios (only 16% of injurious cases reported - Table 4.2, rank 1). While nearside-hooks are not common among fatal and serious cases with bonnet-type vehicles (3% - Table 5.2), they comprise a large share of fatalities with HGVs (44% - Table 5.5). Furthermore, findings indicate that many collisions with HGVs result from the cyclist being positioned at the front/nearside of the HGV (Table 5.6), sup-

plementing international findings that indirect/direct vision issues in this region (the blind zone) are a contributing factor in most of these impacts [114]. Historically, European regulations limiting HGV lengths (for trailer and tractor) has led to designs with the driver cabin placed high above the engine. However, cabin height has been shown to reduce direct vision for drivers [113]. Currently, this is primarily mitigated using a range of mirrors, providing indirect vision for the space around the cabin, and underrun protection systems to prevent cyclists falling under the wheels in the case of impact. However, the effectiveness of underrun systems is unclear, as the majority of the cases in chapter 5 resulted in the HGV overrunning the cyclist (Table 5.6). Furthermore, incorrectly adjusted mirrors often result in impacts [115], and direct vision is preferable since the need to check multiple mirrors reduces reaction times, resulting in a temporal blind zone. Indeed, as indicated in Table 5.7, cyclists may often be available to be seen by the driver through indirect vision (mirrors) at some point before impact. Therefore, recent HGV designs have included Advanced Driver Assistance Systems (ADAS) for the blind zone, i.e., collision warning, and emergency braking systems. As detailed in section 2.6.2, upcoming European regulation will include mandatory blind zone detection systems and direct vision standards. ADAS blind spot detection systems also exist for bonnet-type vehicles with larger fields of view (e.g., Cieslik et al. (2019) [77]) which may mitigate nearside-hook collisions and collisions involving a vehicle changing lanes across a cyclist's path (CL/SD, which comprise a further 11% of self-reported collisions with bonnet-type vehicles - Table 4.2, rank 3) [253, 254, 263]. Staggered stop lines at intersections are a common approach to reducing collisions with HGVs, however, they are ineffective for prevention of those involving bonnet-type vehicles [264]. Furthermore, staggered stop lines (and similarly, advanced traffic light signalling for cyclists) would be ineffective for preventing nearside-hook collisions in free-flowing traffic. Therefore, the need for safer intersection design is clear, i.e., the use of separated and recessed cycle lanes, with cyclist crossings.

9.2.2 Lateral/crossing & oncoming directions of travel

Lateral/crossing and oncoming collisions involving bonnet-type vehicles are less frequent than same travel direction collisions, but these are more injurious, likely due to the larger velocity differentials (Table 4.1). Collisions preceded by the cyclist approaching an intersection from the right of the vehicle also at the intersection and taking a left turn, a right turn, or proceeding straight ahead comprise 11% of self-reported collisions (LT/RD, SCP/RD, RT/RD) (Table 4.6). These cases are a focus of current ADAS type-testing [74, 76, 80], and AEB/AES systems are effective in reducing their occurrence and severity [253, 254, 263]. These generally occur at T-junctions or entrances to houses, filling stations etc. (Table 4.2, ranks 5b, 7, and 8), though a large share (56%) of collisions involving the vehicle turning left into the path of a cyclist approaching from the right (LT/RD) occurred at roundabouts, again implying the need for safer intersection/roundabout design. Offside-hook collisions (RT/OD), i.e., those preceded by the vehicle/cyclist travelling in opposing directions with a collision resulting from the vehicle turning right across the cyclist's path are infrequent but injurious among self-reported cases (89% resulted in injuries) (Table 4.2, rank 5a). Furthermore, this scenario is common among fatal and serious collisions in Ireland (Table 5.2). This scenario is also common among injuries internationally [83, 74, 76], and accordingly, it is included in recently proposed ADAS type-testing from PROSPECT [78]. Current ADAS systems may be effective for reducing many of these collisions [253, 254, 263], however, many likely result from the view of the oncoming cyclist being obstructed by slow/stationary traffic or road furniture, and lateral offset (as indicated by Lindman et al. (2015) [83]), which is known to inhibit ADAS [263]. Therefore, further investigation is required.

9.2.3 Impact configurations

Internationally, the majority of serious and fatal cyclist collisions with bonnet-type vehicles result from impact with the vehicle front [88, 107, 83, 87, 86]. Findings from chapter 5 indicate

that this is also the case in Ireland, with 31% of cases involving impact between the front of the vehicle and rear of the cyclist (Rear-Cyclist), and 24% involving impact between the front of the vehicle and the side of the cyclist (Side-Cyclist) (Table 5.3). However, findings demonstrate that priorities for impact configurations differ for self-reported lower severity and underreported cases. Though impacts with vehicle fronts still result in a high share of serious injuries (Table 4.1, row 4), other impact configurations comprise larger shares of both serious injuries and lower severity collisions. Specifically, we now see the importance of impacts between the side of the vehicle and the side of the cyclist/bicycle (Side-Side), which comprise the largest shares of both injurious and non-injurious cases (Table 4.1, row 4). Indeed, Side-Side impact types are generally the result of same direction of travel scenarios which have the lowest police reporting level (only 31% of injurious cases reported) (Table 4.1, rank 1). Collisions involving the cyclist impacting frontally with the side of the vehicle (Side-MV) and with open(ing) doors of vehicles also contribute large shares of the injuries (Table 4.1, row 4). Therefore, with calls to address less severe collisions, findings from chapter 4 indicate that potential benefits may be gained by reducing the aggressiveness of the sides, and open(ing) doors of vehicles. Dooring collisions were the second most common scenario, comprising 12% of collisions with bonnet-type vehicles (with a high proportion, 64%, resulting in injuries) (Table 4.2, rank 2), compared to 6.6% of injurious collisions in GIDAS (Germany) [74], and 6% in V_CAD (Sweden) [83]. They also have the second lowest police reporting level (only 22% of injurious cases are reported) (Table 4.2, rank 2). To prevent dooring collisions, infrastructural interventions should be implemented, e.g., the use of separated, buffered, or raised bicycle lanes. Many dooring collisions result from the vehicle occupant not looking in the direction of the cyclist [265], highlighting the potential utility of ADAS for notifying vehicle occupants or automatic door locking if a cyclist is approaching from the rear. Dooring impacts are featured as one of the top 5 priority collision scenarios

in PROSPECT for urban areas (Table 2.2, rank 4) [74, 75]. Furthermore, ADAS prototypes (Blind Spot Detection (BSD) system for dooring) have been developed [77, 266] and a type-testing procedure has been defined [77, 78] (see Figure 2.9). However type-testing for these systems is not currently included in New Car Assessment Program (NCAP) and European regulated type-testing ((EU) 2019/2144; [82]). Findings for lower severity and underreported collisions further emphasise the importance of addressing these collisions with ADAS.

9.3 Priorities for single cyclist collisions

For single cyclist collisions, findings from chapters 3 and 4 based on self-reported survey data highlighted the prevalence of single cyclist collisions among non-injurious and lower severity collisions in Ireland [211, 214]. Findings from chapter 5 based on police investigation files show their importance also for serious injury and fatal cases, with 15% of cases in this category, and a further 4% involving a single cyclist collision resulting in a subsequent impact with an in-use motorised vehicle. However, with a small sample size in chapter 5, a meaningful analysis of contributory factors and direct causes was not possible. The causes of single cyclist collisions are frequently multifactorial, with 32% in chapter 4 involving more than one direct cause (Table 4.3), and all have very low police reporting rates (from 0% to 11%) (Table 4.4). Generally, the priorities identified in chapter 4 are similar to other international studies involving self-reporting or hospital data [136] (see section 2.7.2).

9.3.1 Loss of traction

Aligning with international findings (Table 2.3), slippery roads (water, ice, oil, etc.) is the most common factor for single cyclist collisions in this study (a contributing factor in 31% of single cyclist collisions - Table 4.3). This implies the particular need to improve road surface traction for cyclists both in Ireland and Internationally. The second largest share of slippery road collisions result from surface ice (after wet roads). By comparison, ice/snow contributes to the majority (64%) of these falls in countries with more extreme winter climates, e.g., Finland [135], and Sweden (59%) [267]. A large share of these falls in these climates likely relate to operational maintenance, i.e., snow clearance and skid control measures. While snow clearance measures are unlikely to be an important safety consideration in Ireland, skid control measures such as grit application should be a focus during the winter months. Winter bicycle tires could also be encouraged as a measure to improve traction. These

tires are typically made from a softer, more pliable rubber compound, and sometimes have spikes that provide better traction on snow and ice. Testing has shown that winter bicycle tires effectively improve grip in these conditions (studded tires in particular) [268, 269]. Furthermore, slippery metallic surfaces and excessive areas of paint for road markings can pose hazards to cyclists as they may cause loss of traction and increase the risk of a slip or fall, especially in wet conditions (a common factor identified in chapter 4). Therefore, it is recommended that these surfaces be avoided or minimised in places where cyclists travel. Special surface materials with rubber content may also reduce the occurrence and severity of skid-out falls on slippery roads, and reduce ice formation (e.g., Wallqvist et al. (2017) [270], and Sahandifar et al. (2022) [271]).

9.3.2 Infrastructural collision partners

The most common infrastructural collision partners in chapter 4 are tram tracks (a contributing factor in 23% of single cyclist collisions) and kerbs (a contributing factor in 21% of single cyclist collisions). The share of collisions involving tram tracks is similar to a study in Melbourne (19%) [134], and higher than a study in Switzerland (13%) [43]. These cases comprise a high share in chapter 4, considering that in Ireland they are only present in Dublin city. The scale of the issue is supported by results from chapter 6, as well as a recent analysis of Irish hospital data [227]. Many of these collisions involve the cyclist crossing the tracks, or slipping into the tracks due to wet road conditions, which is also common in a study from the Netherlands [44]. Physical separation of cyclists from tram tracks is recommended, and at locations where cyclists are expected to cross tracks sufficient space should be available for a safe approach angle. Descriptive statistics in chapter 6 (Figure 6.8) show that while mean crossing velocities are similar across both successful and unsuccessful crossings (4.8m/s vs. 4.7m/s), mean crossing angles were not (43° vs. 10°). Therefore, as expected, from

multivariable modelling, the crossing angle was found to be a strong predictor of crossing success. Models indicate that the boundary for the definition of a minimum ‘safe’ crossing angle is in the region of 30°, therefore, Infrastructural planners should aim for road designs that allow for and encourage crossing angles of 30° or more. Rubber/plastic rail fillers have also been suggested as a possible timely infrastructural solution. However, there are concerns about their effectiveness and feasibility. One potential issue is that the fillers may not fit perfectly into the gap between the tram tracks and the road surface, which could lead to other safety issues. These may indeed be a viable solution in areas with a high risk of cyclist falls or where there is a large volume of cycling traffic (e.g., at College St/Green - Table 6.1), however, further research is required.

Kerbs serve road safety purposes as a physical demarcation between the roadway and surrounding areas, however, they may also pose safety risks to cyclists if they are high, difficult to see, or if there are no proper accommodations in place for cyclists to navigate them safely. Many collisions with kerbs in chapter 4 involve the cyclist exiting the main roadway to enter an off-road cycle lane, implying the need for more forgiving kerb designs, especially where cyclists are expected to enter/exit cycle lanes, i.e., sloped/levelled kerb types, as described by Janssen et al. (2018) [272].

9.3.3 Avoidance manoeuvres

Avoidance manoeuvres from vehicles comprise 20% of all single cyclist collisions in chapter 4 and many of these then result in impacts with road features (e.g., forced to cycle into the kerb due to avoidance manoeuvre or being boxed in by a motorised vehicle), or falling due to abrupt or adventitious braking/steering in avoidance of a motorised vehicle (Table 4.4, rank 4). This proportion is much higher than findings from Finland (6%) [135], and a study in Queensland (5%) [42]. These have the highest police reporting level (11% of injurious cases

were reported), indicating that the involvement of a motorised vehicle makes the collision more likely to be reported to the police, even if impact with one does not occur. For example, many unsuccessful crossings for tram tracks observed in chapter 6 involve passing/nearby motorised vehicles (N=4, 31%), and indeed, international literature also indicates that traffic pressure contributes to the majority of falls on tram tracks [228]. Interventions which address the causes of cyclist-motorised vehicle collisions (i.e., segregated infrastructure, lower motor traffic volumes and speeds) would likely have the ancillary benefit of reducing these kinds of single cyclist collisions.

9.4 Potentials of AI-based approaches

9.4.1 Surrogate measures of safety

A recent International Transport Forum round table highlighted the potential utility of using CV and AI to acquire relevant information for crash risk in a proactive safety assessment framework [63]. Video-based Surrogate Measures of Safety (SMoS) offer advantages over traditional techniques (e.g., reactive analysis of collision hot-spots) by providing more detailed and accurate data, detecting near-miss events, identifying contributing factors, and enabling advanced data analysis. Therefore, it is expected that these technologies will play an increasingly important role in the future of transportation safety. SMoS are increasingly being used to identify potential safety issues in traffic by identifying high-risk scenarios or locations. SMoS have been developed for cyclist safety using CV and AI algorithms that analyse video footage to detect potentially problematic interactions between cyclists and other road users (see section 2.4.4). Since the causes of single cyclist collisions are often diffuse and multifactorial, novel video-based monitoring technologies could play an important role in targeting and treating their risk factors. The further development of SMoS specifically for single cyclist collisions may allow for the identification of specific road features or environmental factors that increase the risk of falls, such as kerbs, irregular surfaces, or tram tracks (as performed in chapter 6). Future work to combine video analysis techniques with bicycle/rider dynamics knowledge (such as the models described by Åstrom et al. (2005) [273]) may allow for dynamics-informed SMoS for single cyclist collisions from video footage of cyclists, i.e., comparing inferred bicycle/rider motion to mathematically defined thresholds for skidding out, toppling over, or otherwise losing balance. This could provide insights into road factors that contribute to falls such as sharp bends/downhill sections, and inform design guidelines.

Similarly, accelerometers can be used to extract safety insights. For example, the SYNCHRONICITY project from the smart bicycle light company SeeSense has highlighted a variety of cyclist safety issues in Dublin¹, and Belfast² using a combination of naturalistic accelerometer readings and self-reporting. This combination has the potential to allow for proactive and detailed SMoS on single cyclist collisions.

9.4.2 Computational modelling

Computational human body modelling studies have allowed for successful injury prevention strategies for vehicle-cyclist/pedestrian impacts (see section 2.6). As detailed in section 2.7, in recent years, the injury biomechanics of single cyclist falls have become a popular area of research. Accordingly, similar computational modelling efforts have been applied to determine injury prevention strategies for these cases, e.g., effectiveness assessments for helmets. However, due to methodological constraints, previous attempts at reconstructing falls have not considered self-protective response.

However, findings from chapter 8 demonstrate that when a person experiences a fall, they will instinctively initiate a self-protective response to minimise injury. This can lead to variations in both the dynamic conditions and the specific regions where the head is impacted. Moreover, this self-protective response can also affect the estimated impact conditions for other body regions, such as the arms or shoulders. The potential effects of self-protective response have only recently been considered in a computational modelling study of workplace falls [238], using an imposed bracing pose with a single arm extended, with findings indicating that bracing poses significantly reduce head impact speeds, and alter head impact angles.

¹<https://seesense.cc/blogs/see-sense-report-page-blogs/see-sense-report-analysis-for-dublin/>

²<https://seesense.cc/blogs/hub/see-sense-report-analysis-for-belfast/>

Previous attempts at reconstructing falls have been limited by methodological constraints. The use of CV and AI for the reconstruction of impacts and falls is still in its nascent stage of development, however, the advancements presented in chapters 7, and 8 have allowed for greater reconstruction fidelity for a better understanding of fall kinematics and dynamics. A better understanding of fall kinematics and dynamics may help inform the design of protective gear and interventions aimed at reducing fall-related injuries.

However, frame-matched comparisons to fall footage show the further effect of the active component on protective response during the ground impact phase of the fall, i.e., muscle activation, which currently is not accounted for (Figure 8.8). Therefore, future work should include an optimisation procedure for active (dynamic) response in the ground impact phase. The specific movements and forces generated during a fall will depend on a variety of factors, including the height and speed of the fall, the surface on which the person lands, and the physical characteristics of the individual. Therefore future work should also include the reconstruction of a wider variety of fall cases.

9.5 Summary list of priorities

- **Targeting & treating risk:**

1. Cycling safety is an emerging road safety issue for Ireland.
2. For monitoring progress towards achieving zero fatalities on our roads (Vision Zero), work is needed to improve data coverage for cyclist collisions.
3. Towards implementing a Safe System on our roads, traffic conflict studies should also be considered for proactively targeting and treating risk factors.

- **Cyclist-motorised vehicle collisions:**

1. Cyclist fatalities and serious injuries in rural environments are commonly a result of failed overtaking/passing manoeuvres.
2. Cyclist fatalities and serious injuries in urban environments are commonly a result of collisions with heavy goods vehicles.
3. Nearside-hooks and dooring impacts are common in urban environments, and often go unreported to the police.
4. To effectively address these cases, a wide range of preventive measures are required. Nonetheless, a combination of vehicle speed reduction strategies and segregated infrastructure provision should be prioritised.

- **Single cyclist collisions:**

1. Single cyclist collisions are common, and often go unreported to the police.
2. Slippery roads, tram tracks, kerbs, and potholes are common contributory factors.
3. Video-based monitoring technologies could play an important role for proactive assessment of safety risks.
4. It is important to implement evidence-based design standards that take into account the risks associated with single cyclist collisions.

Chapter 10

Conclusions

The phenomenon of police underreporting for cyclist collisions leads to an underestimation of their economic burden in Ireland. The results of chapter 3 demonstrate that fatal and serious injury collisions may be well monitored with a combination of police and hospital data, however, self-reporting is highlighted as an important data source for minor injuries. Just over half of cyclist collisions reported to the survey were with a motorised vehicle, and this proportion holds even for serious injuries. Single cyclist collisions accounted for roughly a third of the total, and only a small proportion of these were reported to the police. This suggests that police-based statistics on the burden of cyclist collisions in Ireland are biased towards those involving motorised vehicles, and policymakers should also be aware of the considerable share of single cyclist collisions. Less severe injuries have also been shown to be underreported, and to contribute to the safety problem to a far greater degree than observed in police statistics.

Findings from chapter 4 indicate that current and proposed ADAS systems and type-testing protocols may adequately address many lower severity and non-injurious collisions. However, findings indicate that priorities for pre-crash scenarios and impact configurations

shift with the inclusion of lower severity collisions. This study highlights the relative importance of collisions resulting from the cyclist and vehicle travelling in the same direction, specifically, nearside-hook, vehicle lane changing, and overtaking manoeuvres are emphasised. Furthermore, cases involving the cyclist struck from the side by vehicle fronts comprise a smaller share than previous studies; specifically, impacts with the sides of vehicles, and dooring impacts emerge as important impact configurations with the inclusion of self-reported collisions.

Findings from chapter 5 emphasise the prevalence of 1) left-turning HGVs, and 2) overtaking manoeuvres from bonnet-type vehicles for fatal and serious cyclist collisions in Ireland. Future countermeasures and test protocols should address these pre-crash scenarios and impact scenarios. Furthermore, findings show that single cyclist collisions are an important component of both serious and fatal cycling cases, and that non-traditional impact configurations require further consideration.

Findings from chapter 4 for single cyclist collisions highlight the importance of loss of traction of the tires due to slippery road conditions, and interactions with tram tracks, kerbs, and potholes. Findings indicate that common collision scenarios vary between countries and cycling environments, however, the coding scheme devised here for single cyclist collisions can act as a basis for identifying common collision scenarios in other countries.

Prompted by findings in chapter 4, the analysis in chapter 6 focuses on cyclist-tram track interactions in wet road conditions as a common and safety-critical edge case. Actionable site-specific safety issues at locations in Dublin city centre are highlighted, and model the risk of unsuccessful crossing by crossing angle. As evident by the prevalence of external factors limiting crossing angle (e.g., kerbs, other road users), personal responsibility/educational campaigns targeted towards cyclists are unlikely to address the majority of falls on tracks. In the context of the Safe System approach, these findings imply the need for bolstered data

collection regimes in urban environments, and engineering interventions to facilitate safe crossing angles. The use of the SMoS algorithm developed in this study can help achieve these goals, and an open-source application is provided for this purpose (SafeCross).

In chapters 7, and 8 a novel pipeline is presented for the reconstruction of cyclist falls from monocular footage with the inclusion of kinematic protective response. This approach can be applied to a variety of impact biomechanics tasks not limited to cyclist falls. Furthermore, common kinematic forms for sideways falls in single cyclist collisions are characterised. Findings from this study indicate that the limbs are used to prevent falls, or break falls by absorbing impact energy and protecting the head. The kinematic forms characterised in this study can be used to inform initial conditions for computational modelling and injury estimation in single cyclist falls.

Overall, the findings of this thesis have important implications for improving cyclist safety in Ireland and can benefit policymakers, researchers, and engineers working towards safer cycling environments. Additionally, the methodologies developed here can help identify safety issues and inform engineering interventions for improved cyclist safety.

Appendix A

A.1 Nomenclature & definitions

Table A.1: Nomenclature and definitions.

Nomenclature	Definition	Reference
SCC	Collisions where a cyclist falls or is injured in which no other road user/in-use vehicle is made contact with, either by the cyclist themselves or the bicycle e.g. collision with obstacle, skidding out on a wet road surface, collision with a kerb due to an avoidance manoeuvre etc.	
MVC	Collisions in which contact is made between a cyclist/bicycle and an in-use motorised vehicle	
CCC	Collisions in which contact is made between a cyclist/bicycle and another cyclist/in-use bicycle.	
CPC	Collisions in which contact is made between a cyclist/bicycle and a pedestrian.	Similar to Schepers et al. (2012) [44] and Hertach et al. (2018) [43]
Unreported Collision	A collision which was neither reported by the cyclist to the Police at the scene nor subsequently.	NA
Minor Injury	An injury of a minor character such as a sprain or bruise.	
Serious Injury	An injury for which the person is detained in hospital as an 'in-patient', or any of the following injuries whether or not detained in hospital: fractures, concussion, internal injuries, crushing's, severe cuts and lacerations, severe general shock requiring medical treatment.	Ireland and the UK [209]

A.2 Survey flowchart

A.3 Locations of survey respondents



Figure A.2: Survey respondent numbers by county ($N = 2,509$), compared to census data for commuting cyclists in the Republic of Ireland in 2016 ($N = 82,123$) (in parentheses: ‘()’), and Cycling Ireland’s membership in 2017 ($N = 21,470$) (in square brackets: ‘[]’).

A.4 Modelling results

Table A.2: Pooled results of 30 imputations for the binary logistic regression on Police reporting.

Variables in the equation	β	S.E.	Sig.	Fraction Missing Info.	Relative Increase Variance	Relative Efficiency
Sex: (ref: Male)						
Female	-.245	.244	.314	.007	.007	1.000
Age	.016	.010	.104	.038	.039	.999
Locus familiarity: (ref: Familiar)						
Unfamiliar	-.445	.661	.501	.007	.007	1.000
Setting: (ref: Urban)						
Rural	-.630	.433	.146	.027	.027	.999
Day: (ref: Weekday)						
Weekend	.025	.333	.941	.031	.032	.999
Time: (ref: 18:00 to 24:00)						
00:00 to 06:00	.653	.659	.322	.009	.009	1.000
06:00 to 12:00	.013	.296	.964	.025	.026	.999
12:00 to 18:00	-.487	.322	.131	.020	.020	.999
Trip purpose: (ref: Leisure/Training/Racing)						
Commuting/Utility/Work trip	-.131	.335	.696	.022	.022	.999
Location: (ref: County Dublin)						
Rest of Ireland	.800	.301	.008	.046	.048	.998
Collision Type: (ref: MVC)						
Single Cyclist Collision (SCC)	2.991	.375	.000	.005	.005	1.000
Cyclist – Cyclist Collision (CCC)	2.281	.536	.000	.006	.006	1.000
Cyclist – Pedestrian Collision (CPC)	1.416	.523	.007	.009	.009	1.000
Injury Severity: (ref: Serious injury)						
No injury	3.194	.318	.000	.020	.021	.999
Minor injury	1.942	.276	.000	.017	.017	.999
Constant	.544	.592	.358	.032	.032	.999

Appendix B

B.1 Taxonomy for collisions with bonnet-type vehicles

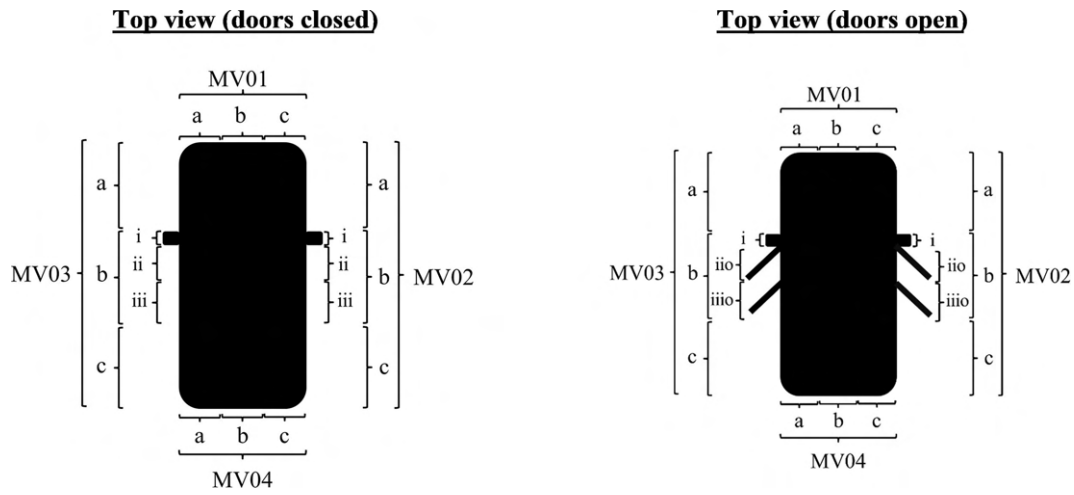


Figure B.1: Impact location map used in coding impacts with bonnet-type vehicles for both door closed and door open situations.

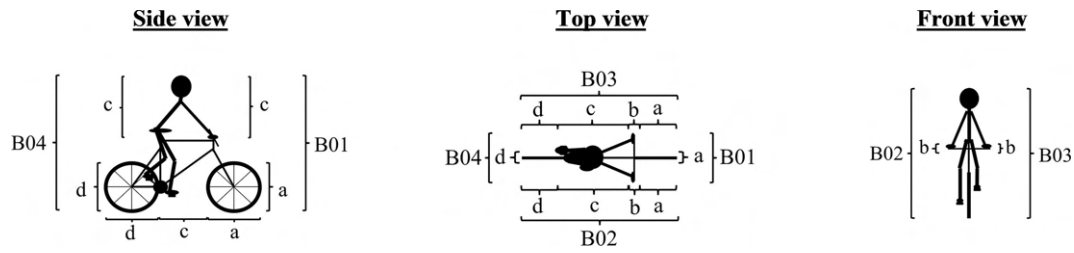


Figure B.2: Impact location map used for cyclists/bicycles.

Table B.1: Traffic environment and pre-crash scenario coding scheme used in cyclist-motorised vehicle collisions with bonnet-type vehicles.

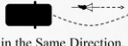
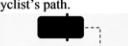
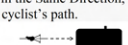
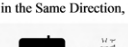
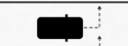
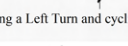
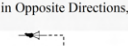
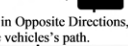
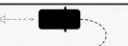
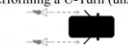
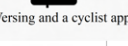
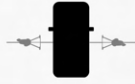
Same directions of travel scenarios, 237, 51%					
Code, N, %	Representative diagram and description		Code, N, %	Representative diagram and description	
OT/SD 38, 8%			CL/SD 50, 11%		
LT/SD 88, 19%			SD/CL 18, 4%		
RT/SD 1, 0%			SD/SS 4, 1%		
SS/SD 6, 1%			BR/SD 10, 2%		
SD/BR 1, 0%			UT/SD 5, 1%		
SD 16, 3%					
Lateral directions of travel scenarios, 113, 25%					
Code, N, %	Representative diagram and description		Code, N, %	Representative diagram and description	
LT/RD 36, 8%			RT/RD 27, 6%		
SCP/RD 34, 7%			LT/LD 1, 0%		
SCP/LD 5, 1%			SCP 10, 2%		
Opposing directions of travel scenarios, 44, 10%					
Code, N, %	Representative diagram and description		Code, N, %	Representative diagram and description	
UT/OD 4, 1%			RT/OD 36, 8%		
OD/RT 1, 0%			OD 2, 0%		
CL/OD 1, 0%					
Other scenarios, 67, 15%					
Code, N, %	Representative diagram and description		Code, N, %	Representative diagram and description	
UT 1, 0%			CLP 2, 0%		
D 56, 12%			RV/SD 1, 0%		
RV/RD 1, 0%			RV/LD 5, 1%		
RV 1, 0%					

Table B.2: Coding of general impact configurations.

Impact configuration	Collision configuration code		Representative diagram
	Striking body	Struck body	
Side-MV	B01 ^a	MV02 ^a or MV03 ^a	
Side-Cyclist	MV01 ^a	B02 ^a or B03 ^a	
Rear-MV	B01 ^a	MV04 ^a	
Rear-Cyclist	MV01 ^a	B04 ^a	
Side-Side	MV02 ^a or MV03 ^a	B02 ^a or B03 ^a	
Dooring (-Nearside/-Offside)	B01 ^a or B02 ^a or B03 ^a	MV03biiio or MV03biiio or MV02biiio or MV02biiio	
Head on	MV01 ^a or B01 ^a	B01 ^a or MV01 ^a	

a: including sub locations

B.2 Taxonomy for single cyclist collisions

Table B.3: Coding of direct causes for single cyclist collisions.

1 Infrastructure related:	
a	Preceded by the cyclist inadvertently taking a dangerous riding line:
i	Colliding with an obstacle on the roadway designed and built by road authorities, such as a road narrowing or bollard on the bicycle track to prevent cars from entering, and parked vehicles.
ii	Riding off the road and colliding with a kerb or off-road obstacle.
b	Linked to road surface quality:
i	Skidding due to a slippery road surface.
ii	loss of control due to an uneven road-surface (e.g. a pothole or damage from tree roots) or a loose object on the road surface (e.g. a branch).
2 Road user related:	
a	At low speed when it requires more effort to stabilise the bicycle, e.g. (dis)mounting.
b	Due to something becoming lodged in or hitting the front wheel. e.g. baggage
c	Road user behaviour:
i	Cyclist taking an abrupt or adventitious steering/braking avoidance manoeuvre.
ii	Cyclist making a braking mistake.
iii	Cyclist making a turning mistake.
iv	Cyclist doing a stunt/trick.
v	Cycling too fast for the conditions
d	Cyclist boxed in by traffic
3 Bicycle malfunction, e.g. chain break, broken part of the frame, etc.	
4 Other, or no recall.	

Table B.4: Pre-crash scenario coding scheme used in single cyclist collisions.

Coding Scheme for pre-crash scenarios of single cyclist collisions			
rank	N, %		rank N, %
1	52, 19%	Iai: Colliding with an obstacle on the roadway (deliberately) designed and build by road authorities.	
		N, %	
		29, 56%	TT/C: Crossing Tram Tracks.
		10, 19%	TT: Interacting with Tram Tracks (manoeuvre unknown).
		5, 10%	TT/S: Cycling Straight alongside Tram Tracks.
		3, 6%	MD: Cycling over a Manhole cover/Drain.
		2, 4%	SB: Cycling over a Speed Bump.
		1, 2%	PO: Cycling into a POle.
		1, 2%	RT/C: Crossing Railway Tracks.
		1, 2%	BO: Cycling into a BOllard.
3	30, 11%	Iaii: Riding off the road and colliding with a kerb or an off-road obstacle.	
		N, %	
		10, 33%	K/EXC: Clipping or cycling over a Kerb while EXiting the main road and entering a Cycle lane from the main roadway.
		7, 23%	K/T: Clipping or cycling over a Kerb while Turning around a bend.
		4, 13%	K/EX: Clipping or cycling over a Kerb while EXiting the roadway.
		3, 10%	K: Clipping or cycling over a Kerb (other/unspecified).
		2, 7%	K/S: Clipping or cycling over a Kerb while travelling Straight.
		2, 7%	PO: Cycling into a POle.
		1, 3%	WG: Cycling into a Wall/Gate.
		1, 3%	CB: Cycling into a Concrete Block.
5	23, 8%	Iai & Ibi: Colliding with an obstacle on the roadway (deliberately) designed and build by road authorities, and loss of traction due to the road surface conditions.	
		N, %	
		8, 35%	WTT/C: Crossing Wet Tram Tracks.
		6, 26%	WMD: Cycling over a Wet Manhole cover/Drain.
		3, 13%	WRT/C: Crossing Wet Railway Tracks.
		2, 9%	WTT/S: Cycling Straight alongside Wet Tram Tracks.
		2, 9%	WTT: Interacting with Wet Tram Tracks (manoeuvre unknown).
		1, 4%	ITT/C: Crossing Icy/frosty Tram Tracks.
		1, 4%	WSB: Cycling over a Wet Speed Bump.
7	20, 7%	2ci: Involving an abrupt or adventitious steering/braking avoidance manoeuvre.	
		N, %	
		9, 45%	AB/AVVM: Abrupt Braking manoeuvre to AVoid a Moving Vehicle.
		5, 25%	AB/AVP: Abrupt Braking manoeuvre to AVoid a Pedestrian.
		2, 10%	AB/AVB: Abrupt Braking manoeuvre to AVoid a Bicycle rider(s).
		2, 10%	AVVM: Manoeuvre to AVoid a Moving Vehicle.
		1, 5%	AT/AVVM: Abrupt Turning manoeuvre to AVoid a Moving Vehicle.
		1, 5%	AVVP: Manoeuvre to AVoid a Parked Vehicle.
9	7, 3%	Ibi & 2ci: Involving an abrupt or adventitious steering/braking avoidance manoeuvre, and loss of traction due to the road surface conditions.	
		N, %	
		2, 29%	WR/AVVM: Taking an AVoidancemanoeuvre from a Moving Vehicle on a Wet Road.
		2, 29%	IR/AVVM: Taking an AVoidancemanoeuvre from a Moving Vehicle on an Icy/frosty Road.
		1, 14%	MR/AVVM: Taking an AVoidancemanoeuvre from a Moving Vehicle on a Muddy Road.
		1, 14%	IR/AVPH: Taking an AVoidancemanoeuvre from a PotHole on an Icy/frosty Road.
		1, 14%	MR/AVB: Taking an AVoidancemanoeuvre from another Bicycle rider(s) on a Muddy
2	43, 16%	Ibi: Loss of traction due to the road surface conditions.	
		N, %	
		7, 16%	WR/T: Turning on a Wet Road.
		6, 14%	WRM/T: Turning on Wet Road Markings.
		6, 14%	IR: Cycling on an Icy Road.
		4, 9%	IR/T: Turning on an Icy Road .
		4, 9%	WR: Cycling on a Wet Road .
		3, 7%	IR/B: Braking on an Icy Road .
		2, 5%	G/T: Turning on a road surface with Gravel on it.
		2, 5%	WRM: Cycling on Wet Road Markings.
		2, 5%	OR/T: Turning on a road surface with Oil on it.
		1, 2%	OR/B: Braking on a road surface with Oil on it.
		1, 2%	RS/B: Braking on an road with other waste on it.
		1, 2%	WR/B: Braking on a Wet Road.
		1, 2%	G: Cycling forward on a road with Gravel on the surface.
		1, 2%	RM/T: Turning on Road Markings.
		1, 2%	MR/T: Turning on a Muddy Road surface.
		1, 2%	IRM/T: Turning on Icy Road Markings.
3	30, 11%	Iaii & 2ci: Riding off the road and colliding with a kerb or off-road obstacle, involving an abrupt or adventitious steering/braking avoidance manoeuvre.	
		N, %	
		16, 53%	K/AVVM: Clipping or cycling over a Kerb while AVoiding a Moving Vehicle.
		3, 10%	K/AVP: Clipping or cycling over a Kerb while AVoiding a Pedestrian.
		3, 10%	WG/AVP: Cycling into a Wall/Gate afterAVoiding a Pedestrian.
		2, 7%	K/AVVP: Clipping or cycling over a Kerb while AVoiding a Parked Vehicle.
		1, 3%	K/AVB: Clipping or cycling over a Kerb while AVoiding other Bicycle rider(s).
		1, 3%	D/AVA: Cycling into a Ditch after AVoiding an Animal.
		1, 3%	WG/AVVM: Cycling into a Wall/Gate after AVoiding a Moving Vehicle.
		1, 3%	D/AVVM: Cycling into a Ditch after AVoiding a Moving Vehicle.
		1, 3%	CB/AVP: Cycling into a Concrete Block after AVoiding a Pedestrian.
		1, 3%	MD/AVVM: Cycling over a Manhole cover/Drain while AVoiding a Moving Vehicle.
6	22, 8%	Ibii: loss of control due to an uneven road-surface, or a loose object on the road surface.	
		N, %	
		9, 43%	PH: Cycling into a PotHole.
		4, 19%	PH/SM: Cycling into a SubMerged PotHole.
		3, 14%	ST: Cycling into a STone.
		1, 5%	TB: Cycling into a Tree Branch.
		1, 5%	R: Cycling into a Rope.
		1, 5%	HP: Cycling into a Hose Pipe.
		1, 5%	BB: Cycling into a Bin Bag.
		1, 5%	UD: Cycling into Unknown Debris on the road.
		1, 5%	WB: Cycling into a Water/drinking Bottle.
8	8, 3%	Iai & 2ci: Involving an abrupt or adventitious steering/braking avoidance manoeuvre, and colliding with an obstacle on the roadway (deliberately) designed and build by road authorities.	
		N, %	
		3, 38%	TT/AVVM: Interacting with Tram Tracks after taking an AVoidance manoeuvre from a Moving Vehicle.
		1, 13%	AVMD: Taking an AVoidance manoeuvre from a Manhole cover/Drain.
		1, 13%	AVGL: Taking an AVoidance manoeuvre from broken GLass on the road.
		1, 13%	PV/AVVM: Colliding with a Parked Vehicle after taking an AVoidance manoeuvre from a Moving Vehicle.
		1, 13%	RT/AVVM: Interacting with Railway Tracks after taking an AVoidance manoeuvre from a Moving Vehicle.
		1, 13%	TT/AVP: Interacting with Tram Tracks after taking an AVoidance manoeuvre from a Pedestrian.
10	6, 2%	Iaii & Ibi: Riding off the road and colliding with a kerb or off-road obstacle, and loss of traction due to the road surface conditions.	
		N, %	
		3, 50%	WK/EX: Clipping or cycling over a Wet Kerb while EXiting the main roadway.
		1, 17%	GK/EXC: Clipping or cycling over a Kerb with Gravel while EXiting the main roadway and entering a Cycle lane from the main roadway.
		1, 17%	IK/EXC: Clipping or cycling over an Icy Kerb while EXiting the main roadway and entering a Cycle lane from the main roadway.
		1, 17%	WLK: Clipping or cycling over a Kerb with Wet Leaves on the surface.

Cont...

10 6, 2% 3: Bicycle malfunction. N, % 2, 33% BM/P: Bicycle Malfunction: Puncture. 1, 17% BM/S: Bicycle Malfunction: broken handlebar Stem. 1, 17% BM/G: Bicycle Malfunction: slipped Gear chain. 1, 17% BM/MG: Bicycle Malfunction: broken MudGuard. 1, 17% BM/B: Bicycle Malfunction: non-functioning Brakes.	12 4, 1% 1bii & 2d: Cyclist boxed in by traffic, and loss of control due to an uneven road-surface, or a loose object on the road surface. N, % 4, 100% PH/BI: Cyclist Boxed In by a vehicle, resulting in cycling into a PotHole.
13 3, 1% 1bi & 2cv: Loss of traction due to the road surface conditions, while cycling too fast for the conditions. N, % 2, 67% WR/TF: Turning on a Wet Road, while travelling too Fast for the conditions. 1, 33% WRM/TF: Turning on Wet RoadMarkings, while travelling too Fast for the conditions.	14 2, 1% 2b: Due to something becoming lodged or hitting the front wheel. N, % 1, 50% B/FW: Bag becoming lodged in the Front Wheel. 1, 50% J/FW: Jacket becoming lodged in the Front Wheel
14 2, 1% 1aii & 2d: Cyclist boxed in by traffic, and riding off the road and colliding with a kerb or off-road obstacle. N, % 2, 100% K/BI: Cycling over a Kerb, due to being Boxed In.	14 2, 1% 1ai & 2d: Cyclist boxed in by traffic, and colliding with an obstacle on the roadway (deliberately designed and build by road authorities). N, % 1, 50% CE/BI: Cycling into a Cat's Eye due to being Boxed In. 1, 50% TT/BI: Interacting with Tram Tracks due to being Boxed In.
14 2, 1% 2ciii: Cyclist making a turning mistake. N, % 2, 100% LC/T: Lost Control of the bicycle when taking a Turn too fast.	14 2, 1% 1bii & 2ci: Involving an abrupt or adventitious steering/braking avoidance manoeuvre, and loss of control due to an uneven road-surface, or a loose object on the road surface. N, % 1, 50% AVPH: AVoiding a PotHole. 1, 50% PH/AVVM: Cycling into a PotHole after taking an AVoidance manoeuvre from a Moving Vehicle.
19 1, 0% 1bi & 2a: Loss of traction due to the road surface conditions, at a low speed. N, % 1, 100% G/D: Dismounting on a road surface with Gravel on it.	19 1, 0% 2cii: Cyclist making a braking mistake. N, % 1, 100% OH/B: Braking with One Hand on the handlebar.
19 1, 0% 2civ: Cyclist doing a stunt/trick. N, % 1, 100% STNT: Doing a STuNT on the bicycle.	4, 1% 4: Other. N, % 3, 75% A: Cycling into an Animal. 1, 25% W: Lost control due to strong Wind.

Note: The total number of SCCs included in this analysis is 295 (as opposed to 298 reported in Gildea and Simms (2021)), this is because 3 were excluded due to substantially incomplete responses on page 6.

Appendix C

C.1 Single cyclist collisions

Table C.1 shows direct causes for single cyclist collisions (based on indications in the investigation file), with the inclusion of those resulting in a secondary impact with a vehicle. This coding scheme is detailed in Table B.3. Direct causes are frequently multifactorial, with more than 1 direct cause (N=6, 30%), and a large share of cases involved the cyclist colliding with an obstacle on the roadway designed and build by road authorities (1ai) (N=5, 25%).

Table C.1: Direct causes for single cyclist collisions (including those involving secondary impact with a vehicle).

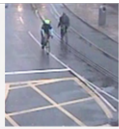
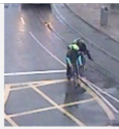
	Serious		Fatal		Total	
	N	%	N	%	N	%
1 direct cause						
1ai	1 ^a	13%	2 ^a	17%	3	15%
1aii	0	0%	1	8%	1	5%
1bi	0	0%	1 ^a	8%	1	5%
1bii	1	13%	0	0%	1	5%
2b	0	0%	1	8%	1	5%
2ci	1	13%	1	8%	2	10%
2cii	1	13%	0	0%	1	5%
2cv	0	0%	1 ^a	8%	1	5%
3	0	0%	1	8%	1	5%
4	0	0%	1	8%	1	5%
2 direct causes						
1ai & 1bi	1	13%	0	0%	1	5%
1ai & 2ciii	1	13%	0	0%	1	5%
2cv & 4	0	0%	1	8%	1	5%
1aii & 2ciii	1	13%	0	0%	1	5%
1bi & 2cii	0	0%	1	8%	1	5%
1bii & 2ciii	1	13%	0	0%	1	5%
Unknown	0	0%	1	8%	1	5%

a: one case in this cell involved a secondary impact with a vehicle

Appendix D

D.2 Unsuccessful crossings

Table D.1: All UCs noted in this study.

Case 1 • Camera 1 • Cat 3.			
Case 2 • Camera 3 • Cat 2.			
Case 3 • Camera 5 • Cat 2.			
Case 4 • Camera 7 • Cat 2.			
Case 5 • Camera 7 • Cat 2.			
Case 6 • Camera 7 • Cat 3.			
Case 7 • Camera 7 • Cat 1.			
Case 8 • Camera 7 • Cat 1.			

Cont...

Case 9

- Camera 7
- Cat 3.

**Case 10**

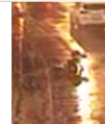
- Camera 7
- Cat 1.

**Case 11**

- Camera 7
- Cat 2.

**Case 12**

- Camera 8
- Cat 3.

**Case 13**

- Camera 9
- Cat 1.



D.3 Predictive modelling results

Table D.2: Results for regression model (a).

	β	S.E	Wald	df	Sig.	Exp(β)	95% C.I.for Exp(β)	
							Lower	Upper
Crossing angle	.489	.215	5.152	1	.023	1.630	1.069	2.486
Velocity	.671	.745	.812	1	.368	1.957	.454	8.431
Constant	-9.621	5.804	2.748	1	.097	.000		

Table D.3: Results for regression model (b).

	β	S.E	Wald	df	Sig.	Exp(β)	95% C.I.for Exp(β)	
							Lower	Upper
Crossing angle	.405	.161	6.328	1	.012	1.500	1.094	2.057
Constant	-5.317	2.478	4.605	1	.032	.005		

Table D.4: Results for regression model (c).

	β	S.E	Wald	df	Sig.	Exp(β)	95% C.I.for Exp(β)	
							Lower	Upper
EW	-.043	.014	9.949	1	.002	.958	.932	.984
Constant	8.294	2.170	14.608	1	.000132	4000.460198		

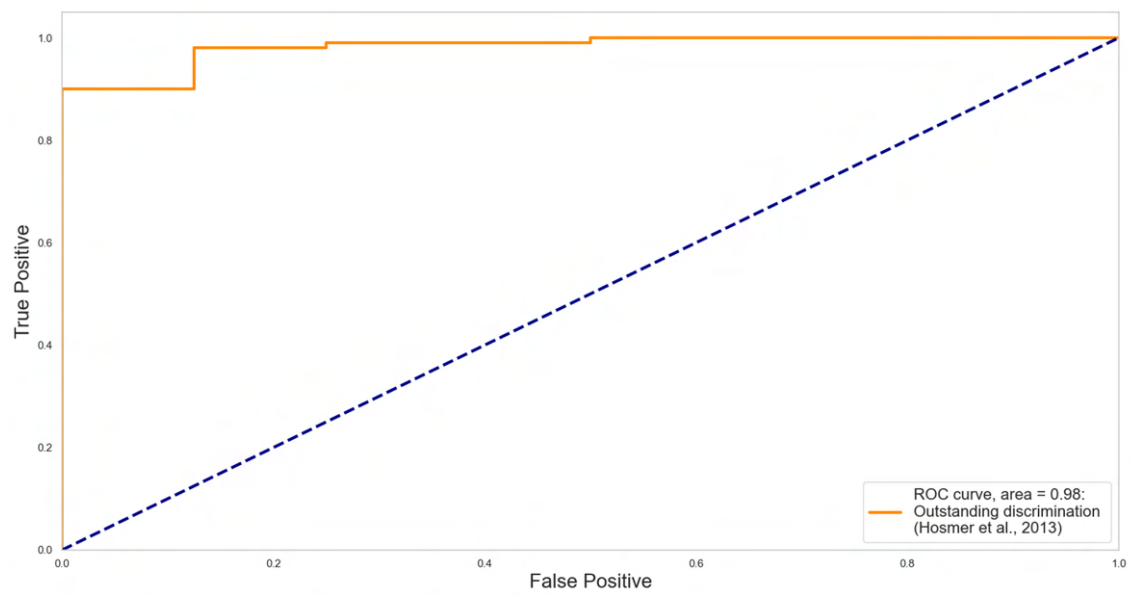


Figure D.2: Receiver Operating Characteristic (ROC) curve for model (b).

Appendix E

E.1 Boundary cases for twist angle ambiguity

Here we investigate how the IK algorithms handle twist angle ambiguity in boundary cases with extended/straight limbs (co-linear sequential links). This is demonstrated for two 15-frame motion sequences involving a phase of bent limbs, and fully extended limbs:

Case 1: Bent limbs (frames 1-11) $\rightarrow$ Extended limbs (frames 13-15)

Case 2: Extended limbs (frames 1-3) $\rightarrow$ Bent limbs (frames 4-15)

Case 1 $MPJAS_1$ errors for limb joints in the motion sequence are shown in Figure E.1. Note that 1_a results in the highest errors when limbs are extended, and improvements are achieved by 1_b , 2_3 , and 2_5 .

Case 2 results are shown in Figure E.2. 1_a , 1_b , and 2_3 result in high errors when limbs are extended, and improvements are only achieved by 2_5 . 1_b fails in this case because there are no preceding frames with bent limbs to use as initialisation. The accuracy of 2_3 is generally lower than 2_5 in this case because its initial batch does not include frames with bent limbs, with lower peak errors throughout.

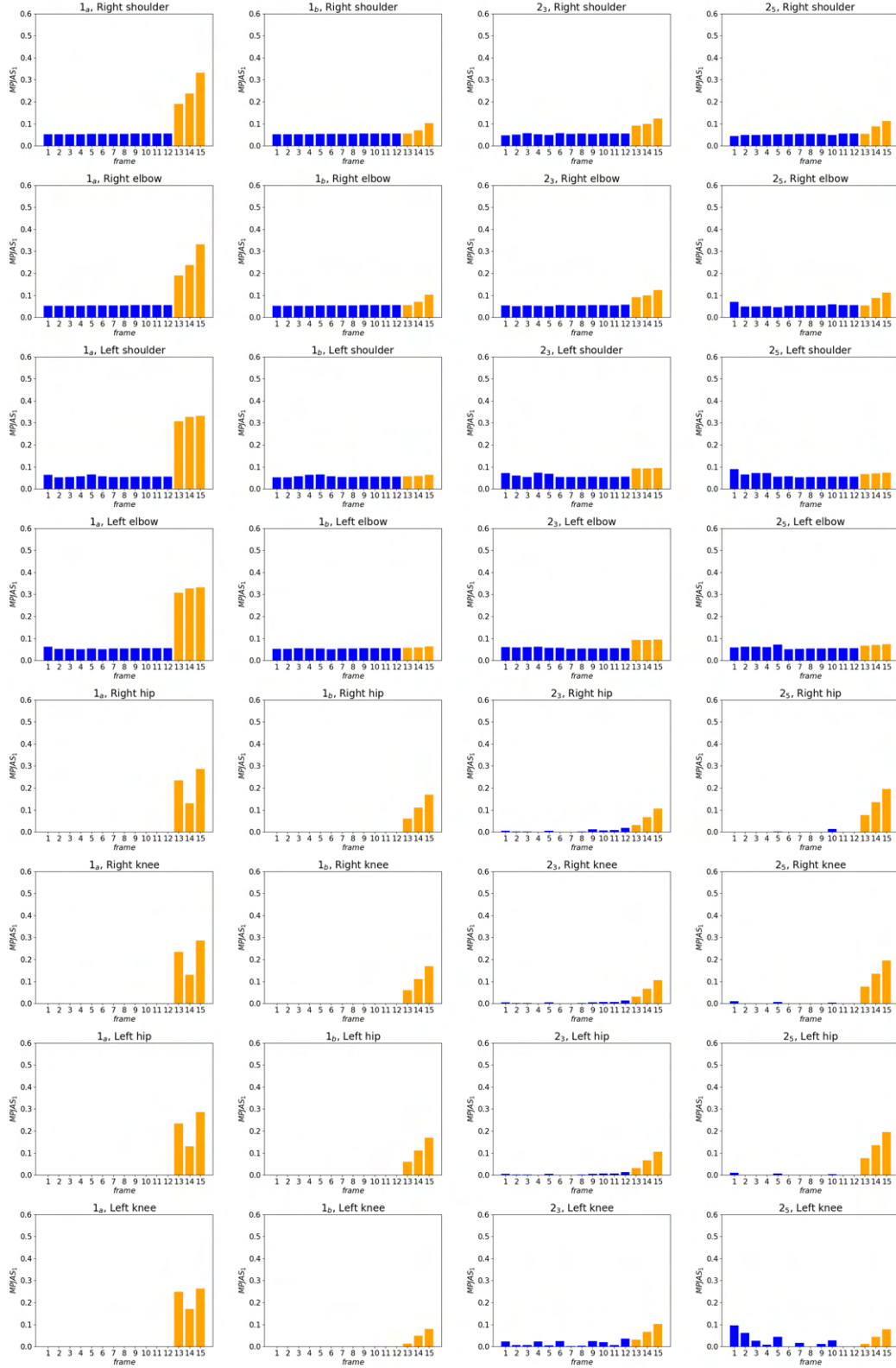


Figure E.1: $MPJAS_1$ errors for limb joints in a 15-frame motion sequence involving an initial phase of bent limbs (blue), followed by a phase extended limbs (orange) (mean values over 10 IK runs).



Figure E.2: $MPJAS_1$ errors for limb joints in a 15-frame motion sequence involving an initial phase of extended limbs (orange), followed by a phase bent limbs (blue) (mean values over 10 IK runs).

E.2 Convergence to local minimum

Convergence of local optimisation methods depends on the initial guess. Since IK algorithms feed optimised parameters from previous frames, having an initial guess closer to the target pose may be beneficial. Therefore, in practical applications, the subject may initially adopt a pose similar to the rest pose. Alternatively, the initial guess (i.e., Θ_0 in Algorithm 1) for model parameters could be defined closer to the target pose. For this, we include a tool for manual setting of the initial guess (Figure E.3).

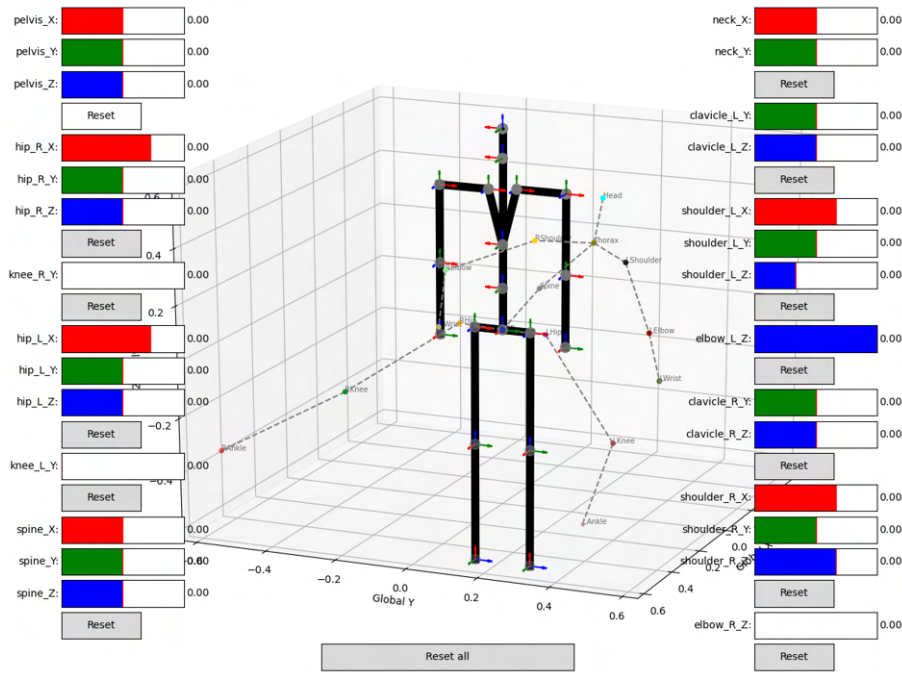


Figure E.3: Optional tool for manual setting of the initial guess for model parameters in frame 1.

Bibliography

- [1] World Health Organisation, “Global status report on road safety 2018,” tech. rep., 2018.
- [2] Road Safety Authority, “Road Collision Factbook, 2013,” tech. rep., 2016.
- [3] K. E. Björnberg, S. O. Hansson, M. Åke Belin, and C. Tingvall, *The Vision Zero Handbook: Theory, Technology and Management for a Zero Casualty Policy*. Springer Nature, 2023.
- [4] Road Safety Authority, “Road Safety Strategy 2021-2030,” tech. rep., 2021.
- [5] International Transport Forum, “Zero Road Deaths and Serious Injuries Leading a Paradigm Shift to a Safe System,” tech. rep., OECD, 2016.
- [6] International Transport Forum, “Cycling, Health and Safety,” 2013.
- [7] N. Cavill, S. Kahlmeier, H. Rutter, F. Racioppi, and P. Oja, “Economic Assessment of Transport Infrastructure and Policies. Methodological guidance on the economic appraisal of health effects related to walking and cycling The WHO Regional Office for Europe,” tech. rep., World Health Organisation, 2007.
- [8] Department of Health, “A Healthy Weight For Ireland, Obesity Policy and Action Plan 2016 - 2025,” tech. rep., Department of Health, 2016.

- [9] McKinsey Global Institute, “Overcoming obesity, An initial economic analysis,” tech. rep., McKinsey Global Institute, 2014.
- [10] Climate Action Network, “Off target: Ranking of EU countries’ ambition and progress in fighting climate change,” tech. rep., Climate Action Network, Brussels, 2018.
- [11] Government of Ireland, “Climate action plan 2021,” tech. rep., 2021.
- [12] Central Statistics Office, “StatBank - Profile 6 - Commuting in Ireland - E6010,” 2016.
- [13] C. Brand, E. Dons, E. Anaya-Boig, I. Avila-Palencia, A. Clark, A. de Nazelle, M. Gascon, M. Gaupp-Berghausen, R. Gerike, T. Götschi, F. Iacorossi, S. Kahlmeier, M. Laere-mans, M. J. Nieuwenhuijsen, J. Pablo Orjuela, F. Racioppi, E. Raser, D. Rojas-Rueda, A. Standaert, E. Stigell, S. Sulikova, S. Wegener, and L. Int Panis, “The climate change mitigation effects of daily active travel in cities,” *Transportation Research Part D: Transport and Environment*, vol. 93, p. 102764, apr 2021.
- [14] Department of Transport Tourism and Sport, “Ireland’s First National Cycle Policy Framework,” tech. rep., Department of Transport Tourism and Sport, 2009.
- [15] A. R. Lawson, V. Pakrashi, B. Ghosh, and W. Szeto, “Perception of safety of cyclists in Dublin City,” *Accident Analysis & Prevention*, vol. 50, pp. 499–511, jan 2013.
- [16] Department of Transport Tourism and Sport, “The Design Manual for Urban Roads & Streets (DMURS),” tech. rep., 2013.
- [17] Department of Transport, “NGS Circular 3 of 2022.” 2022.
- [18] European Commission, “Towards a european road safety area: policy orientations on road safety 2011-2020,” 2010.

-
- [19] European Commission, *Next steps towards ‘Vision Zero’ : EU road safety policy framework 2021-2030*. Publications Office, 2020.
 - [20] European Transport Safety Council, “Ranking EU progress on road safety, 13th Road Safety Performance Index Report,” tech. rep., 2019.
 - [21] European Transport Safety Council, “How safe is walking and cycling in Europe?,” tech. rep., European Transport Safety Council, 2020.
 - [22] Road Safety Authority, “Road Casualties and Collisions in Ireland 2018,” tech. rep., 2020.
 - [23] Road Safety Authority, “Cyclist Injury Trends 2006-2018: With an in-depth review of 2016,” tech. rep., 2020.
 - [24] Road Safety Authority, “Cyclist Injuries, A Review of 2012 Casualties,” tech. rep., Road Safety Authority, 2014.
 - [25] Road Safety Authority, “Pedal Cyclists Road Casualties,” tech. rep., Road Safety Authority, 2010.
 - [26] J. Short and B. Caulfield, “The safety challenge of increased cycling,” *Transport Policy*, vol. 33, pp. 154–165, may 2014.
 - [27] Department for Transport, “Reported Road Casualties Great Britain: 2016 Annual Report,” tech. rep., 2017.
 - [28] T. Madsen, A. Várhelyi, E. Polders, S. Reumers, P. Hosta, D. J. Bibiloni, A. Ramellini, N. Agerholm, and H. Lahrmann, “Assessment of Safety of VRUs Based on Self-Reporting of Accidents and Near-Accidents,” tech. rep., InDeV: In-Depth understanding of accident causation for Vulnerable road users, 2018.

- [29] M. Rizzi, H. Stigson, and M. Krafft, “Cyclist Injuries Leading to Permanent Medical Impairment in Sweden and the Effect of Bicycle Helmets,” in *International Research Council on Biomechanics of Injury Europe (IRCOBI Europe)*, pp. 412–423, 2013.
- [30] D. Shinar, P. Valero-Mora, M. van Strijp-Houtenbos, N. Haworth, A. Schramm, G. De Bruyne, V. Cavallo, J. Chliaoutakis, J. Dias, O. Ferraro, A. Fyhri, A. H. Sajatovic, K. Kuklane, R. Ledesma, O. Mascarell, A. Morandi, M. Muser, D. Otte, M. Papadakaki, J. Sanmartín, D. Dulf, M. Saplioglu, and G. Tzamalouka, “Under-reporting bicycle accidents to police in the COST TU1101 international survey: Cross-country comparisons and associated factors,” *Accident Analysis & Prevention*, vol. 110, pp. 177–186, jan 2018.
- [31] A. Watson, B. Watson, and K. Vallmuur, “Estimating under-reporting of road crash injuries to police using multiple linked data collections,” *Accident Analysis & Prevention*, vol. 83, pp. 18–25, oct 2015.
- [32] D. Bedford, A. Sheridan, F. Howell, and N. McKeown, “Admission to acute hospitals for injuries as a result of road traffic collisions in Ireland,” tech. rep., 2011.
- [33] J. Foley, J. Cronin, A. Gheorghescu, D. Chetrit, D. Evoy, and J. Ryan, “Cycling Injuries Presenting to an Irish Emergency Department,” *Irish Medical Journal*, 2016.
- [34] B. de Geus, G. Vandenbulcke, L. Int Panis, I. Thomas, B. Degraeuwe, E. Cumps, J. Aertsens, R. Torfs, and R. Meeusen, “A prospective cohort study on minor accidents involving commuter cyclists in Belgium,” *Accident Analysis & Prevention*, vol. 45, pp. 683–693, mar 2012.
- [35] M. Salifu and W. Ackaah, “Under-reporting of road traffic crash data in Ghana,” *In-*

- ternational Journal of Injury Control and Safety Promotion*, vol. 19, pp. 331–339, dec 2012.
- [36] M. Hours, L. Chossegros, P. Charnay, H. Tardy, H. T. Nhac-Vu, D. Boisson, J. Luauté, and B. Laumon, “Outcomes one year after a road accident: Results from the ESPARR cohort,” *Accident Analysis & Prevention*, vol. 50, pp. 92–102, jan 2013.
- [37] R. Aldred and S. Crosweller, “Investigating the rates and impacts of near misses and related incidents among UK cyclists,” *Journal of Transport & Health*, vol. 2, pp. 379–393, sep 2015.
- [38] R. L. Sanders, “Perceived traffic risk for cyclists: The impact of near miss and collision experiences,” *Accident Analysis & Prevention*, vol. 75, pp. 26–34, 2015.
- [39] R. Elvik and T. Bjørnskau, “Safety-in-numbers: A systematic review and meta-analysis of evidence,” *Safety Science*, vol. 92, pp. 274–282, feb 2017.
- [40] M. Boele-Vos, K. Van Duijvenvoorde, M. Doumen, C. Duivenvoorden, W. Louwerse, and R. Davidse, “Crashes involving cyclists aged 50 and over in the Netherlands: An in-depth study,” *Accident Analysis & Prevention*, vol. 105, pp. 4–10, aug 2017.
- [41] C. Engbers, R. Dubbeldam, M. Brusse-Keizer, J. Buurke, D. de Waard, and J. Rietman, “Characteristics of older cyclists (65+) and factors associated with self-reported cycling accidents in the Netherlands,” *Transportation Research Part F: Traffic Psychology and Behaviour*, vol. 56, pp. 522–530, jul 2018.
- [42] K. C. Heesch, J. Garrard, and S. Sahlqvist, “Incidence, severity and correlates of bi-cycling injuries in a sample of cyclists in Queensland, Australia,” *Accident Analysis & Prevention*, vol. 43, pp. 2085–2092, nov 2011.

- [43] P. Hertach, A. Uhr, S. Niemann, and M. Cavegn, “Characteristics of single-vehicle crashes with e-bikes in Switzerland,” *Accident Analysis & Prevention*, vol. 117, pp. 232–238, aug 2018.
- [44] P. Schepers and K. K. Wolt, “Single-bicycle crash types and characteristics,” *Cycling Research International*, vol. 2, no. 1, pp. 119–135, 2012.
- [45] Tyréns, “Trafikutredning-Analys av Cykel-singelolyckor-enkätstudie och analys av resultaten Status: Slutrapport,” tech. rep., Gothenburg, 2013.
- [46] S. A. Useche, F. Alonso, L. Montoro, and C. Esteban, “Explaining self-reported traffic crashes of cyclists: An empirical study based on age and road risky behaviors,” *Safety Science*, vol. 113, pp. 105–114, mar 2019.
- [47] Road Safety Authority, “Fatal Collisions 2008-2012: Excessive speed as a factor,” tech. rep., 2016.
- [48] Road Safety Authority, “Fatal Collisions 2008-2012: Alcohol as a factor,” tech. rep., 2016.
- [49] Road Safety Authority, “Fatal Collisions 2008-2012: Motorcyclists,” tech. rep., 2016.
- [50] Road Safety Authority, “Fatal Collisions 2008-2012: Vehicle factors,” tech. rep., 2016.
- [51] C. Hydén, “The development of a method for traffic safety evaluation: The swedish traffic conflicts technique,” *Bulletin Lund Institute of Technology, Department*, no. 70, 1987.
- [52] A. Laureshyn, Åse Svensson, and C. Hydén, “Evaluation of traffic safety, based on micro-level behavioural data: Theoretical framework and first implementation,” *Accident Analysis & Prevention*, vol. 42, no. 6, pp. 1637–1646, 2010.

- [53] C. Johnsson, A. Laureshyn, and T. D. Ceunynck, “In search of surrogate safety indicators for vulnerable road users: a review of surrogate safety indicators,” *Transport Reviews*, vol. 38, no. 6, pp. 765–785, 2018.
- [54] M. Johnson, J. Charlton, J. Oxley, and S. Newstead, “Naturalistic Cycling Study: Identifying Risk Factors for On-Road Commuter Cyclists,” *Annals of Advances in Automotive Medicine / Annual Scientific Conference*, vol. 54, p. 275, 2010.
- [55] Z. Ling, C. R. Cherry, and N. Dhakal, “Factors influencing single-bicycle crashes at skewed railroad grade crossings,” *Journal of Transport & Health*, vol. 7, pp. 54–63, dec 2017.
- [56] J. Hayward, *Near Misses as a Measure of Safety at Urban Intersections - John Charles Hayward*. PhD thesis, Pennsylvania State, USA, 1971.
- [57] B. Allen, T. Shin, and P. Cooper, “Analysis of traffic conflicts and collisions,” *Transportation Research Record*, vol. 667, pp. 67–74, 1978.
- [58] J. Strauss, S. Zangenehpour, L. F. Miranda-Moreno, and N. Saunier, “Cyclist deceleration rate as surrogate safety measure in Montreal using smartphone GPS data,” *Accident Analysis & Prevention*, vol. 99, pp. 287–296, feb 2017.
- [59] A. Laureshyn, T. De Ceunynck, C. Karlsson, Å. Svensson, and S. Daniels, “In search of the severity dimension of traffic events: Extended Delta-V as a traffic conflict indicator,” *Accident Analysis & Prevention*, vol. 98, pp. 46–56, jan 2017.
- [60] C. Johnsson, H. Norén, A. Laureshyn, and D. Ivina, “InDev Deliverable 6.1: T-Analyst - semi-automated tool for traffic conflict analysis,” tech. rep., 2018.
- [61] M. Bornø Jensen, M. Ahrnbom, M. Kruithof, K. Åström, M. Nilsson, H. Ardö, A. Laureshyn, C. Johnsson, and T. Moeslund, “A framework for automated traffic safety

- analysis from video using modern computer vision,” in *Transportation Research Board Annual Meeting 2019*, Jan. 2019.
- [62] C. Johnsson, A. Laureshyn, and C. Dágostino, “Validation of surrogate measures of safety with a focus on bicyclist–motor vehicle interactions,” *Accident Analysis & Prevention*, vol. 153, p. 106037, apr 2021.
- [63] International Transport Forum, “Artificial Intelligence in Proactive Road Infrastructure Safety Management,” tech. rep., 2021.
- [64] Y. Ali, M. M. Haque, and F. Mannering, “A bayesian generalised extreme value model to estimate real-time pedestrian crash risks at signalised intersections using artificial intelligence-based video analytics,” *Analytic Methods in Accident Research*, vol. 38, p. 100264, 6 2023.
- [65] TASS, “MADYMO manual: Human Models,” tech. rep., 2019.
- [66] TASS, “MADYMO manual: Theory,” tech. rep., 2019.
- [67] J. Wittenburg, “Dynamics of multibody systems,” *Dynamics of Multibody Systems*, pp. 1–223, 2008.
- [68] G. J. Tierney and C. Simms, “Predictive capacity of the madymo multibody human body model applied to head kinematics during rugby union tackles,” *Applied Sciences 2019, Vol. 9, Page 726*, vol. 9, p. 726, 2 2019.
- [69] S. Shang, C. Masson, M. Llari, M. Py, Q. Ferrand, P. J. Arnoux, and C. Simms, “The predictive capacity of the MADYMO ellipsoid pedestrian model for pedestrian ground contact kinematics and injury evaluation,” *Accident Analysis & Prevention*, vol. 149, p. 105803, jan 2021.

-
- [70] K.-U. Schmitt, P. F. Niederer, and F. Walz, *Trauma Biomechanics*. Berlin, Heidelberg: Springer Berlin Heidelberg, 2004.
- [71] A. Öztürk, C. Mayer, H. Kumar, G. Pronoy, G. Atul, M. Ravi, K. Chitteti, and D. Fressmann, “A Step Towards Integrated Safety Simulation Through Pre-Crash to in-Crash Data Transfer,” in *International Technical Conference on the Enhanced Safety of Vehicles (ESV)*, 2019.
- [72] F. Wang, C. Yu, B. Wang, G. Li, K. Miller, and A. Wittek, “Prediction of pedestrian brain injury due to vehicle impact using computational biomechanics models: Are head-only models sufficient?,” *Traffic Injury Prevention*, vol. 21, pp. 102–107, jan 2019.
- [73] F. Wang, J. Wu, L. Hu, C. Yu, B. Wang, X. Huang, K. Miller, and A. Wittek, “Evaluation of the head protection effectiveness of cyclist helmets using full-scale computational biomechanics modelling of cycling accidents,” *Journal of Safety Research*, vol. 80, pp. 109–134, feb 2022.
- [74] J. Stoll, A. Schneider, M. Wisch, P. Seiniger, and T. Schaller, “The addressed VRU scenarios within PROSPECT and associated test catalogue (D3.1),” tech. rep., PROSPECT, 2016.
- [75] M. Wisch, M. Lerner, J. Kovaceva, A. Bálint, I. Gohl, A. Schneider, J. Juhász, and M. Lindman, “Car-to-cyclist crashes in Europe and derivation of use cases as basis for test scenarios of next generation advanced driver assistance systems – results from PROSPECT,” in *Enhanced Safety of Vehicles Conference*, (Detroit), 2017.
- [76] J. Uittenbogaard, C. Rodarius, and O. Op den Camp, “CATS car-to-cyclist accident scenarios (D1.2),” tech. rep., TNO, 2016.

- [77] I. Cieřlik, J. Kovaceva, M.-P. Bruyas, D. R. Large, M. Kunert, S. Krebs, and M. Arbitmann, “Improving the Effectiveness of Active Safety Systems to Significantly Reduce Accidents With Vulnerable Road Users - the Project Prospect (Proactive Safety for Pedestrians and Cyclists),” in *International Technical Conference on the Enhanced Safety of Vehicles (ESV)*, (Eindhoven), 2019.
- [78] Á. Esquer and J. Bräutigam, “Report on vehicle based functional tests (D7.1),” tech. rep., PROSPECT, 2018.
- [79] O. Op den Camp, S. van Montfort, J. Uittenbogaard, and J. Welten, “Cyclist target and test setup for evaluation of cyclist-autonomous emergency braking,” *International Journal of Automotive Technology*, vol. 18, pp. 1085–1097, dec 2017.
- [80] C. van der Zweep, M. Pla, M. Wisch, T. Schaller, S. de Hair, and P. Lemmen, “ASPECSS Assessment methodologies for forward looking Integrated Pedestrian and further extension to Cyclists Safety,” tech. rep., ASPECSS, 2014.
- [81] S. van Montfort, J. Uittenbogaard, and O. Op den Camp, “CATS test protocol (D5.2),” tech. rep., TNO, 2016.
- [82] Euro NCAP, “Test Protocol-AEB VRU systems,” tech. rep., 2020.
- [83] M. Lindman, S. Jonsson, L. Jakobsson, T. Karlsson, D. Gustafson, and A. Fredriksson, “Cyclists interacting with passenger cars; a study of real world crashes,” in *International Research Council on Biomechanics of Injury Europe (IRCOBI Europe)*, pp. 1–12, 2015.
- [84] C. Orsi, C. Montomoli, D. Otte, and A. Morandi, “Road accidents involving bicycles: configurations and injuries,” *International Journal of Injury Control and Safety Promotion*, vol. 24, pp. 534–543, oct 2017.

-
- [85] M. Wisch, M. Lerner, A. Schneider, A. Bálint, and M. Lindman, “Accident Analysis, Naturalistic Observations and Project Implications (D2.1),” tech. rep., PROSPECT, 2016.
- [86] C. K. Simms and D. Wood, *Pedestrian and cyclist impact : a biomechanical perspective*. Springer, 2009.
- [87] D. Otte, “A Review of Different Kinematic Forms in Two-Wheel Accidents -Their Influence on Effectiveness of Protective Measures,” in *Stapp Car Crash Conference*, sep 1980.
- [88] J. J. W. Huijbers, “A description of Bicycle and Moped Rider accidents aimed to indicate priorities for injury prevention research,” in *International Research Council on Biomechanics of Injury Europe (IRCOBI Europe)*, pp. 11–23, SWOV, 1984.
- [89] T. Maki, J. Kajzer, K. Mizuno, and Y. Sekine, “Comparative analysis of vehicle–bicyclist and vehicle–pedestrian accidents in Japan,” *Accident Analysis & Prevention*, vol. 35, pp. 927–940, nov 2003.
- [90] R. Fredriksson and E. Rosén, “Priorities for Bicyclist Protection in Car Impacts – a Real life Study of Severe Injuries and Car Sources,” in *International Research Council on Biomechanics of Injury Europe (IRCOBI Europe)*, 2012.
- [91] D. Otte, M. Jänsch, and C. Haasper, “Injury protection and accident causation parameters for vulnerable road users based on German In-Depth Accident Study GIDAS,” *Accident Analysis & Prevention*, vol. 44, pp. 149–153, jan 2012.
- [92] Y. Peng, Y. Chen, J. Yang, D. Otte, and R. Willinger, “A study of pedestrian and bicyclist exposure to head injury in passenger car collisions based on accident data and simulations,” *Safety Science*, vol. 50, pp. 1749–1759, nov 2012.

- [93] M. van Schijndel, S. de Hair, C. Rodarius, and R. Fredriksson, "Cyclist kinematics in car impacts reconstructed in simulations and full scale testing with Polar dummy," in *International Research Council on Biomechanics of Injury Europe (IRCOBI Europe)*, vol. IRC-12-85, pp. 800–812, 2012.
- [94] O. Fanta, J. Boucek, D. Hadraba, and K. Jelen, "Influence of the front part of the vehicle and cyclist's sitting position on the severity of head injury in side collision," *Acta of Bioengineering and Biomechanics*, vol. Vol. 15, no. nr 1, 2013.
- [95] T. Katsuhara, H. Miyazaki, Y. Kitagawa, and T. Yasuki, "Impact Kinematics of Cyclist and Head Injury Mechanism in Car-to-Bicycle Collision," *International Research Council on Biomechanics of Injury Europe (IRCOBI Europe)*, vol. IRC-14-76, pp. 670–684, 2014.
- [96] J. Nie, G. Li, and J. Yang, "A Study of Fatality Risk and Head Dynamic Response of Cyclist and Pedestrian Based on Passenger Car Accident Data Analysis and Simulations," *Traffic Injury Prevention*, vol. 16, pp. 76–83, jan 2015.
- [97] X. Lv, W. Liu, D. Zhou, H. Zhang, and X. Gu, "A Comparative Study of Vehicle Front Shape Based on Multi-Objective Optimization for Minimizing Injury Risks in Pedestrian and Cyclist Impact," in *WCX World Congress Experience*, apr 2018.
- [98] J. Nie and J. Yang, "A study of bicyclist kinematics and injuries based on reconstruction of passenger car–bicycle accident in China," *Accident Analysis & Prevention*, vol. 71, pp. 50–59, oct 2014.
- [99] N. Lubbe, Y. Wu, and H. Jeppsson, "Safe speeds: fatality and injury risks of pedestrians, cyclists, motorcyclists, and car drivers impacting the front of another passenger

- car as a function of closing speed and age,” *Traffic Safety Research*, vol. 2, p. 000006, apr 2022.
- [100] K. Mizuno, H. Yamada, H. Mizuguchi, D. Ito, Y. Han, and M. Hitosugi, “The influence of lower extremity postures on kinematics and injuries of cyclists in vehicle side collisions,” *Traffic Injury Prevention*, vol. 17, pp. 618–624, aug 2016.
- [101] T. Maki and J. Kajzer, “The behavior of bicyclists in frontal and rear crash accidents with cars,” *JSAE Review*, vol. 22, pp. 357–363, jul 2001.
- [102] T. Maki, J. Kajzer, and T. Asai, “The Behavior of Bicyclists in Accidents with Cars,” in *Human Biomechanics and Injury Prevention*, pp. 123–128, Tokyo: Springer Japan, 2000.
- [103] E. L. Carter, C. E. Neal-Sturgess, and R. N. Hardy, “APROSYS in-depth database of serious pedestrian and cyclist impacts with vehicles,” *International Journal of Crashworthiness*, vol. 13, pp. 629–642, dec 2008.
- [104] A. Badea-Romero and J. Lenard, “Source of head injury for pedestrians and pedal cyclists: Striking vehicle or road?,” *Accident Analysis & Prevention*, vol. 50, pp. 1140–1150, jan 2013.
- [105] M. Mackay, “IRCOBI-Past, Present and Future,” in *International Research Council on Biomechanics of Injury Europe (IRCOBI Europe)*, 2013.
- [106] M. Richter, H. C. Pape, D. Otte, and C. Krettek, “Improvements in passive car safety led to decreased injury severity - A comparison between the 1970s and 1990s,” *Injury*, vol. 36, pp. 484–488, apr 2005.
- [107] G. Li, K. Gildea, M. Wisch, O. Zander, and C. Simms, “An investigation into the effects of European vehicle type testing regulations on cyclist injury occurrence,” in

- International Research Council on Biomechanics of Injury Europe (IRCOBI Asia)*, pp. 80–84, 2020.
- [108] K.-U. Schmitt and M. Muser, “Study on Safer Motor Vehicles for Cyclists in the context of the EU Pedestrian Protection Regulations,” tech. rep., 2016.
- [109] K. Nagatomi, K. Hanayama, T. Ishizaki, S. Sasaki, and K. Matsuda, “Development and Full-Scale Dummy Tests of a Pop-Up Hood System for Pedestrian Protection,” in *International Technical Conference on the Enhanced Safety of Vehicles (ESV)*, 2005.
- [110] A. Gupta, T. Alvarez, and D. Daniel, “Investigating the Use of Adhesively-Coated External Airbag to Reduce Post-Impact Kinematics,” in *International Research Council on Biomechanics of Injury Europe (IRCOBI Europe)*, 2017.
- [111] H. Chajmowicz, J. Saadé, and S. Cuny, “Prospective assessment of the effectiveness of autonomous emergency braking in car-to-cyclist accidents in France,” *Traffic Injury Prevention*, vol. 20, pp. S20–S25, nov 2019.
- [112] Road Safety Authority, “HGV Road Safety: An analysis of HGVs involved in Fatal and Serious injury collisions,” tech. rep., 2022.
- [113] Transport for London, “Understanding Direct and Indirect Driver Vision from Heavy Goods Vehicles,” tech. rep., 2016.
- [114] T. O’Brien and R. Edmunds, “Cost-Benefit Analysis of Blind Spot Mirrors,” Tech. Rep. 2, 2004.
- [115] Danish Road Accident Investigation Board, “Ulykker mellem højresvingende lastbiler og ligeudkørende cyklister,” tech. rep., 2006.

-
- [116] P. Schepers, N. Agerholm, E. Amoros, R. Benington, T. Bjørnskau, S. Dhondt, B. de Geus, C. Hagemeister, B. P. Y. Loo, and A. Niska, “An international review of the frequency of single-bicycle crashes (SBCs) and their relation to bicycle modal share,” *Injury Prevention*, vol. 21, pp. e138–43, apr 2015.
- [117] J. Foley, M. Cronin, L. Brent, T. Lawrence, C. Simms, K. Gildea, J. Ryan, C. Deasy, and J. Cronin, “Cycling related major trauma in Ireland,” *Injury*, 2020.
- [118] P. Schepers, B. de Geus, J. van Cauwenberg, T. Ampe, and C. Engbers, “The perception of bicycle crashes with and without motor vehicles: Which crash types do older and middle-aged cyclists fear most?,” *Transportation Research Part F: Traffic Psychology and Behaviour*, vol. 71, pp. 157–167, may 2020.
- [119] M. Reurings and N. Bos, “Ernstig verkeersgewonden in de periode 1993-2009,” tech. rep., Leidschendam: Institute for Road Safety Research, 1993.
- [120] European Commission, “Future of transport,” tech. rep., 2011.
- [121] Statistics Denmark, “Traffic Accidents,” 2013.
- [122] S. Dhondt, C. MacHaris, N. Terryn, F. Van Malderen, and K. Putman, “Health burden of road traffic accidents, an analysis of clinical data on disability and mortality exposure rates in Flanders and Brussels,” *Accident Analysis & Prevention*, vol. 50, pp. 659–666, jan 2013.
- [123] J. Larsson, “Trafikskador 1998-2005 enligt patientstatistik,” 2008.
- [124] S. Olkkonen, U. Lahdenranta, P. Slätis, and R. Honkanen, “Bicycle accidents often cause disability—an analysis of medical and social consequences of nonfatal bicycle accidents,” *Scandinavian journal of social medicine*, vol. 21, no. 2, pp. 98–106, 1993.

- [125] J. Pucher and R. Buehler, “Making Cycling Irresistible: Lessons from The Netherlands, Denmark and Germany,” *Transport Reviews*, vol. 28, pp. 495–528, jul 2008.
- [126] Ottawa: Canadian Institute for Health Information, “The National Trauma Registry (NTR),” tech. rep., 2012.
- [127] H. Purcell, “An overview of non-motor vehicle bicycle crashes in Oregon,” in *WREN Conference*, 2008.
- [128] Australian Institute of Health and Welfare., “Serious injury due to land transport accidents, Australia 2008-09,” p. 50, 2012.
- [129] E. Amoros, M. Chiron, B. Thélot, and B. Laumon, “The injury epidemiology of cyclists based on a road trauma registry,” *BMC Public Health*, vol. 11, pp. 1–12, aug 2011.
- [130] M. Karkhaneh, M. Naghavi, B. H. Rowe, B. E. Hagel, N. Jafari, and L. D. Saunders, “Epidemiology of bicycle injuries in 13 health divisions, Islamic Republic of Iran 2003,” *Accident; analysis and prevention*, vol. 40, pp. 192–199, jan 2008.
- [131] C. Juhra, B. Wieskötter, K. Chu, L. Trost, U. Weiss, M. Messerschmidt, A. Malczyk, M. Heckwolf, and M. Raschke, “Bicycle accidents - Do we only see the tip of the iceberg?: A prospective multi-centre study in a large German city combining medical and police data,” *Injury*, vol. 43, pp. 2026–2034, dec 2012.
- [132] Wellington: Ministry of Transport, “Cyclists; crash factsheet 2012.,” tech. rep., 2012.
- [133] Wellington: Ministry of Transport, “Raising the profile of walking and cycling in New Zealand.,” tech. rep., 2008.
- [134] B. Beck, M. R. Stevenson, P. Cameron, J. Oxley, S. Newstead, J. Olivier, S. Boufous,

- and B. J. Gabbe, “Crash characteristics of on-road single-bicycle crashes: An under-recognised problem,” *Injury Prevention*, 2019.
- [135] R. Utriainen, “Characteristics of Commuters’ Single-Bicycle Crashes in Insurance Data,” *Safety*, vol. 6, p. 13, feb 2020.
- [136] R. Utriainen, S. O’hern, and M. Pöllänen, “Review on single-bicycle crashes in the recent scientific literature,” *Transport Reviews*, 2022.
- [137] M. S. Myhrmann, K. H. Janstrup, M. Møller, and S. E. Mabit, “Factors influencing the injury severity of single-bicycle crashes,” *Accident Analysis & Prevention*, vol. 149, p. 105875, jan 2021.
- [138] M. Ohlin, B. Algurén, and A. Lie, “Analysis of bicycle crashes in Sweden involving injuries with high risk of health loss,” *Traffic Injury Prevention*, vol. 20, no. 6, pp. 613–618, 2019.
- [139] A. V. Olesen, T. K. O. Madsen, T. Hels, M. Hosseinpour, and H. S. Lahrman, “Single-bicycle crashes: An in-depth analysis of self-reported crashes and estimation of attributable hospital cost,” *Accident Analysis & Prevention*, vol. 161, p. 106353, oct 2021.
- [140] L. De Rome, S. Boufous, T. Georgeson, T. Senserrick, D. Richardson, and R. Ivers, “Bicycle Crashes in Different Riding Environments in the Australian Capital Territory,” *Traffic Injury Prevention*, vol. 15, pp. 81–88, jan 2013.
- [141] L. B. Meuleners, M. Fraser, M. Johnson, M. Stevenson, G. Rose, and J. Oxley, “Characteristics of the road infrastructure and injurious cyclist crashes resulting in a hospitalisation,” *Accident Analysis & Prevention*, vol. 136, p. 105407, mar 2020.

- [142] A. J. Van Den Kroonenberg, W. C. Hayes, and T. A. McMahon, “Hip impact velocities and body configurations for voluntary falls from standing height,” *Journal of Biomechanics*, vol. 29, pp. 807–811, jun 1996.
- [143] B. E. Maki, W. E. McIlroy, and S. D. Perry, “Influence of lateral destabilization on compensatory stepping responses,” *Journal of Biomechanics*, vol. 29, pp. 343–353, mar 1996.
- [144] E. T. Hsiao and S. N. Robinovitch, “Common protective movements govern unexpected falls from standing height,” *Journal of Biomechanics*, vol. 31, pp. 1–9, nov 1997.
- [145] F. Feldman and S. N. Robinovitch, “Reducing hip fracture risk during sideways falls: Evidence in young adults of the protective effects of impact to the hands and stepping,” *Journal of Biomechanics*, vol. 40, pp. 2612–2618, jan 2007.
- [146] N. Bourdet, C. Deck, R. P. Carreira, and R. Willinger, “Head impact conditions in the case of cyclist falls,” *Proceedings of the Institution of Mechanical Engineers, Part P: Journal of Sports Engineering and Technology*, vol. 226, pp. 282–289, sep 2012.
- [147] D. S. McNally and N. M. Rosenberg, “MADYMO simulation of children in cycle accidents: A novel approach in risk assessment,” *Accident Analysis & Prevention*, vol. 59, pp. 469–478, oct 2013.
- [148] M. Fahlstedt, P. Halldin, and S. Kleiven, “The protective effect of a helmet in three bicycle accidents—A finite element study,” *Accident Analysis & Prevention*, vol. 91, pp. 135–143, jun 2016.
- [149] F. Feist and C. Klug, “A Numerical Study on the Influence of the Upper Body and Neck on Head Kinematics in Tangential Bicycle Helmet Impact,” in *International Research Council on Biomechanics of Injury Europe (IRCOBI Europe)*, pp. 162–184, 2016.

-
- [150] R. Meijer, H. Elrofai, J. Broos, and E. van Hassel, “Evaluation of an Active Multi-Body Human Model for Braking and Frontal Crash Events,” in *International Technical Conference on the Enhanced Safety of Vehicles (ESV)*, 2013.
- [151] M. Valdano, J. R. Jiménez-Octavio, C. M. Vives-Torres, F. J. López-Valdés, and B. Pipkorn, “Assessment of Madymo Active Human Body Model Kinematics and Dynamics by means of Human Volunteer Response at Low-Speed Frontal Impacts,” in *International Research Council on Biomechanics of Injury Europe (IRCOBI Europe)*, pp. 122–135, 2021.
- [152] J. Östh, K. Brolin, and D. Bråse, “A Human Body Model With Active Muscles for Simulation of Pretensioned Restraints in Autonomous Braking Interventions,” *Traffic Injury Prevention*, vol. 16, pp. 304–313, jan 2015.
- [153] M. Paudel, F. F. Yap, T. B. M. Rosli, K. H. Tan, H. Xu, N. Vahdati, H. Butt, and O. Shiryayev, “A computational study on the basis for a safe speed limit for bicycles on shared paths considering the severity of pedestrian head injuries in bicyclist-pedestrian collisions,” *Accident Analysis & Prevention*, vol. 176, p. 106792, oct 2022.
- [154] P. Matt, M. Jenerowicz, T. Schweiger, F. Heisch, J. Lienhard, and M. Boljen, “Investigation of e-scooter drivers colliding with kerbs – a parametric numerical study,” in *International Research Council on Biomechanics of Injury Europe (IRCOBI Europe)*, 2022.
- [155] P. Posirisuk, C. Baker, and M. Ghajari, “Computational prediction of head-ground impact kinematics in e-scooter falls,” *Accident Analysis & Prevention*, vol. 167, p. 106567, mar 2022.
- [156] A. Høy, “Bicycle helmets – To wear or not to wear? A meta-analyses of the effects

- of bicycle helmets on injuries,” *Accident Analysis & Prevention*, vol. 117, pp. 85–97, 2018.
- [157] P. Sahandifar, *Biomechanical Analysis of Fall Injuries using Finite Element Modeling*. PhD thesis, KTH Royal Institute of Technology, 2022.
- [158] M. Milanowicz and K. Kędzior, “Active numerical model of human body for reconstruction of falls from height,” *Forensic Science International*, vol. 270, pp. 223–231, jan 2017.
- [159] X. Gu, Y. Zhang, W. Sun, Y. Bian, D. Zhou, and P. Ola Kristensson, “Dexmo: An Inexpensive and Lightweight Mechanical Exoskeleton for Motion Capture and Force Feedback in VR,” *Conference on Human Factors in Computing*, 2016.
- [160] S. Yabukami, H. Kikuchi, M. Yamaguchi, K. I. Arai, K. Takahashi, A. Itagaki, and N. Wako, “Motion capture system of magnetic markers using three-axial magnetic field sensor,” in *IEEE Transactions on Magnetism*, vol. 36, pp. 3646–3648, sep 2000.
- [161] R. Hartley and A. Zisserman, *Multiple View Geometry in Computer Vision*. Cambridge University Press, mar 2004.
- [162] Z. Cao, G. Hidalgo, T. Simon, S. E. Wei, and Y. Sheikh, “OpenPose: Realtime Multi-Person 2D Pose Estimation using Part Affinity Fields,” *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 43, pp. 172–186, dec 2018.
- [163] C. Ionescu, D. Papava, V. Olaru, and C. Sminchisescu, “Human3.6m: Large scale datasets and predictive methods for 3d human sensing in natural environments,” *IEEE transactions on pattern analysis and machine intelligence*, vol. 36, pp. 1325–1339, 2014.
- [164] N. Dinesh Reddy, L. Guigues, L. Pishchulin, J. Eledath, and S. G. Narasimhan, “TeseTrack: End-to-End Learnable Multi-Person Articulated 3D Pose Tracking,” in *Pro-*

- ceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, pp. 15190–15200, 2021.
- [165] K. Isakov, E. Burkov, V. Lempitsky, and Y. Malkov, “Learnable Triangulation of Human Pose,” *Proceedings of the IEEE International Conference on Computer Vision*, vol. 2019-October, pp. 7717–7726, may 2019.
- [166] Y. Cai, L. Ge, J. Liu, J. Cai, T. J. Cham, J. Yuan, and N. M. Thalmann, “Exploiting spatial-temporal relationships for 3D pose estimation via graph convolutional networks,” *Proceedings of the IEEE International Conference on Computer Vision*, vol. 2019-October, pp. 2272–2281, oct 2019.
- [167] T. Chen, C. Fang, X. Shen, Y. Zhu, Z. Chen, and J. Luo, “Anatomy-aware 3D Human Pose Estimation with Bone-based Pose Decomposition,” *IEEE Transactions on Circuits and Systems for Video Technology*, feb 2020.
- [168] Y. Cheng, B. Yang, B. Wang, and R. T. Tan, “3D Human Pose Estimation using Spatio-Temporal Networks with Explicit Occlusion Training,” *AAAI 2020 - 34th AAAI Conference on Artificial Intelligence*, pp. 10631–10638, apr 2020.
- [169] Y. Cheng, B. Yang, B. Wang, Y. Wending, and R. Tan, “Occlusion-aware networks for 3D human pose estimation in video,” *Proceedings of the IEEE International Conference on Computer Vision*, vol. 2019-October, pp. 723–732, oct 2019.
- [170] W. Li, H. Liu, R. Ding, M. Liu, P. Wang, and W. Yang, “Exploiting Temporal Contexts with Strided Transformer for 3D Human Pose Estimation,” *IEEE Transactions on Multimedia*, mar 2021.
- [171] J. Liu, J. Rojas, Y. Li, Z. Liang, Y. Guan, N. Xi, and H. Zhu, “A Graph Attention

- Spatio-temporal Convolutional Network for 3D Human Pose Estimation in Video,” pp. 3374–3380, mar 2020.
- [172] D. Pavllo, C. Feichtenhofer, D. Grangier, and M. Auli, “3D human pose estimation in video with temporal convolutions and semi-supervised training,” *Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, vol. 2019-June, pp. 7745–7754, nov 2018.
- [173] Y. Yuan, K. Kitani, Y. Yuan, and K. Kitani, “DLow: Diversifying Latent Flows for Diverse Human Motion Prediction,” *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, vol. 12354 LNCS, pp. 346–364, mar 2020.
- [174] C. Zheng, S. Zhu, M. Mendieta, T. Yang, C. Chen, and Z. Ding, “3D Human Pose Estimation with Spatial and Temporal Transformers,” *IEEE/CVF International Conference on Computer Vision (ICCV)*, mar 2021.
- [175] X. Zhou, X. Sun, W. Zhang, S. Liang, and Y. Wei, “Deep Kinematic Pose Regression,” *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, vol. 9915 LNCS, pp. 186–201, sep 2016.
- [176] D. Pavllo, D. Grangier, and M. Auli, “QuaterNet: A Quaternion-based Recurrent Model for Human Motion,” *British Machine Vision Conference 2018, BMVC 2018*, may 2018.
- [177] M. Kocabas, N. Athanasiou, and M. J. Black, “VIBE: Video Inference for Human Body Pose and Shape Estimation,” *Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, pp. 5252–5262, dec 2019.

- [178] N. Kolotouros, G. Pavlakos, and K. Daniilidis, “Convolutional Mesh Regression for Single-Image Human Shape Reconstruction,” *Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, vol. 2019-June, pp. 4496–4505, may 2019.
- [179] M. Loper, N. Mahmood, J. Romero, G. Pons-Moll, and M. J. Black, “SMPL: A Skinned Multi-Person Linear Model,” *ACM Transactions on Graphics (TOG)*, vol. 34, oct 2015.
- [180] M. Schachner, B. Schneider, W. Sinz, and C. Klug, “Extracting Quantitative Descriptions of Pedestrian Pre-crash Postures from Real-world Accident Videos,” in *International Research Council on Biomechanics of Injury Europe (IRCOBI Europe)*, 2020.
- [181] A. Soni, T. Robert, F. Rongiéras, and P. Beillas, “Observations on pedestrian pre-crash reactions during simulated accidents,” *Stapp car crash journal*, vol. 57, nov 2013.
- [182] Y. Han, Q. Li, W. He, F. Wan, B. Wang, and K. Mizuno, “Analysis of Vulnerable Road User Kinematics Before/During/After Vehicle Collisions Based on Video Records,” in *International Research Council on Biomechanics of Injury Europe (IRCOBI Europe)*, 2017.
- [183] A. Qammaz and A. Argyros, “MocapNET: Ensemble of SNN Encoders for 3D Human Pose Estimation in RGB Images,” in *Proceedings of the British Machine Vision Conference (BMVC)*, 2019.
- [184] R. Villegas, J. Yang, D. Ceylan, and H. Lee, “Neural Kinematic Networks for Unsupervised Motion Retargetting,” *Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, pp. 8639–8648, dec 2018.
- [185] D. Pagnon, M. Domalain, and L. Reveret, “Pose2Sim: An End-to-End Workflow for

- 3D Markerless Sports Kinematics—Part 1: Robustness,” *Sensors*, vol. 21, p. 6530, sep 2021.
- [186] D. Pagnon, M. Domalain, and L. Reveret, “Pose2Sim: An End-to-End Workflow for 3D Markerless Sports Kinematics—Part 2: Accuracy,” *Sensors*, vol. 22, apr 2022.
- [187] L. Peneo, B. Clement, V. Moduano, E. Mingo Hoffman, G. Nava, D. Pucci, N. G. Tsagarakis, J. B. Mourert, and S. Ivaldi, “Robust Real-Time Whole-Body Motion Retargeting from Human to Humanoid,” *IEEE-RAS International Conference on Humanoid Robots*, vol. 2018-November, pp. 425–432, jan 2019.
- [188] Dutch Cycling Embassy, “Dutch Cycling Vision,” tech. rep., 2018.
- [189] Department of Transport Tourism and Sport, “Ireland’s First National Cycle Policy Framework,” tech. rep., Department of Transport Tourism and Sport, 2009.
- [190] European Commission, “cycling: the way ahead for towns and cities,” tech. rep., 1999.
- [191] M. A. Hollingworth, A. J. Harper, and M. Hamer, “Risk factors for cycling accident related injury: The UK Cycling for Health Survey,” *Journal of Transport & Health*, vol. 2, pp. 189–194, jun 2015.
- [192] D. B. Rubin, “Inference and Missing Data,” *Biometrika*, vol. 63, p. 581, dec 1976.
- [193] R. J. A. Little and N. Schenker, “Missing Data,” in *Handbook of Statistical Modeling for the Social and Behavioral Sciences*, pp. 39–75, Boston, MA: Springer US, 1995.
- [194] D. B. Rubin, “Multiple Imputation for Nonresponse in Surveys,” tech. rep., 1987.
- [195] R. Lall, “How multiple imputation makes a difference,” *Political Analysis*, vol. 24, pp. 414–433, oct 2016.

-
- [196] I. R. White, P. Royston, and A. M. Wood, “Multiple imputation using chained equations: Issues and guidance for practice,” *Statistics in Medicine*, vol. 30, pp. 377–399, feb 2011.
- [197] F. E. Harrell, *Regression Modeling Strategies*. Springer Series in Statistics, Springer International Publishing, 2015.
- [198] D. W. Hosmer, S. Lemeshow, and R. X. Sturdivant, *Applied logistic regression*. 2013.
- [199] L. Micallef and P. Rodgers, “eulerAPE: Drawing Area-Proportional 3-Venn Diagrams Using Ellipses,” *PLoS ONE*, vol. 9, p. e101717, jul 2014.
- [200] International Transport Forum, “Cycling Safety - Summary and Conclusions,” tech. rep., 2018.
- [201] R. Elvik, A. Høye, T. Vaa, and M. Sørensen, *The Handbook of Road Safety Measures*. Emerald Group Publishing Limited, oct 2009.
- [202] J. Thompson, J. S. Wijnands, G. Savino, B. Lawrence, and M. Stevenson, “Estimating the safety benefit of separated cycling infrastructure adjusted for behavioral adaptation among drivers; an application of agent-based modelling,” *Transportation Research Part F: Traffic Psychology and Behaviour*, vol. 49, pp. 18–28, aug 2017.
- [203] European Commission, “Attitudes of Europeans towards Urban Mobility, Special Eurobarometer 406,” tech. rep., European Commission, 2013.
- [204] Road Safety Authority, “Road Collision Factbook, 2015,” tech. rep., 2018.
- [205] Road Safety Authority, “Road Collision Factbook, 2014,” tech. rep., 2016.
- [206] Department for Transport, “Linking Police and Hospital data on Road Accidents in England: 1999 to 2009 results,” tech. rep., 2012.

- [207] Central Statistics Office, “StatBank - Profile 6 - Commuting in Ireland - E6010,” 2016.
- [208] I. Krumpal, “Determinants of social desirability bias in sensitive surveys: a literature review,” *Quality & Quantity*, vol. 47, pp. 2025–2047, jun 2013.
- [209] European Commission, “Serious Injuries 2015,” tech. rep., 2015.
- [210] L. Allen, A. O’Connell, and V. Kiermer, “How can we ensure visibility and diversity in research contributions? How the Contributor Role Taxonomy (CRediT) is helping the shift from authorship to contributorship,” *Learned Publishing*, vol. 32, pp. 71–74, jan 2019.
- [211] K. Gildea and C. Simms, “Characteristics of cyclist collisions in Ireland: Analysis of a self-reported survey,” *Accident Analysis & Prevention*, vol. 151, p. 105948, mar 2021.
- [212] A. C. Lusk, M. Asgarzadeh, and M. S. Farvid, “Database improvements for motor vehicle/bicycle crash analysis,” *Injury Prevention*, vol. 21, pp. 221–230, aug 2015.
- [213] A. MacAlister and D. S. Zubry, “Cyclist Crash Scenarios and Factors Relevant to the Design of Cyclist Detection Systems,” in *International Research Council on Biomechanics of Injury Europe (IRCOBI Europe)*, pp. 373–384, 2015.
- [214] K. Gildea, D. Hall, and C. Simms, “Configurations of underreported cyclist-motorised vehicle and single cyclist collisions: Analysis of a self-reported survey,” *Accident Analysis & Prevention*, vol. 159, p. 106264, sep 2021.
- [215] UITP, “Light rail and tram: The European outlook,” tech. rep., 2019.
- [216] D. Skelton, “Tram/Cycle infrastructure Review Study,” tech. rep., Sheffield City Council, 2016.

- [217] R. Y. Tsai, “A Versatile Camera Calibration Technique for High-Accuracy 3D Machine Vision Metrology Using Off-the-Shelf TV Cameras and Lenses,” *IEEE Journal on Robotics and Automation*, vol. 3, no. 4, pp. 323–344, 1987.
- [218] C.-Y. Wang, A. Bochkovskiy, and H.-Y. M. Liao, “YOLOv7: Trainable bag-of-freebies sets new state-of-the-art for real-time object detectors,” jul 2022.
- [219] T.-Y. Lin, M. Maire, S. Belongie, J. Hays, P. Perona, D. Ramanan, P. Dollar, and L. Zitnick, “Microsoft coco: Common objects in context,” in *ECCV*, European Conference on Computer Vision, September 2014.
- [220] A. Bewley, Z. Ge, L. Ott, F. Ramos, and B. Upcroft, “Simple online and realtime tracking,” in *2016 IEEE International Conference on Image Processing (ICIP)*, IEEE, sep 2016.
- [221] N. Wojke, A. Bewley, and D. Paulus, “Simple online and realtime tracking with a deep association metric,” in *2017 IEEE International Conference on Image Processing (ICIP)*, pp. 3645–3649, 2017.
- [222] A. Arun, M. M. Haque, A. Bhaskar, S. Washington, and T. Sayed, “A bivariate extreme value model for estimating crash frequency by severity using traffic conflicts,” *Analytic Methods in Accident Research*, vol. 32, p. 100180, 2021.
- [223] Y. Ali, M. M. Haque, and F. Mannering, “A bayesian generalised extreme value model to estimate real-time pedestrian crash risks at signalised intersections using artificial intelligence-based video analytics,” *Analytic Methods in Accident Research*, vol. 38, p. 100264, 2023.
- [224] A. Arun, M. M. Haque, S. Washington, and F. Mannering, “A physics-informed road

- user safety field theory for traffic safety assessments applying artificial intelligence-based video analytics,” *Analytic Methods in Accident Research*, vol. 37, p. 100252, 2023.
- [225] S. Tabassum, M. S. Ullah, N. H. Al-Nur, and S. Shatabda, “Native Vehicles Classification on Bangladeshi Roads Using CNN with Transfer Learning,” *2020 IEEE Region 10 Symposium, TENSYP 2020*, pp. 40–43, jun 2020.
- [226] J. Huang, V. Rathod, C. Sun, M. Zhu, A. Korattikara, A. Fathi, I. Fischer, Z. Wojna, Y. Song, S. Guadarrama, and K. Murphy, “Speed/accuracy trade-offs for modern convolutional object detectors,” *Proceedings - 30th IEEE Conference on Computer Vision and Pattern Recognition, CVPR 2017*, vol. 2017-January, pp. 3296–3305, nov 2017.
- [227] O. Smith, C. McCabe, and E. Kidney, “Tram-track cycling injuries: a significant public health issue,” *Irish Journal of Medical Science*, pp. 1–4, 1 2023.
- [228] J. F. Maempel, S. P. Mackenzie, P. H. C. Stirling, C. McCann, C. W. Oliver, and T. O. White, “Tram system related cycling injuries,” *Archives of Orthopaedic and Trauma Surgery*, pp. 1–8, jan 2018.
- [229] H. Zhang, F. Li, S. Liu, L. Zhang, H. Su, J. Zhu, L. M. Ni, and H.-Y. Shum, “DINO: DETR with Improved DeNoising Anchor Boxes for End-to-End Object Detection,” *International Conference on Learning Representations*, 2023.
- [230] A. Laureshyn, “Application of automated video analysis to road user behaviour,” 2010.
- [231] M. Ahrnbom, I. Persson, H. Ardo, and M. Nilsson, “Generalized urban traffic surveillance (guts): World-coordinate tracking for traffic safety applications,” vol. 2022-October, pp. 3813–3818, Institute of Electrical and Electronics Engineers Inc., 2022.
- [232] J. Denavit and R. S. Hartenberg, “A kinematic notation for lower-pair mechanisms based on matrices,” *Journal of Applied Mechanics*, vol. 22, no. 2, pp. 215–221, 1955.

-
- [233] L. Euler, “Novi commentarii academiae scientiarum petropolitanae,” *Nr*, vol. 20, pp. 189–207, 1776.
- [234] P. Baerlocher and R. Boulic, “Parametrization and Range of Motion of the Ball-and-Socket Joint,” *Deformable Avatars*, pp. 180–190, 2001.
- [235] D. Kraft, *A software package for sequential quadratic programming*. 1988.
- [236] P. Beeson and B. Ames, “TRAC-IK: An open-source library for improved solving of generic inverse kinematics,” *IEEE-RAS International Conference on Humanoid Robots*, vol. 2015-December, pp. 928–935, dec 2015.
- [237] L. Needham, M. Evans, D. P. Cosker, L. Wade, P. M. McGuigan, J. L. Bilzon, and S. L. Colyer, “The accuracy of several pose estimation methods for 3D joint centre localisation,” *Nature*, vol. 11, pp. 1–11, oct 2021.
- [238] X. Yu, C. E. Baker, and M. Ghajari, “Head impact location, speed and angle from falls and trips in the workplace,” *Annals of Biomedical Engineering*, pp. 1–16, 2 2023.
- [239] K. Sun, B. Xiao, D. Liu, and J. Wang, “Deep High-Resolution Representation Learning for Human Pose Estimation,” *Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, vol. 2019-June, pp. 5686–5696, feb 2019.
- [240] K. Gildea, C. Mercadal-Baudart, R. Blythman, A. Smolic, and C. Simms, “Kinepose: A temporally optimized inverse kinematics technique for 6dof human pose estimation with biomechanical constraints,” in *Irish Machine Vision & Image Processing Conference (IMVIP)*, 2022.
- [241] J. Van Hoof, R. De Lange, and J. S. Wismans, “Improving pedestrian safety using numerical human models,” *Stapp car crash journal*, vol. 47, oct 2003.

- [242] J. M. Asensio-Gil, R. Lancashire, E. J. Dijkstra, A. Carnicero, and F. J. López-Valdés, “Development of a multibody 50th percentile model for Euro NCAP’s Pedestrian Test Protocol,” in *International Research Council on Biomechanics of Injury Europe (IR-COBI Europe)*, 2022.
- [243] J. Short and B. Caulfield, “Record linkage for road traffic injuries in Ireland using police hospital and injury claims data,” *Journal of Safety Research*, vol. 58, pp. 1–14, sep 2016.
- [244] J. Short, “Traffic injuries in ireland: a neglected problem,” *Journal of the Statistical and Social Inquiry Society of Ireland*, 2018.
- [245] J. Tyndall, “Pedestrian deaths and large vehicles,” *Economics of Transportation*, vol. 26-27, p. 100219, jun 2021.
- [246] Environmental Protection Agency, “The 2020 EPA Automotive Trends Report: Greenhouse Gas Emissions, Fuel Economy, and Technology since 1975,” tech. rep., 2021.
- [247] M. Edwards and D. Leonard, “Effects of large vehicles on pedestrian and pedalcyclist injury severity,” *Journal of Safety Research*, vol. 82, pp. 275–282, sep 2022.
- [248] M. A. Harris, C. C. Reynolds, M. Winters, P. A. Crompton, H. Shen, M. L. Chipman, M. D. Cusimano, S. Babul, J. R. Brubacher, S. M. Friedman, G. Hunte, M. Monro, L. Vernich, and K. Teschke, “Comparing the effects of infrastructure on bicycling injury at intersections and non-intersections using a case-crossover design,” *Injury Prevention*, vol. 19, pp. 303–310, oct 2013.
- [249] A. Hull and C. O’Holleran, “Bicycle infrastructure: can good design encourage cycling?,” *Urban, Planning and Transport Research*, vol. 2, pp. 369–406, jan 2014.

-
- [250] S. Kraus and N. Koch, “Provisional COVID-19 infrastructure induces large, rapid increases in cycling.,” *Proceedings of the National Academy of Sciences of the United States of America*, vol. 118, apr 2021.
- [251] R. Aldred, A. Goodman, J. Gulliver, and J. Woodcock, “Cycling injury risk in London: A case-control study exploring the impact of cycle volumes, motor vehicle volumes, and road characteristics including speed limits,” *Accident Analysis & Prevention*, vol. 117, pp. 75–84, 2018.
- [252] Road Safety Authority, “Provisional Review of Fatal Collisions 2017,” tech. rep., Road Safety Authority, 2018.
- [253] H. Jeppsson and N. Lubbe, “Simulating Automated Emergency Braking with and without Torricelli Vacuum Emergency Braking for cyclists: Effect of brake deceleration and sensor field-of-view on accidents, injuries and fatalities,” *Accident Analysis & Prevention*, vol. 142, p. 105538, jul 2020.
- [254] J. Kovaceva, A. Bálint, R. Schindler, and A. Schneider, “Safety benefit assessment of autonomous emergency braking and steering systems for the protection of cyclists and pedestrians based on a combination of computer simulation and real-world test results,” *Accident Analysis & Prevention*, vol. 136, p. 105352, mar 2020.
- [255] M. Dozza, R. Schindler, G. Bianchi-Piccinini, and J. Karlsson, “How do drivers overtake cyclists?,” *Accident Analysis & Prevention*, vol. 88, pp. 29–36, mar 2016.
- [256] A. Rasch, C. N. Boda, P. Thalya, T. Aderum, A. Knauss, and M. Dozza, “How do oncoming traffic and cyclist lane position influence cyclist overtaking by drivers?,” *Accident Analysis & Prevention*, vol. 142, p. 105569, jul 2020.

- [257] Department of Transport Tourism and Sport, “Guidelines for setting and managing speed limits in Ireland,” tech. rep., 2015.
- [258] Road Safety Authority, “6 Month Road Safety Review: January to 15 July 2021,” tech. rep., 2022.
- [259] Department of Transport Tourism and Sport, “Speed Limits Review,” tech. rep., 2013.
- [260] R. Elvik, “A re-parameterisation of the power model of the relationship between the speed of traffic and the number of accidents and accident victims,” *Accident Analysis & Prevention*, vol. 50, pp. 854–860, 1 2013.
- [261] Road Safety Authority, “Free speed study,” 2018.
- [262] The Road Safety Trust, “How effective is reducing speed limits on rural roads? phase 1 final report,” 2022.
- [263] Y. Zhao, D. Ito, and K. Mizuno, “AEB effectiveness evaluation based on car-to-cyclist accident reconstructions using video of drive recorder,” *Traffic Injury Prevention*, vol. 20, pp. 100–106, jan 2019.
- [264] T. Buch and S. Jensen, “Incidents between Straight-ahead Cyclists and Right-turning Motor Vehicles at Signalised Junctions,” *Accident Analysis & Prevention*, vol. 105, pp. 44–51, 2017.
- [265] M. Johnson, S. Newstead, J. Oxley, and J. Charlton, “Cyclists and open vehicle doors: Crash characteristics and risk factors,” *Safety Science*, vol. 59, pp. 135–140, nov 2013.
- [266] M. Zhu, L. Han, F. Liang, C. Xi, L. Wu, and Z. Zhang, “A novel vehicle open door safety system based on cyclist detection using fisheye camera and improved deep convolutional generative adversarial nets,” in *IEEE Intelligent Vehicles Symposium, Proceed-*

- ings, vol. 2019-June, pp. 2195–2201, Institute of Electrical and Electronics Engineers Inc., jun 2019.
- [267] J. Eriksson, P. Henriksson, and M. Rizzi, “Oskyddade trafikanter inblandning i olyckor och deras skadeutfall,” 2022.
- [268] K. P. Rekilä and A. Klein-Paste, “Measuring bicycle braking friction in winter conditions,” *Cold Regions Science and Technology*, vol. 125, pp. 108–116, 5 2016.
- [269] A. Niska, G. Blomqvist, and M. Hjort, “Cykelvägars friktion mätningar i fält i jämförelse med cykeldäcks friktion på olika underlag i vti:s däckprovningsanläggning,” 2018.
- [270] V. Wallqvist, G. Kjell, E. Cupina, L. Kraft, C. Deck, and R. Willinger, “New functional pavements for pedestrians and cyclists,” *Accident Analysis & Prevention*, vol. 105, pp. 52–63, aug 2017.
- [271] P. Sahandifar, C. Makoundou, M. Fahlstedt, C. Sangiorgi, K. Johansson, V. Wallqvist, and S. Kleiven, “A rubberized impact absorbing pavement can reduce the head injury risk in vulnerable road users: A bicycle and a pedestrian accident case study,” *Traffic Injury Prevention*, vol. 23, pp. 315–320, 2022.
- [272] B. Janssen, P. Schepers, H. Farah, and M. Hagenzieker, “Behaviour of cyclists and pedestrians near right angled, sloped and levelled kerb types: Do risks associated to height differences of kerbs weigh up against other factors?,” *European Journal of Transport and Infrastructure Research*, vol. 18, pp. 360–371, sep 2018.
- [273] K. J. Astrom, R. E. Klein, and A. Lennartsson, “Bicycle dynamics and control: Adapted bicycles for education and research,” *IEEE Control Systems*, vol. 25, pp. 26–47, 2005.