Neural processing of context and information: Implications for behavioural modelling

Submitted in accordance with the requirements
for the degree of Doctor of Philosophy
by

Martyna Bogacz

University of Leeds
June 2021

Intellectual property and publications

The candidate confirms that the work submitted is her own, except where work which has formed part of jointly authored publications has been included. The contribution of the candidate and the other authors to this work has been explicitly indicated below. The candidate confirms that appropriate credit has been given within the thesis where reference has been made to the work of others.

The work in Chapter 2 of this thesis has appeared in publication as follows:
Bogacz, M., Hess, S., Choudhury, C., Calastri, C., Mushtaq, F., Awais, M., Nazemi, M., van Eggermondd, M. & Erath, A. (2020). *Cycling in virtual reality: modelling behaviour in an immersive environment*, Transportation Letters, 1-15.

I developed the main idea for this work, under the guidance of Stephane Hess, Charisma Choudhury and Chiara Calastri. I performed the data collection and analysis, the modelling work and wrote the manuscript. Stephane Hess, Charisma Choudhury, and Chiara Calastri provided recommendations on the modelling and comments on the results. Faisal Mushtaq and Muhammad Awais provided guidance for the analysis of the neuroimaging data. Mohsen Nazemi, Michael van Eggermond and Alexander Erath provided visual resources used in the experiment. All authors provided recommendations for the experimental design. The manuscript was improved by comments from all the co-authors.

The work in Chapter 3 of this thesis has appeared in publication as follows:
Bogacz, M., Hess, S., Calastri, C., Choudhury, C.F., Erath, A., van Eggermond, M., Mushtaq, F., Nazemi, M. & Awais, M. (2020). *A Comparison of Cycling Behaviour between Keyboard-Controlled and Instrumented Bicycle Experiments in Virtual Reality*, Transportation Research Record, 2674(7), 244-257.

I developed the idea for this work together with Stephane Hess and under the guidance of Charisma Choudhury and Chiara Calastri. I performed the data collection and analysis and wrote the manuscript. Charisma Choudhury, and Chiara Calastri provided comments on the results. Faisal Mushtaq and Muhammad Awais provided support for the analysis of the neuroimaging data and its interpretation. Mohsen Nazemi, Michael van Eggermond and Alexander Erath provided physical equipment and graphical resources used in the experiment. All authors provided recommendations for the experimental design. The manuscript was improved by comments from all the co-authors.

The work in Chapter 4 of this thesis is a manuscript under review:
Bogacz, M., Hess, S., Calastri, C., Choudhury, C.F., Erath, A., van Eggermond, M., Mushtaq, F., Nazemi, M. & Awais, M. (under review). *Modelling risk perception using a dynamic hybrid choice model and brain-imaging data: application to virtual reality cycling.*

I developed the main idea for this work, under the guidance of Stephane Hess, Charisma Choudhury and Chiara Calastri. I performed the data analysis, the modelling work and wrote the manuscript. Stephane Hess, Chiara Calastri and Charisma Choudhury provided recommendations on the modelling and comments on the results. Faisal Mushtaq and Muhammad Awais provided guidance for the analysis of the neuroimaging data. Micheal van Eggermond and Mohsen Nazemi provided support with interpreting and using the dataset. The manuscript was improved by comments from all the co-authors.

Acknowledgments

I would like to say a huge thank you to my supervisors, Stephane Hess, Charisma Choudhury and Chiara Calastri who gave me an opportunity to pursue a PhD in the first place, and then patiently guided me, and provided immense support throughout, which contributed to my growth as an academic and personally. In particular, I would like to thank Stephane Hess who introduced me into the world of choice modelling, Charisma Choudhury for sharing her ideas and feedback on my work and Chiara Calastri for the insightful discussions and invaluable personal support.

Moreover, my thesis would have not been possible without the contribution and help of two amazing research groups. Firstly, I would like to thank all the members of research team in the Psychology Department at University of Leeds. In particular, Faisal Mushtaq who welcomed me to the group, enabled the collaboration and provided guidance on the incorporation of neuroimaging component into my research. I am also thankful to Muhammad Awais who shared his knowledge and guided me through the technicalities of the analysis of neural data. Secondly, I would like to thank the whole research team in the ETH Centre in Singapore and Zürich, espacially Micheal van Eggermond, Alexander Erath and Mohsen Nazemi for the continuous support, hosting me in Singapore and making data collection, that constitutes large part of my thesis, possible.

Beyond, I would like to thank my examiners Samantha Jamson and Bilal Farooq for an interesting discussion during the Viva and useful feedback on my work, which helped my reflect on its strengths and weaknesses and improve my thesis to make it more comprehensive. Additionally, thanks to Samantha for her comments and directing me towards new perspectives during my first year transfer exam.

Moreover, I have been lucky to have spent last four years in the ITS with many wonderful colleagues. In particular, I would like to thank Thomas Hancock, Panos Tsoleridis, Evangelos Paschalidis, Rodrigo Tapia, David Palma and Romain Crastes dit Sourd not only for their feedback on my work but also moral support and friendship. I also owe a big thank you to Robin Lovelace who gave me an opportunity to develop as a tutor while working alongside him as a teaching assistant.

Next, I would like to acknowledge the financial support by the European Research Council through the consolidator grant 615596-DECISIONS and by the University of Leeds through their 'LeedsForLife' conference participation programme.

Most of all, I would like to thank my family who has been standing by me throughout these four years. In particular, my parents, Ewa and Jacek who believed that I could pursue a PhD and supported me, not only with their love, tireless encouragement and advice but also with inspiring conversations which allowed me to gain different perspective on my work. Moreover, I am very thankful to my siblings, Weronika and Wojciech who have always been there for me. Finally, I owe a huge thank you to my partner Martin for his love, constant belief in me and endless support during this time.

Abstract

Many disciplines focus on the exploration of human choices, hence considerable progress has been made with respect to understanding how people make decisions within different fields. Nonetheless, cross-disciplinary efforts are still limited. This is especially apparent for the fields of choice modelling and neuroscience, mainly due to their contrasting focus. In particular, choice modelling seeks to understand why specific decisions are made, through capturing the differential influence of explanatory variables on that decision process. On the other hand, neuroscience is focused on a direct measurement of the biological activity of the brain under specific circumstances to infer the neurological foundations of the observed behaviour. For decades, these two disciplines have been developing in parallel, separated by the lack of practical and theoretical grounds to build on, and also separated by major differences in the type of data used. While choice modelling has looked at complex multi-alternative, multi-attribute settings, using either revealed or stated preference data, neuroscience has focussed on simple tasks that are repeated a very large number of times in a laboratory setting. Technological advancements such as virtual reality have recently allowed for more dynamic and complex situations to be reproduced in experimental (lab-based) settings, while further developments on non-intrusive sensors have made it possible to collect physiological and neural data in a way that is more comfortable for the participant and allows for more flexible experimental design. The emergence of these novel opportunities gave the basis for the work gathered in this thesis which adopted an integrative approach, combining choice modelling with virtual reality data collection and neurological measurement, with an applied focus on cycling behaviour. The conducted studies demonstrate the feasibility of such complex data collection efforts and evaluate the impact of the experimental design in virtual reality on the elicited behaviour and neural data. With the employed choice models, we demonstrate the differences in behaviour and neural reaction as a result of the adoption of immersive and non-immersive visual stimuli and changes in the riskiness of simulated road scenarios. Furthermore, a statistical analysis of the cycling behaviour and neural data, when two different input devices are employed, yields intuitive findings providing practical implications for researchers who plan to use virtual reality in their future research. In the final study of this thesis a hybrid choice model framework is proposed to simultaneously model cycling behaviour and brainwaves data. It shows that neural inputs can successfully be used as indicators for a latent construct in a hybrid model structure to capture risk, serving as an alternative to traditional measures e.g. attitudinal scales. This work not only demonstrates how to operationalise such modelling efforts but the addition of a neural perspective allows us to improve the understanding of cycling behaviour achieved with the existing models. Taken together, the findings presented in this thesis allow us to gain a better understanding of determinants which influence cyclists' choices in risky road situations, which we would not be able to explore in the real world due to safety concerns. Finally, they provide evidence of the potential for collaborative research between choice modelling and neuroscience to encourage more studies in this new direction that would stimulate the development of new modelling structures incorporating biometric data, enable more extensive exploration of different stages of the choice process, and consequently lead to more informed decision-making.

Contents

List of Tables

List of Figures

Chapter 1

Introduction

1 Background

Our everyday life encompasses hundreds of choices ranging from near-automatic reactions through habitual selections to deliberate decisions typically associated with long-term consequences. These choices have influences on resource planning and are crucial for the development of the built environment. Therefore, it is natural that human decision-making is a common interest for a wide spectrum of disciplines such as neuroscience, philosophy, or economics. This has, in turn, resulted in the development of a variety of approaches and methods to explore this phenomenon. In this thesis, two fields, in particular, are of interest, namely choice modelling, which aims at using mathematical models to understand decisions of individuals or groups, and neuroscience which uses a biological basis to explain human behaviour and choices.

Choice modelling

Choice modelling uses a range of theories and modelling techniques to provide a representation of how individuals choose (Ben-Akiva et al., 1985). Choice models operate in a defined framework with three key elements: *(a)* a decision-maker, who makes the choice, *(b)* a choice set of collectively exhaustive and mutually exclusive alternatives that can be chosen, defined by a set of attributes, and *(c)* a decision rule which determines how the choice is made (Ben-Akiva and Bierlaire, 1999). While the mathematical models allow for some degree of flexibility concerning underlying decision rules, including, for example, the most widely used random utility maximisation (RUM) (McFadden and Zarembka, 1974) or the random regret minimisation (RRM) (Chorus et al., 2008) framework, they largely focus on the outcome of the decision process rather than the process itself.

Furthermore, the methodological approach to data collection for choice modelling purposes typically employs stated or revealed preference choice experiments involving many multi-attribute alternatives (Louviere et al., 2000). A stated preference (SP) approach elicits responses to a set of hypothetical scenarios (Arentze et al., 2003; Eboli and Mazzulla, 2008) whereas revealed preference method is based on a direct observation of individuals' choices to infer their preferences (Brownstone and Small, 2005; Isacsson, 2007). Traditionally, the studies have been conducted on large groups (Earnhart, 2002; Lusk, 2003), nevertheless, more efficient study designs (Bliemer and Rose, 2005) allow for a significant reduction in the sample size (Hall et al., 2002; Leitham et al., 2000).

Neuroscience

On the other hand, neuroscience, and more specifically behavioural neuroscience, focuses on a direct measurement of the physical activity of the brain functions given a specific context. For this reason, neuroscientific experiments are usually performed in a laboratory setting, repetitive in nature and based on simple tasks. They employ a range of neuroimaging devices such as magnetoencephalography (MEG), electroencephalography (EEG), functional magnetic resonance imaging (fMRI) and functional near-infrared spectroscopy (fNIRS) to make inferences about the decision process (Carlson, 2007). The EEG measures the electrical activity of the brain, whereas MEG records the magnetic fields produced by the electrical current. Both techniques have high temporal, at the level of milliseconds, and low spatial resolution (da Silva, 2013). On the other hand, fMRI is a brain scanner that monitors changes in the blood flow relying on the fact that these are coupled with the activation of the neurons (Logothetis et al., 2001). It has a lower temporal resolution as compared to MEG or EEG, however, due to the very high spatial resolution, it is a suitable tool for mapping brain activations (Glover, 2011). Finally, the latest equipment is the fNIRS. It can be described as a trade-off between the fMRI and the EEG because it relies on hemodynamic responses of the brain similar to the fMRI while being a less expensive and portable device with higher temporal resolution (Naseer and Hong, 2015). This thesis employs the EEG equipment due to its accessibility, portability, a lower cost relative to the fMRI equipment and the nature of current research, which requires high temporal resolution of the EGG, to track real-time neural activations associated with decision-making processes in a dynamic context (Gui et al., 2010).

Following Glimcher and Fehr (2013) *"neuroscience is interested in the investigation of neurobiological hardware that supports choice behaviour"*. Therefore, rather than proposing a general model of decision-making, behavioural neuroscience explores associations between activation of a particular brain region and a stimulus, behavioural task or emotional state through the means of statistical models and tests (Wilcox and Rousselet, 2018). Moreover, it investigates highly correlated brain regions that exhibit a similar pattern of activity over time (Bowman et al., 2007). For example, in the case of fMRI, visual neuroimaging techniques such as voxel-wise analysis[1] or Region of Interest (ROI) analysis are used to identify the differences in signal intensity across experimental conditions (Carter and Shieh, 2015). Overall, the focus of neuroscientific studies is on identifying neural substrates of different types of decisions such as sensorimotor (Gold and Shadlen, 2007), value-based (Hunt et al., 2012; Rangel et al., 2008) or perceptual choices (Wong and Wang, 2006) in a variety of contexts (Clark et al., 2013; Paulus et al., 2003; Rilling and Sanfey, 2011). For instance, Mohr et al. (2010) employed fMRI to propose a neural model of risk processing, differentiating brain parts involved at each stage. Furthermore, a number of studies focused on identifying a structural basis for heterogeneity in human choices (Kable and Levy, 2015; Kanai and Rees, 2011), or aimed at predicting individuals' choices solely based on their neural responses (Knutson et al., 2007; Levy et al., 2011; Smith et al., 2014; Tusche et al., 2010). These neuroscientific studies provide a basis for understanding human behaviour by making a direct link between the chemical or biological brain responses and the changes in the external environment under specific circumstances.

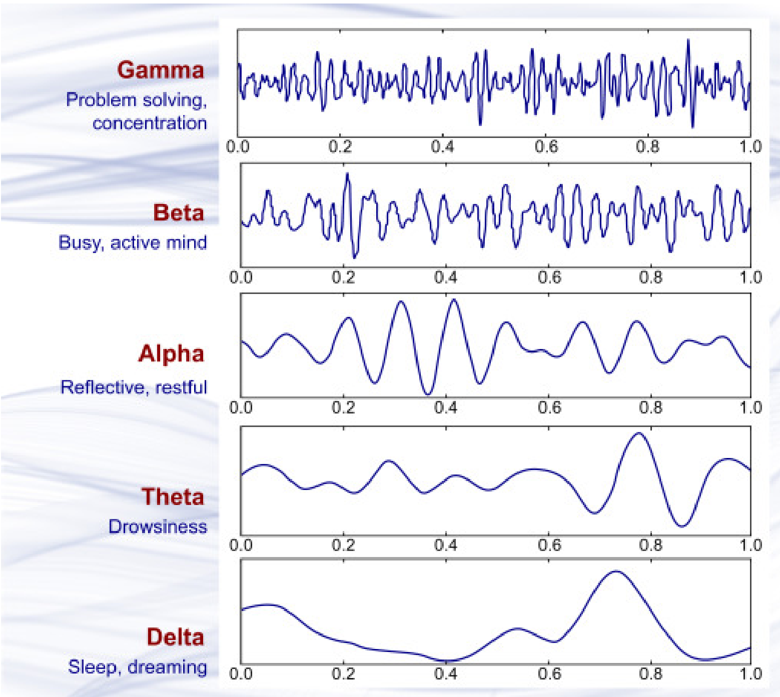
The EEG

As previously mentioned the EEG is based on the recording of the electrical activity of the brain that produces waveforms (brainwaves) of different frequencies, measured in cycles per second (Hertz) and amplitude, measured in micro voltages. The waveforms are typically classified into five main categories based on their characteristics (ie. frequency and amplitude). The most commonly studied brainwaves are delta (0.5-4 Hz), theta (4-8 Hz), alpha (8-14 Hz), beta (14-30 Hz) and gamma (more than 30 Hz), which are visually demonstrated in Figure 1.1.

A further division of brainwaves can be made according to the brain region in which they occurred such as frontal, occipital, parietal and temporal, as showed in Figure 1.2. They are interesting for researchers because brainwaves of different frequencies, stemming from specific brain regions are associated with distinct cognitive functions and mental states such as certain levels of intellectual efficiency or different levels of awareness, alertness or attention.

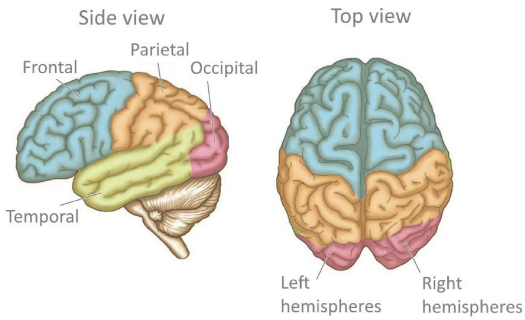
[1] Voxel is a three-dimensional visual representation of the brain structure.

Fig. 1.1: Classification of main brainwaves (Teplan et al., 2002)



Consequently, they allow for a better understanding of the biological foundations of human behaviour. Delta wave is the slowest wave and it is the most prominent in the frontocentral brain region during deep sleep or drowsiness (Britton et al., 2016). Next, theta wave is typically found during the early stages of sleep, deep relaxation, fatigue, mediation or daydreaming (Nayak and Anilkumar, 2021). As a consequence, these two waves are frequently used in the transport context as a well-established marker of drowsiness and fatigue in drivers (Awais et al., 2014; Jabbar et al., 2018). Further, during a normal awake state beta brainwave is the dominant one, and it has been showed to increase with concentration and higher engagement in cognitive tasks such as stimulus assessment or decision making (Kropotov, 2009). Moreover, gamma is the fastest of all waves and it has been attributed to sensory perception integrating different areas, and in previous research has been of interest in the context of epilepsy diagnosis (Nayak and Anilkumar, 2021). Therefore, it is less frequently used in research beyond medical disciplines. Finally, the alpha wave is observed in a normal awake state in adults. It tends to decrease under stress (Nishifuji et al., 2010), and has been pre-

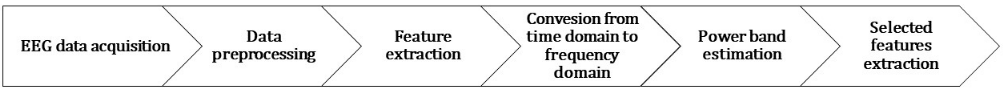
Fig. 1.2: Brain lobes (Lim et al., 2018).



viously linked to attentional processing (Klimesch, 2012). Importantly, the alpha wave that emerges in the occipital brain region has been demonstrated to be associated with visual attention (Ergenoglu et al., 2004; Mathewson et al., 2009). As a result, this particular wave will be explored in this thesis as a neural marker of visual attention in virtual reality scenarios where the sight is the key sense employed.

Importantly, a transformation of raw EEG signal into a useable measure re-

Fig. 1.3: EEG data processing pipeline.



quires a rigorous pre-processing and cleaning procedure. Steps involved in EEG processing can be seen in Figure 1.3. Firstly, EEG data is recorded using an EEG cap which allows collecting the signal from chosen electrodes, where each stream of the continuous raw EEG signal corresponds to one electrode. Secondly, in the data pre-processing phase the band pass filtering (BPF) is applied to remove the frequencies that researchers are not interested in and keep those of interest. In the current thesis, the frequencies 1-20 Hz are retained. Band pass filtering is a combination of low and high pass filters, where low pass keep only low frequencies (0-20 Hz), whereas higher frequencies are dropped to eliminate so-called line noise, emerging due to the operating frequency of electrical devices. Further, the high pass filters drop frequencies below 1 Hz to remove the noise stemming from direct current (DC) (Teplan et al., 2002). The next step within data pre-processing is the manual removal of artefacts using multiple source analysis method within BESA 6.0 software (MEGIS Software GmbH, Gräfelfing, Germany), where different sources of mixed frequency signal are identified. These can be eye blinks, movements or coughing. Based on this classification of sources, it is possible to determine which parts of the signal need to be retained and which discarded. For example, the frequency of an eye blink often overlaps with that of a delta wave, hence, it is desirable to remove it to achieve a clean picture of the brainwave (Kanoga et al., 2016). Once, the data undergoes the pre-processing stage, it needs to be converted from the time domain to the frequency domain using Fast-Fourier Transform (FFT) (Brigham and Morrow, 1967). This step is required because in the time domain the amplitude of the EEG signal is reported for each time point, as showed in Sun (2019). This is unsatisfactory because the EEG signal at each time point consists of different frequencies. This, in turn, makes it is impossible to establish which frequency is dominant at each time to then detect any changes in the signal along the time. For this reason, it is more appropriate to look at the signal in the frequency domain which then represents the strength of the signal in different frequencies, which are later classified as specific brainwaves. Lastly, the time perspective is added again to achieve the time-frequency domain which is a mixture of two and provides information of the power of a specific frequency at a given time point (discrete unit) (Dipoppa et al., 2016). Importantly, the strength of the signal within each frequency is extremely difficult to extract, hence Welch's method is used to compute the estimates of the power within each frequency (Solomon Jr, 1991). Ultimately, after the subsequent classification of different frequencies into specific brainwaves, an EEG dataset is produced containing the strength (voltage) of given brainwave at each time-point.

Overarching aims

The conclusion from the above is that choice modelling and neuroscience, although methodologically different, both have a coinciding goal as they attempt to understand human behaviour, either through the mathematical models or through the investigation of the brain. Despite this shared ambition, a cross-disciplinary approach is still scarce. Some have been sceptical about the applicability of neuroscientific inputs in the choice modelling field due to the limited existing evidence of choice modelling contributions to the neuroscientific field and to the understanding of underlying biological mechanisms of choices (Gul and Pesendorfer, 2008; Yoon et al., 2012). Nonetheless, there have been previous attempts, for instance in mathematical psychology and Decision Field Theory (DFT), that drew on the findings of neuroscience to understand the decision process better. In particular, DFT proposed a dynamic model which allows for a stochastic evolution of an individual's preferences over time until the decision is made (Busemeyer and Johnson, 2004; Hancock et al., 2018). Such an approach allowed for inferences about the choice process including the time dedicated to each alternative or the characteristics of unchosen options. Interestingly, DFT draws on the drift-diffusion model used in neuroscience to explain the perceptual decision-making process where neurons accumulate the evidence in favour of given alternatives and remove the noise over time (Britten et al., 1992). Therefore, these existing studies demonstrate that neuroscience has the potential to improve current mathematical models of choice by shedding light on the neural correlates of the decision process. Furthermore, in the recent transport studies, a new trend has been gaining popularity which aimed at the incorporation of physiological indicators in choice models. For example, Paschalidis et al. (2019) used a latent variable model with heart rate and skin conductance as indicators of unobserved stress to explore its impact on car-following behaviour in the driving simulator. Further, Castro et al. (2020) proposed a framework to use electrodermal activity in modelling choices of public transport users, while Tarabay and Abou-Zeid (2021) developed a hybrid choice model of drivers' stress using heart rate data. Given these promising developments, this thesis attempts to contribute to the field by providing evidence of the potential that stems from bridging choice modelling and neuroscience, where it incorporates the neuroimaging data into the existing modelling framework to test and explore the advantages that it may yield for understanding the drivers of modelled behaviour.

The introduction of the neuroscientific perspective can influence the choice modelling discipline in several ways, firstly, neural data, if employed in the study jointly with existing choice modelling methods can provide an additional source of information on the conclusions reached by the study. For example, differences in response times in choice experiments may have different sources such as task being too complex (or easy) or the participant being inattentive or inexperienced. These have implications for the results obtained with the surveys. The employment of neuroscientific data could help to discriminate between these underlying reasons by looking at the cognitive load of an individual. In this sense, neural data yields an additional angle and depth to the results obtainable with existing methods and provides additional constraints on the interpretation of choice data (Yoon et al., 2012).

Secondly, neural data can be seen as an unfiltered alternative to traditional, self-reported measures aimed at deepening the understanding of underlying drivers of choice such as attitudinal scales or self-reported questionnaires. They have been widely used in social sciences to explore people's feelings towards certain situations or issues. For example, a DOSPERT scale has often been used in psychology to explore domain-specific risk attitudes (Blais and Weber, 2006). Further, in environmental research, the contingent valuation method (CVM) has been employed to evaluate willingness to pay for environment preservation or wildlife conservation (Pedroso and Kung'u, 2019). In economics, self-reported measures have been used to elicit consumer valuation of goods and services (Hao et al., 2019), and in the health domain to assess the severity of patients' symptoms and physical difficulties (Tuominen et al., 2011). In transport, self-reported questionnaires and attitudinal scales have been previously used to obtain insights on the perception of different modes, usually public transport, and willingness to pay for their use (Román et al., 2014) as well as to assess road users' risk and safety perception (Zhang et al., 2011). Therefore, Driver Behaviour Questionnaire (Reason et al., 1990), Young Driver Attitude Scale (Malfetti et al., 1989) or Sensation Seeking Scale (Zuckerman et al., 1964) are commonly used measures. They are claimed to perform well when respondents have sufficient experience or general knowledge about the context to reliably compare the situation in question, assess and report it (Mummolo and Peterson, 2019). Nonetheless, these explicit approaches have also been demonstrated to be susceptible to biases stemming from different sources, such as experimenter effect (Iyengar, 2011), degree of familiarity with the topic (Patterson and Mattila, 2008), survey wording or social desirability bias (Näher and Krumpal, 2012). Therefore, some studies attempted to resort to more implicit approaches to alleviate the issues associated with self-reported measures (Bennett and Vijaygopal, 2018). One of the examples is the Implicit Attitude Test (IAT) that measures the strength of association between concepts (e.g. man, woman) and evaluations (e.g. good, bad). It is based on the principle that the response time for the associations which are consistent with respondents' beliefs will be shorter than for the inconsistent ones (Greenwald et al., 1998). However, these implicit approaches are not problem less, where a study by Kim (2003) showed that the respondents can be successfully taught how to influence the IAT results. Beyond, De Houwer et al. (2007) demonstrated that experimenters were able to induce the formation of new attitudes in participants, which, in turn, had an impact on the outcome of the IAT measure. On the other hand, Healy et al. (2015) used electroencephalography (EEG) jointly with IAT to provide neural correlates of decision-making in the test context. As a result, a top-down cognitive control was found as a source of noise in IAT results, confirming the voluntary modulation of responses. For this reason, instead of self-reported responses, which are prone to errors, neural or physiological activations can be measured to provide a raw, neural (or bodily) response to a specific situation.

Thirdly, neuroscience can help in understanding the connection between decisions and the context in which they occurred to explain how the interaction between them leads to different choices. This is particularly important in the context of an increasing consensus that despite the brain's biological foundations, it is strongly conditioned by the contextual, environmental, and cultural determinants (Yoon et al., 2012). For example, a study by Schwartz and Cuadros (2017) showed that individuals under cognitive strain tend to be more vigilant, trust less intuitive answers and consequently produce more rational choices, as compared to individuals in a relaxed environment.

Finally, neural data may form novel foundations for the comparison of existing choice models and therefore, allow for the discrimination between them in terms of a better representation of the human decision-making process with respect to the neural mechanisms. For example, assuming that there are two models which perform equally well in terms of mathematical efficiency, it is possible to use insights from neuroscience to distinguish between them based on how well they mimic the neural process that led to a given decision.

Overall, it can be argued that the incorporation of neuroscientific inputs in choice modelling field opens many exciting opportunities, nonetheless, thus far there have observed limited examples of such efforts. Consequently, this works aims at addressing some of these gaps by jointly using behavioural and neural data. In particular, it demonstrates how the neural perspective complements behavioural results and it employs neural data in a hybrid choice model to show their usability in a novel context and give evidence of how their incorporation into mathematical models can increase current understanding of human choices.

The advancements in neuroimaging equipment and virtual reality technology

One of the many challenges that hinder more pronounced cross-fertilisation between these two fields is a considerable methodological mismatch where the complexity of neuroimaging techniques strongly limits its applicability in a wider context, outside of laboratories. This can be alleviated, to some extent, by the advent of new technologies which allows to take a new approach to the investigation of human choices and gives an opportunity to accelerate interdisciplinary research.

On one hand, the emergence of multiple ambulatory (mobile) EEG devices is observed, offering more flexibility and sufficient performance capabilities, which has been demonstrated in multiple previous studies. For example, Aspinall et al. (2015) used Emotiv EPOC to investigate the impact of urban designs on the emotional experience of pedestrians. Further, Liu et al. (2013)

used the MindWave device to record drivers' brainwaves and detect their drowsiness. Moreover, Doppelmayr et al. (2012) investigated the impact of long-lasting exercise on alpha (α) rhythm with Varioport EEG, while Askamp and van Putten (2014) employed Mobita device for at-home EEG recordings of epileptic patients. Finally, Debener et al. (2012) and Lotte et al. (2009) used Oldenburg Hybrid-1, a modified EPOC device and Polymate AP216 in outdoor and indoor walking contexts, respectively. The proliferation of mobile EEG devices in non-medical research in the last decade was possible due to its low costs, small dimensions, and high temporal resolution, at the level of milliseconds, which made it highly relevant for dynamic studies (da Silva, 2013). Another available equipment, the fMRI has not been used outside the laboratory to a similar degree, mainly due to its considerable size and lower temporal resolution as compared to MEG or EEG (Glover, 2011). Nevertheless, a step towards higher accessibility to fMRI beyond static environments lies in the fNIRS, which can be seen as a middle ground between the magnetic resonance and EEG because it relies on haemodynamic responses of the brain similar to the fMRI while being a less expensive and portable device with higher temporal resolution (Naseer and Hong, 2015).

On the other hand, a strand of technology that allows for the application of these compact EEG devices to a wide range of situations is augmented (AR) and virtual reality (VR), where simulated scenarios are accessed through head-mounted displays (HMD), immersive caves or driving simulators (Cordeil et al., 2016). A virtual environment is defined as an interface that creates the effect of a three-dimensional world, in which the user directly interacts with virtual objects and it has been around for more than two decades (Bryson, 1996). However, only recent technological advancements which reduced the costs and computational requirements of the displays while maintaining, or frequently increasing, the visual quality of the environments resulted in their wider adaptation for research purposes (Slater and Sanchez-Vives, 2016). Virtual reality provides a unique opportunity to investigate the situations which we would not be able to explore in real life while maintaining a high level of controllability over confounding factors to ensure internal validity of the study. The internal validity is concerned with experimental procedure and reflects the degree to which an experiment allows to reliably establish the causal effect between the treatment and outcome (Nilsson and Kinateder, 2015). In general, the internal validity of the VR studies is widely recognised and supported by the existing literature (Dixit et al., 2017; Goedicke et al., 2018; Reimer et al., 2006), nonetheless, it is beneficial to provide more evidence in this regard, especially in new contexts and with novel devices. On the other hand, virtual reality is an inherently safe environment, which may lead to participants not behaving in the same way as they would in reality, which raises concerns about the external validity of the VR studies (Hock et al., 2018). External validity, also called ecological validity, is defined as the extent to which the result of the study is generalisable to the real world and applicable to other settings (Harrison et al., 2011). Therefore, external validity is more difficult to capture because it requires the comparison of behaviour in similar conditions between the simulation and the world outside the laboratory. This, consequently, limits the phenomena which can be safely and reasonably investigated. Moreover, studies that aim at establishing external validity are associated with much higher costs, if, for example, driving performance in the simulator is to be compared with driving in a real car (Hussain et al., 2019). Nonetheless, there is a growing number of studies in the transport field that exert such efforts, where they focus on different measures such as the mean speed (Bella, 2008) or variation in speed (Branzi et al., 2017), lateral deviation and lane positioning (Wang et al., 2010), lane changing behaviour (Yun et al., 2017), braking behaviour (Zöller et al., 2019) or driving errors (Mayhew et al., 2011) to examine the external validity. Furthermore, they frequently take into account biometric measures such as eye movement (Fors et al., 2013), heart rate (HR) (Johnson et al., 2011) or EEG signal (Li et al., 2013). Thus far, the literature provides ambiguous evidence on the external validity of virtual environments (Wynne et al., 2019), where some studies including Davenne et al. (2012); Hallvig et al. (2013); Shechtman et al. (2009) found significant differences between the behaviour observed in simulated environments and the real world. While another group of studies provided evidence that the findings are, in fact, externally valid (Bham et al., 2014; Hou et al., 2014; Philip et al., 2005; Risto and Martens, 2014; Yun et al., 2017). Therefore, it results that more research is needed to establish the validity of virtual reality and driving simulator studies to cover a wide range of behaviours, devices, conditions and factors that may influence it.

As previously mentioned, the current use of virtual reality in research context allowed for an exploration of human behaviour in circumstances that could have not been safely investigated in the real-life settings before, such as risky driving (Schwebel et al., 2007), as well as it enabled the joint collection of different data types, such as physiological and eye-tracking measurements, in these novel contexts (Zimasa et al., 2019). Moreover, it opened new paths for medical training (Lemole Jr et al., 2007) and rehabilitation (Cox et al., 2010). Finally, the popularisation of VR served as a catalyst for the use of neuroimaging devices in the dynamic settings, where there is observed a considerable acceleration of such studies in many disciplines (Bischof and Boulanger, 2003; Graefe and Schultheis, 2013; Kober et al., 2012; Lin et al., 2007).

Cycling behaviour context

The work in this thesis focuses on the cycling behaviour and there are several reasons for such a choice. Firstly, most of the current research on dynamic behaviour on the road focuses on drivers. Hence, there is an obvious gap in the literature to explore if the phenomena that are mostly investigated and demonstrated to hold for vehicle drivers are also applicable to cyclists and to what extent. It is particularly interesting, because, on one hand, cycling and driving are perceived as similar activities and, for example, measurement instruments developed for investigation of drivers' behaviour are used to explore behaviour in the cycling context (Feenstra et al., 2011). At the same time, another group of studies suggests that there are considerable differences between driving and cycling, especially in terms of associated risks and behavioural patterns, as car occupants have a significantly higher level of protection in case of an accident, provided by the seatbelts, airbags and impact-absorbing car structure, compared to a bicycle (Griffin et al., 2020; Steriu, 2012). This, in turn, will have an influence on risk perception and resulting behaviour. For instance, studies by Messiah et al. (2012) and Lardelli-Claret et al. (2003) showed that the mere use of a helmet can result in risk compensation mechanism and consequently engagement in more risky cycling behaviour. Beyond, a recent study by Nygårdhs et al. (2020) showed that experience and skills gained as a driver are not transferred to the cyclist role on the road, and vice versa, providing little evidence of behavioural adaptation due to distinct road-user roles. This further reinforces the position that cycling and driving should be seen as different in terms of behavioural analysis. Due to an apparent lack of consensus, if the findings in the driving context are generalisable to cycling, it is important to gather more evidence in this area.

Secondly, cyclists are particularly prone to find themselves in hazardous circumstances involving both drivers and pedestrians. They are claimed to be the most vulnerable road users, where, the annual report by the UK Department of Transport (2016) showed that cyclists are fifteen times more likely to be killed on the UK road than drivers. Therefore, risk, along with the lack of appropriate infrastructure, is one of the main deterrents of bicycle use (Parkin et al., 2007). Consequently, it is crucial to understand better risk perception among cyclists and factors that influence it, to be able to make more informed, evidence-based decisions with respect to infrastructure design, legislation and policy-making. This, then, has the potential to encourage cycling uptake among the entire population which brings multifaceted benefits on different levels. For individuals, cycling promotes health by increasing cardiovascular fitness (Cooper et al., 2006) and muscle endurance

(Andersen et al., 2009), lowering the likelihood of obesity (Wen and Rissel, 2008), reducing the risk of colon cancer (Hou et al., 2004) and cardiovascular mortality (Matthews et al., 2007) as well as being a cheap and fast form of transport. Further, on a system level, an increase in the cycling population leads to the 'Safety in Numbers' mechanism (Elvik and Bjørnskau, 2017) where more cyclists on the roads contribute to the higher drivers' awareness which, in turn, decreases the accident risk faced by an average cyclist (Fyhri et al., 2017).

Thirdly, cycling has an indirect impact on individuals' health by reducing air pollution if cars are substituted with bicycles for commuting purposes since automobiles contribute to about half of the overall world production of carbon dioxide (Cerovsky and Mindl, 2008), with significantly elevated emissions in the time of the traffic congestions that are frequent during short, urban trips (Barth and Boriboonsomsin, 2008). Furthermore, swapping the car for a bicycle allows for the reduction in the water use and contamination associated with car manufacturing where it is estimated that production of a single vehicle requires approximately 39.000 gallons of water, making the automobile industry one of the heaviest users of water (Isaiah, 2014). Therefore, an increase in bicycles use as opposed to motor vehicles yields obvious environmental benefits. Moreover, a large-scale implication of improvement in populations' general health is the reduction of the financial burden on the public health services (Oja et al., 2011). Furthermore, poor citizens' health hinders sustainable economic growth and workers productivity, for example, a study by Bloom et al. (2004) suggests that a one-year increase in population's life expectancy rises economic output by 4%.

Moreover, when considering human behaviour, different levels have been recognised in the previous literature (see eg. Antonini et al. (2006) for pedestrian behaviour). In driving context Michon (1985) proposed three levels of behaviour. Firstly, the strategical level which encompasses trip planning activities, such as destination, route or mode choice. Further, the tactical level involves mid-term manoeuvring actions in response to changing road circumstances, for example overtaking or lane changing. Finally, the lowest, operational level of behaviour captures immediate manoeuvres such as steering or accelerating. Michon's hierarchical model of drivers' behaviour has been further extended to the cycling context in the recent study by Gavriilidou et al. (2019), where the operational level of cycling behaviour has been split further into mental and physical processes. The mental process encompasses path choice within the entire route and the physical process entails the control of bicycle dynamics through pedalling and steering. Following this categorisation, the focus of this thesis is the physical process in the operational level of cycling behaviour including acceleration, deceleration, braking, speed maintenance and waiting (standstill).

As demonstrated in the preceding sections, there is an obvious potential for an integrative research between the neuroscience and choice modelling, that is particularly relevant in a transport context to allow for data collection in the dynamic environments with respect to cycling, driving, pedestrian mobility as well as other micro-mobility alternatives.

2 Research gaps

The previous section showed that choice modelling and neuroscience share a common goal to better understand human decision making. It highlighted the main methodological differences between these two disciplines and reviewed recent technological advancements which show potential for accelerating this interdisciplinary research. Therefore, the identified research gaps are presented below and subsequently addressed in this thesis.

Gap 1: Scarce interdisciplinary approach to the investigation of human behaviour on the road

The first gap emerges with the scant evidence of the studies which adopt a neuroscientific and behavioural approach jointly, to explore the differences in human choices, particularly in a dynamic context. Some headway has been achieved recently, where Cherchi et al. (2020) incorporated the EEG component into the stated choice experiment to contrast easy and hard consumer choices. Nonetheless, the experimental design was based on a number of static questions administered via an online survey. Therefore, it is not applicable in the more dynamic settings such as road scenarios and it does not allow for capturing dynamic changes in perception. The main reason for the scarcity of such combined experimental designs is their practical complexity and novelty, where only recent technological advancement of VR technology and EEG devices allows for undertaking such attempts. Furthermore, it can be argued that it is feasible in certain cases to use data collected previously for different purposes. In this instance, possible candidate datasets could be found in the psychology field which offers studies that use biometric data for safety research, for example, to detect drivers' fatigue or drowsiness (Furman and Baharav, 2010; Hu et al., 2009). However, the majority of them focuses on the induction of different mental states such as tiredness and does not involve any choice to enable the construction of the model. For example, in the study by Awais et al. (2017), participants were required to drive in a simulator at a constant speed for a prolonged period to evoke drowsiness.

Meanwhile, their electrical activity of the brain and heart rate data were recorded to then make inferences about the relationship between these biometric measures and drivers' state. Therefore, this research gap has been identified because of the scarcity of joint data collection efforts for choice modelling purposes.

Gap 2: Need for the internal validation of the studies in virtual reality

Since the emergence of virtual and augmented reality environments, researchers aimed at identifying the factors which influence the degree of immersion and presence in the virtual environment defined as *"the participant's sense of 'being there' in the virtual environment"* (Slater et al., 1994). Previous theoretical research put forward several hypothesised aspects that were claimed to influence a person's immersion, such as the degree and immediacy of control within the environment, sensory richness, the extent of isolation from the outside world, scene realism or simulation's consistency with the real world (Witmer and Singer, 1998). Interestingly, the impact of these different features was almost exclusively established and tested through the questioning of participants about their perceived presence or realism (Davis et al., 1999; Dinh et al., 1999). However, little has been done to directly compare the behaviour under these different settings. Therefore, the second gap is driven by the fact that virtual reality is still a novel approach to explore human behaviour and the evidence of the influence of different experimental conditions is continuously gathered. In the transport context, previous studies compared behaviour between real and simulated car (Godley et al., 2002) as well as attempted to validate the stated responses to assess risk perception (Andersson, 2013). However, dynamic behaviour under different presentation methods within the simulated environment has not been compared, hence, their impact on the elicited choices or the neural processing remains unknown.

Moreover, virtual reality is typically used to test and compare the effects of alternative scenarios in question. For example, the study by Nazemi et al. (2021) looked at the safety perception of cyclists between multiple designs of bicycle lanes, whereas Jiang and Kang (2016) looked at the impact of traffic noise on the perceived changes in visual landscape quality of a motorway. However, little attention was given to the impact of input devices employed in the virtual reality studies to manifest a person's responses beyond visual stimuli. It is particularly surprising given the multitude of equipment available to researchers and the differences in the extent to which they can replicate real human behaviour. For instance, previous study by Rutledge (1990) compared the performance of a joystick and mouse in a pointing task, whereas Sutter and Ziefle (2005) looked at the speed and accuracy of a touchpad and mini-joystick as a notebook input device. It resulted that the performance of input devices depends on the design and characteristics of motion required in the experiment. Therefore, it is necessary to advance the knowledge on their impact on elicited behaviour in specific conditions to allow for more informed decisions concerning study designs.

Gap 3: Lack of a choice model that incorporates dynamic behavioural and neural data

The third gap reflects the lack of evidence in the existing literature of the use of dynamic behavioural and neural data in a single model structure, where these distinct data types have the potential to complement one another in the attempt to increase the overall explanatory power of the model. For example, even though, there have been efforts to investigate the effect of dynamic behaviour (cycling) on neural response using a stationary bicycle (Scanlon et al., 2017) or naturalistic cycling in the outdoor setting (Scanlon et al., 2020), the analysis focused on the comparison of neural activations between different conditions without providing a modelling framework. On the other hand, Turner et al. (2016) intended to integrate behavioural, EEG and fMRI data into one model framework and demonstrated that such approach provides better insights than behavioural data alone. Nevertheless, the behavioural data were collected in a static, laboratory experiment based on a choice between delayed and immediate rewards, which limits the scope of the study with respect to explaining human choices in a dynamic context. Henceforth, the feasibility and appropriate methodology for the joint use of neural and behavioural data in a single model to explain complex human choices should be explored.

3 Objectives

The broad goal of this thesis is to attempt bridging the gap between choice modelling and neuroscience and show that the neuroscientific inputs can, in fact, complement and enrich the choice modelling findings. It will be achieved through case studies of cycling behaviour in virtual reality which were designed to enable the simultaneous collection of behavioural and neuroimaging data. They are used to compare and analyse the behaviour elicited in these studies from distinct perspectives. They allow us to *(a)* explore the interplay between observed behaviour and its neural underpinnings using comparative and descriptive analyses as well as the choice models, *(b)* assess the appropriateness of virtual reality as a research tool in this context and *(c)* provide an example of preliminary efforts in this cross-disciplinary research. The specific objectives are described below.

Objective 1: To design an experiment to collect jointly behavioural responses and neuroimaging data

There is scarce evidence of cross-disciplinary data collection attempts involving EEG and VR to explore dynamic human behaviour. Therefore, work in this thesis exerts effort to gather simultaneously behavioural data including cycling behaviour (eg. to accelerate, brake etc.) and stated data (e.g. reported risk perception) as well as neural measurements in a single experimental design. The collection of these different types of data allows for obtaining a more complete perspective on the behaviour of the cyclists in the simulated environment and enables their joint use to construct a mathematical model. An example of cross-disciplinary research is provided to encourage more development in this new direction but also highlight the challenges associated with such data collection tasks.

Objective 2: To evaluate the impact of different experimental designs on the behaviour in virtual reality

The objective is to evaluate the influence of visually different simulated scenarios on the cyclist neural processing, behaviour, and risk perception to provide a multi-angled analysis and identify factors in experimental design which have an impact on the elicited behaviour. Next, the aim is to compare the effect of different input devices on cycling performance in VR by exploring the differences that emerged in the behaviour evoked by the same visual stimulus but distinct input instruments. Beyond, the differences in neural response as a result of the incorporation of these different pieces of equipment are tested. The aim of this work is to provide guidance and advance the knowledge concerning the internal validity of VR research studies to improve the confidence in the findings of such research.

Objective 3: To apply a joint model structure for behavioural and neural data

The final objective is to apply a mathematically tractable framework to dynamic behavioural and neural data at the same time. While dynamic choice models have been used before (Arcidiacono and Miller, 2011), there has not been any attempts to jointly model cycling behaviour and complementing individuals' neural responses in a dynamic framework. The aim of the proposed model is to gain a better understanding of the link between neural processing and the observable choices and expand the understanding achieved by the previous models.

4 Thesis outline and contributions

This section provides an outline of each chapter of the thesis, focusing on their contribution in addressing the research gaps and associated objectives presented in sections 2 and 3, respectively.

Chapter 2 presents a paper titled *"Cycling in virtual reality: modelling behaviour in an immersive environment"* which intends to compare and understand the impact of immersive versus non-immersive presentation method in VR on cycling behaviour, perceived riskiness and willingness to cycle as well as neural processing. Different methods are used to analyse the impact of these two simulation types on each of these components. In particular, multinomial logit model (MNL) is used to explore the dynamic behavioural cycling data, next the ordered logit models are estimated to investigate stated risk perception and willingness to cycle and finally the paired t-test on the peak α amplitude in each condition is performed to establish differences of these two presentation formats on an α brainwave. The results from behavioural and neural data congruently show significant differences between responses elicited with immersive and non-immersive scenario while stated data are not consistent with them. This work, hence, addresses the first research gap, where findings based on a primary data collection provide evidence of an interdisciplinary approach to the exploration of human behaviour and demonstrate the interplay between different data types, allowing to gain a three-angled perspective on the dynamic risky cycling behaviour.

Chapter 3 presents a paper titled *"A comparison of cycling behaviour between keyboard-controlled and instrumented bicycle experiments in virtual reality"* where we compare cycling behaviour with respect to acceleration, braking, speed and head movement between virtual reality experiments where one used keyboard and the other instrumented bicycle as an input device. On top of that, the α amplitudes are contrasted to investigate the level of mental engagement in these two studies. This work is motivated and partly builds on the findings of work in Chapter 2 where a seemingly small change in the presentation method leads to the elicitation of different responses. Similarly, in the current study, considerable differences in behaviour as well as neural processing are found resulting solely from the adoption of distinct input equipment. This work further reinforces the findings of the previous chapter demonstrating the implications of appropriate design in the case of VR study beyond visual stimulus. Importantly, the employment of neuroimaging data allows us to obtain a wider perspective on these differences. Together, these results address the second research gap as they provide crucial guidance for researchers who intend to employ VR and EEG in their studies where the impact of distinct designs for these novel methods is not fully understood. Notably, the work presented in this chapter required additional data collection, which was similar to the first experiment, but it used an instrumented bicycle instead of a keyboard. The employment of the bicycle allows us to test the mobile EEG headset in a more flexible setting and demonstrate its performance in a case where physical effort and head movements are significant.

Chapter 4 presents a paper titled *"Modelling risk perception using a dynamic hybrid choice model and brain-imaging data: application to virtual reality cycling"* which focuses on an application of a dynamic hybrid choice model to behavioural and neural data simultaneously. Henceforth, it addresses the third research gap, where it, firstly, shows that the developed choice model is suitable to explain cyclists' behaviour in the simulated scenarios. In particular, the dynamic features of the scenarios, such as other moving agents on the road, are included to capture a complex situation that the cyclist faces. Secondly, the results demonstrate that neural data can be successfully incorporated into the mathematical model to provide an additional dimension in understanding cyclists' behaviour and improve the efficiency of the model. A number of steps is taken to ensure the usability of EEG data in the model, where various specifications are tested to replicate to a large degree the mechanisms of the choice.

Chapter 5 contains the discussion and conclusions that link the work presented throughout the chapters, reiterate the contribution of this work with respect to the presented research gaps and objectives as well as it presents the potential future direction of this research.

References

Andersen, L. B., Lawlor, D. A., Cooper, A. R., Froberg, K., and Anderssen, S. A. (2009). Physical fitness in relation to transport to school in adolescents: the Danish youth and sports study. *Scandinavian Journal of Medicine & Science in Sports*, 19(3):406–411.

Andersson, H. (2013). Consistency in preferences for road safety: An analysis of precautionary and stated behavior. *Research in Transportation Economics*, 43(1):41–49.

Antonini, G., Bierlaire, M., and Weber, M. (2006). Discrete choice models of pedestrian walking behavior. *Transportation Research Part B: Methodological*, 40(8):667–687.

Arcidiacono, P. and Miller, R. A. (2011). Conditional choice probability estimation of dynamic discrete choice models with unobserved heterogeneity. *Econometrica*, 79(6):1823–1867.

Arentze, T., Borgers, A., Timmermans, H., and DelMistro, R. (2003). Transport stated choice responses: effects of task complexity, presentation format and literacy. *Transportation Research Part E: Logistics and Transportation Review*, 39(3):229–244.

Askamp, J. and van Putten, M. J. (2014). Mobile EEG in epilepsy. *International Journal of Psychophysiology*, 91(1):30–35.

Aspinall, P., Mavros, P., Coyne, R., and Roe, J. (2015). The urban brain: analysing outdoor physical activity with mobile EEG. *Br J Sports Med*, 49(4):272–276.

Awais, M., Badruddin, N., and Drieberg, M. (2014). Driver drowsiness detection using EEG power spectrum analysis. In *2014 IEEE Region 10 Symposium*, pages 244–247. IEEE.

Awais, M., Badruddin, N., and Drieberg, M. (2017). A hybrid approach to detect driver drowsiness utilizing physiological signals to improve system performance and wearability. *Sensors*, 17(9):1991.

Barth, M. and Boriboonsomsin, K. (2008). Real-world carbon dioxide impacts of traffic congestion. *Transportation Research Record*, 2058(1):163–171.

Bella, F. (2008). Driving simulator for speed research on two-lane rural roads. *Accident Analysis & Prevention*, 40(3):1078–1087.

Ben-Akiva, M. and Bierlaire, M. (1999). Discrete choice methods and their applications to short term travel decisions. In *Handbook of Transportation Ccience*, pages 5–33. Springer.

Ben-Akiva, M. E., Lerman, S. R., and Lerman, S. R. (1985). *Discrete choice analysis: theory and application to travel demand*. MIT press, Cambridge, MA.

Bennett, R. and Vijaygopal, R. (2018). Consumer attitudes towards electric vehicles. *European Journal of Marketing*, 53(3/4):499–527.

Bham, G. H., Leu, M. C., Vallati, M., and Mathur, D. R. (2014). Driving simulator validation of driver behavior with limited safe vantage points for data collection in work zones. *Journal of Safety Research*, 49:53–60.

Bischof, W. F. and Boulanger, P. (2003). Spatial navigation in virtual reality environments: an EEG analysis. *CyberPsychology & Behavior*, 6(5):487–495.

Blais, A.-R. and Weber, E. U. (2006). A domain-specific risk-taking (DOSPERT) scale for adult populations. *Judgment and Decision Making*, 1(1):33–47.

Bliemer, M. C. and Rose, J. M. (2005). *Efficiency and sample size requirements for stated choice studies.* (Working Paper ITLS-WP-05-08). Institute of Transport and Logistics Studies, University of Sydney.

Bloom, D. E., Canning, D., and Sevilla, J. (2004). The effect of health on economic growth: a production function approach. *World development*, 32(1):1–13.

Bowman, F. D., Guo, Y., and Derado, G. (2007). Statistical approaches to functional neuroimaging data. *Neuroimaging Clinics of North America*, 17(4):441–458.

Branzi, V., Domenichini, L., and La Torre, F. (2017). Drivers' speed behaviour in real and simulated urban roads–a validation study. *Transportation research part F: traffic psychology and behaviour*, 49:1–17.

Brigham, E. O. and Morrow, R. (1967). The fast Fourier transform. *IEEE spectrum*, 4(12):63–70.

Britten, K. H., Shadlen, M. N., Newsome, W. T., and Movshon, J. A. (1992). The analysis of visual motion: a comparison of neuronal and psychophysical performance. *Journal of Neuroscience*, 12(12):4745–4765.

Britton, J. W., Frey, L. C., Hopp, J. L., Korb, P., Koubeissi, M. Z., Lievens, W. E., Pestana-Knight, E. M., and St Louis, E. K. (2016). *Electroencephalography (EEG): an introductory text and atlas of normal and abnormal findings in adults, children, and infants.* American Epilepsy Society, Chicago.

Brownstone, D. and Small, K. A. (2005). Valuing time and reliability: assessing the evidence from road pricing demonstrations. *Transportation Research Part A: Policy and Practice*, 39(4):279–293.

Bryson, S. (1996). Virtual reality in scientific visualization. *Communications of the ACM*, 39(5):62–71.

Busemeyer, J. R. and Johnson, J. G. (2004). Computational models of decision making. In *Blackwell handbook of judgment and decision making*, pages 133–154. Wiley Online Library.

Carlson, N. (2007). *Physiology of Behaviour.* Allyn & Bacon, Boston.

Carter, M. and Shieh, J. C. (2015). *Guide to research techniques in neuroscience.* Academic Press.

Castro, M., Guevara, C. A., and Jimenez-Molina, A. (2020). A methodological framework to incorporate psychophysiological indicators into transportation modeling. *Transportation research part C: emerging technologies*, 118:102712.

Cerovsky, Z. and Mindl, P. (2008). Hybrid electric cars, combustion engine driven cars and their impact on environment. In *2008 International Symposium on Power Electronics, Electrical Drives, Automation and Motion*, pages 739–743. IEEE.

Cherchi, E., Vuong, Q., and Stergiou, A. (2020). Using EEG to understand how our brain elaborate information in stated choice experiments: Easy versus hard tasks in the choice of vehicles. *bioRxiv*, pages 1–14.

Chorus, C. G., Arentze, T. A., and Timmermans, H. J. (2008). A random regret-minimization model of travel choice. *Transportation Research Part B: Methodological*, 42(1):1–18.

Clark, L., Averbeck, B., Payer, D., Sescousse, G., Winstanley, C. A., and Xue, G. (2013). Pathological choice: the neuroscience of gambling and gambling addiction. *Journal of Neuroscience*, 33(45):17617–17623.

Cooper, A. R., Wedderkopp, N., Wang, H., Andersen, L. B., Froberg, K., and Page, A. S. (2006). Active travel to school and cardiovascular fitness in Danish children and adolescents. *Medicine and science in sports and exercise*, 38(10):1724–1731.

Cordeil, M., Dwyer, T., Klein, K., Laha, B., Marriott, K., and Thomas, B. H. (2016). Immersive collaborative analysis of network connectivity: cave-style or head-mounted display? *IEEE transactions on visualization and computer graphics*, 23(1):441–450.

Cox, D. J., Davis, M., Singh, H., Barbour, B., Nidiffer, F. D., Trudel, T., Mourant, R., and Moncrief, R. (2010). Driving rehabilitation for military personnel recovering from traumatic brain injury using virtual reality driving simulation: A feasibility study. *Military medicine*, 175(6):411–416.

da Silva, F. L. (2013). EEG and MEG: relevance to neuroscience. *Neuron*, 80(5):1112–1128.

Davenne, D., Lericollais, R., Sagaspe, P., Taillard, J., Gauthier, A., Espié, S., and Philip, P. (2012). Reliability of simulator driving tool for evaluation of sleepiness, fatigue and driving performance. *Accident Analysis & Prevention*, 45:677–682.

Davis, E. T., Scott, K., Pair, J., Hodges, L. F., and Oliverio, J. (1999). Can audio enhance visual perception and performance in a virtual environment? In *Proceedings of the human factors and ergonomics society annual meeting*, volume 43, pages 1197–1201. SAGE Publications Sage CA: Los Angeles, CA.

De Houwer, J., Beckers, T., and Moors, A. (2007). Novel attitudes can be faked on the implicit association test. *Journal of Experimental Social Psychology*, 43(6):972–978.

Debener, S., Minow, F., Emkes, R., Gandras, K., and De Vos, M. (2012). How about taking a low-cost, small, and wireless EEG for a walk? *Psychophysiology*, 49(11):1617–1621.

Dinh, H. Q., Walker, N., Hodges, L. F., Song, C., and Kobayashi, A. (1999). Evaluating the importance of multi-sensory input on memory and the sense of presence in virtual environments. In *Proceedings IEEE Virtual Reality (Cat. No. 99CB36316)*, pages 222–228. IEEE.

Dipoppa, M., Szwed, M., and Gutkin, B. S. (2016). Controlling working memory operations by selective gating: the roles of oscillations and synchrony. *Advances in cognitive psychology*, 12(4):209.

Dixit, V. V., Ortmann, A., Rutström, E. E., and Ukkusuri, S. V. (2017). Experimental economics and choice in transportation: Incentives and context. *Transportation Research Part C: Emerging Technologies*, 77:161–184.

Doppelmayr, M., Sauseng, P., Doppelmayr, H., and Mausz, I. (2012). Changes in EEG during ultralong running. *Journal of Human Performance in Extreme Environments*, 10(1):4.

Earnhart, D. (2002). Combining revealed and stated data to examine housing decisions using discrete choice analysis. *Journal of Urban Economics*, 51(1):143–169.

Eboli, L. and Mazzulla, G. (2008). A stated preference experiment for measuring service quality in public transport. *Transportation Planning and Technology*, 31(5):509–523.

Elvik, R. and Bjørnskau, T. (2017). Safety-in-numbers: a systematic review and meta-analysis of evidence. *Safety science*, 92:274–282.

Ergenoglu, T., Demiralp, T., Bayraktaroglu, Z., Ergen, M., Beydagi, H., and Uresin, Y. (2004). Alpha rhythm of the EEG modulates visual detection performance in humans. *Cognitive Brain Research*, 20(3):376–383.

Feenstra, H., Ruiter, R. A., Schepers, J., Peters, G.-J., and Kok, G. (2011). Measuring risky adolescent cycling behaviour. *International journal of injury control and safety promotion*, 18(3):181–187.

Fors, C., Ahlström, C., and Anund, A. (2013). *Simulator validation with respect to driver sleepiness and subjective experiences: final report of the project SleepEYE II, part 1.* Statens väg-och transportforskningsinstitut, Stockholm.

Furman, G. D. and Baharav, A. (2010). *Investigation of drowsiness while driving utilizing analysis of heart rate fluctuations.* IEEE.

Fyhri, A., Sundfør, H. B., Bjørnskau, T., and Laureshyn, A. (2017). Safety in numbers for cyclists—conclusions from a multidisciplinary study of seasonal change in interplay and conflicts. *Accident Analysis & Prevention*, 105:124–133.

Gavriilidou, A., Daamen, W., Yuan, Y., and Hoogendoorn, S. (2019). Modelling cyclist queue formation using a two-layer framework for operational cycling behaviour. *Transportation research part C: emerging technologies*, 105:468–484.

Glimcher, P. W. and Fehr, E. (2013). *Neuroeconomics: Decision making and the brain.* Academic Press, London.

Glover, G. H. (2011). Overview of functional magnetic resonance imaging. *Neurosurgery Clinics*, 22(2):133–139.

Godley, S. T., Triggs, T. J., and Fildes, B. N. (2002). Driving simulator validation for speed research. *Accident analysis & prevention*, 34(5):589–600.

Goedicke, D., Li, J., Evers, V., and Ju, W. (2018). *VR-OOM: Virtual Reality On-ROad Driving SiMulation*, page 1–11. Association for Computing Machinery, New York.

Gold, J. I. and Shadlen, M. N. (2007). The neural basis of decision making. *Annual review of neuroscience*, 30:535–574.

Graefe, A. C. and Schultheis, M. T. (2013). Examining neurocognitive correlates of risky driving behavior in young adults using a simulated driving environment. In *2013 International conference on Virtual rehabilitation (ICVR)*, pages 235–241. IEEE.

Greenwald, A. G., McGhee, D. E., and Schwartz, J. L. (1998). Measuring individual differences in implicit cognition: the implicit association test. *Journal of personality and social psychology*, 74(6):1464.

Griffin, W., Haworth, N., and Twisk, D. (2020). Patterns in perceived crash risk among male and female drivers with and without substantial cycling experience. *Transportation research part F: traffic psychology and behaviour*, 69:1–12.

Gui, X., Chuansheng, C., Zhong-Lin, L., and Qi, D. (2010). Brain imaging techniques and their applications in decision-making research. *Xin li xue bao. Acta psychologica Sinica*, 42(1):120.

Gul, F. and Pesendorfer, W. (2008). The case for mindless economics. *The foundations of positive and normative economics: A handbook*, 1:3–42.

Hall, J., Kenny, P., King, M., Louviere, J., Viney, R., and Yeoh, A. (2002). Using stated preference discrete choice modelling to evaluate the introduction of varicella vaccination. *Health economics*, 11(5):457–465.

Hallvig, D., Anund, A., Fors, C., Kecklund, G., Karlsson, J. G., Wahde, M., and Åkerstedt, T. (2013). Sleepy driving on the real road and in the simulator—a comparison. *Accident Analysis & Prevention*, 50:44–50.

Hancock, T. O., Hess, S., and Choudhury, C. F. (2018). Decision field theory: Improvements to current methodology and comparisons with standard choice modelling techniques. *Transportation Research Part B: Methodological*, 107:18–40.

Hao, Y., Liu, H., Chen, H., Sha, Y., Ji, H., and Fan, J. (2019). What affect consumers' willingness to pay for green packaging? Evidence from China. *Resources, Conservation and Recycling*, 141:21–29.

Harrison, G. W., Haruvy, E., and Rutström, E. E. (2011). Remarks on virtual world and virtual reality experiments. *Southern Economic Journal*, 78(1):87–94.

Healy, G. F., Boran, L., and Smeaton, A. F. (2015). Neural patterns of the implicit association test. *Frontiers in human neuroscience*, 9:605.

Hock, P., Kraus, J., Babel, F., Walch, M., Rukzio, E., and Baumann, M. (2018). How to design valid simulator studies for investigating user experience in automated driving: Review and hands-on considerations. In *Proceedings of the 10th International Conference on Automotive User Interfaces and Interactive Vehicular Applications*, pages 105–117. Association for Computing Machinery, New York.

Hou, L., Ji, B.-T., Blair, A., Dai, Q., Gao, Y.-T., and Chow, W.-H. (2004). Commuting physical activity and risk of colon cancer in Shanghai, China. *American journal of epidemiology*, 160(9):860–867.

Hou, Y., Zhao, Y., Hulme, K. F., Huang, S., Yang, Y., Sadek, A. W., and Qiao, C. (2014). An integrated traffic-driving simulation framework: Design, implementation, and validation. *Transportation Research Part C: Emerging Technologies*, 45:138–153.

Hu, S., Bowlds, R. L., Gu, Y., and Yu, X. (2009). Pulse wave sensor for non-intrusive driver's drowsiness detection. In *2009 Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, pages 2312–2315. IEEE.

Hunt, L. T., Kolling, N., Soltani, A., Woolrich, M. W., Rushworth, M. F., and Behrens, T. E. (2012). Mechanisms underlying cortical activity during value-guided choice. *Nature neuroscience*, 15(3):470.

Hussain, Q., Alhajyaseen, W. K., Pirdavani, A., Reinolsmann, N., Brijs, K., and Brijs, T. (2019). Speed perception and actual speed in a driving simulator and real-world: A validation study. *Transportation research part F: traffic psychology and behaviour*, 62:637–650.

Isacsson, G. (2007). *The trade off between time and money: Is there a difference between real and hypothetical choices?* (CTS Working Paper 2007:3). Statens väg-och transportforskningsinstitut, Stockholm.

Isaiah, D. (2014). *Water, water, everywhere in vehicle manufacturing - Automotive World.* URL: https://www.automotiveworld.com/analysis/water-water-everywhere-vehicle-manufacturing/ (Accessed: 16/07/2021).

Iyengar, S. (2011). Laboratory experiments in political science. In Druckman, J. N., Greene, D. P., Kuklinski, J. H., and Lupia, A., editors, *Cambridge handbook of experimental political science*, pages 73–88. Cambridge University Press, Cambridge, Cambridge.

Jabbar, R., Al-Khalifa, K., Kharbeche, M., Alhajyaseen, W., Jafari, M., and Jiang, S. (2018). Real-time driver drowsiness detection for android application using deep neural networks techniques. *Procedia computer science*, 130:400–407.

Jiang, L. and Kang, J. (2016). Effect of traffic noise on perceived visual impact of motorway traffic. *Landscape and Urban Planning*, 150:50–59.

Johnson, M. J., Chahal, T., Stinchcombe, A., Mullen, N., Weaver, B., and Bedard, M. (2011). Physiological responses to simulated and on-road driving. *International journal of Psychophysiology*, 81(3):203–208.

Kable, J. W. and Levy, I. (2015). Neural markers of individual differences in decision-making. *Current opinion in behavioral sciences*, 5:100–107.

Kanai, R. and Rees, G. (2011). The structural basis of inter-individual differences in human behaviour and cognition. *Nature Reviews Neuroscience*, 12(4):231–242.

Kanoga, S., Nakanishi, M., and Mitsukura, Y. (2016). Assessing the effects of voluntary and involuntary eyeblinks in independent components of electroencephalogram. *Neurocomputing*, 193:20–32.

Kim, D.-Y. (2003). Voluntary controllability of the implicit association test (IAT). *Social Psychology Quarterly*, pages 83–96.

Klimesch, W. (2012). Alpha-band oscillations, attention, and controlled access to stored information. *Trends in cognitive sciences*, 16(12):606–617.

Knutson, B., Rick, S., Wimmer, G. E., Prelec, D., and Loewenstein, G. (2007). Neural predictors of purchases. *Neuron*, 53(1):147–156.

Kober, S. E., Kurzmann, J., and Neuper, C. (2012). Cortical correlate of spatial presence in 2D and 3D interactive virtual reality: an EEG study. *International Journal of Psychophysiology*, 83(3):365–374.

Kropotov, J. D. (2009). Chapter 3 - Beta rhythms. In *Quantitative EEG, Event-Related Potentials and Neurotherapy*, pages 59–76. Academic Press.

Lardelli-Claret, P., de Dios Luna-del Castillo, J., Jimenez-Moleon, J. J., Garcia-Martin, M., Bueno-Cavanillas, A., and Galvez-Vargas, R. (2003). Risk compensation theory and voluntary helmet use by cyclists in Spain. *Injury Prevention*, 9(2):128–132.

Leitham, S., McQuaid, R. W., and Nelson, J. D. (2000). The influence of transport on industrial location choice: a stated preference experiment. *Transportation Research Part A: Policy and Practice*, 34(7):515–535.

Lemole Jr, G. M., Banerjee, P. P., Luciano, C., Neckrysh, S., and Charbel, F. T. (2007). Virtual reality in neurosurgical education: part-task ventriculostomy simulation with dynamic visual and haptic feedback. *Neurosurgery*, 61(1):142–149.

Levy, I., Lazzaro, S. C., Rutledge, R. B., and Glimcher, P. W. (2011). Choice from non-choice: predicting consumer preferences from blood oxygenation level-dependent signals obtained during passive viewing. *Journal of neuroscience*, 31(1):118–125.

Li, J., Zhao, X., Xu, S., Ma, J., and Rong, J. (2013). The study of driving simulator validation for physiological signal measures. *Procedia-Social and Behavioral Sciences*, 96:2572–2583.

Lim, S. H., Nisar, H., Thee, K. W., and Yap, V. V. (2018). A novel method for tracking and analysis of EEG activation across brain lobes. *Biomedical Signal Processing and Control*, 40:488–504.

Lin, C.-T., Chung, I.-F., Ko, L.-W., Chen, Y.-C., Liang, S.-F., and Duann, J.-R. (2007). EEG-based assessment of driver cognitive responses in a dynamic virtual-reality driving environment. *IEEE Transactions on Biomedical Engineering*, 54(7):1349–1352.

Liu, N.-H., Chiang, C.-Y., and Hsu, H.-M. (2013). Improving driver alertness through music selection using a mobile EEG to detect brainwaves. *Sensors*, 13(7):8199–8221.

Logothetis, N. K., Pauls, J., Augath, M., Trinath, T., and Oeltermann, A. (2001). Neurophysiological investigation of the basis of the fMRI signal. *Nature*, 412(6843):150–157.

Lotte, F., Fujisawa, J., Touyama, H., Ito, R., Hirose, M., and Lécuyer, A. (2009). Towards ambulatory brain-computer interfaces: A pilot study with P300 signals. In *Proceedings of the International Conference on Advances in Computer Enterntainment Technology*, pages 336–339.

Louviere, J. J., Hensher, D. A., and Swait, J. D. (2000). *Stated choice methods: analysis and applications*. Cambridge University Press, Cambridge.

Lusk, J. L. (2003). Effects of cheap talk on consumer willingness-to-pay for golden rice. *American journal of agricultural economics*, 85(4):840–856.

Malfetti, J. L. et al. (1989). *Young Driver Attitude Scale: The Development and Field-Testing of an Instrument To Measure Young Driver Risk-Taking Attitudes*. ERIC,Columbia University, New York, NY. Teachers College.

Mathewson, K. E., Gratton, G., Fabiani, M., Beck, D. M., and Ro, T. (2009). To see or not to see: prestimulus α phase predicts visual awareness. *Journal of Neuroscience*, 29(9):2725–2732.

Matthews, C. E., Jurj, A. L., Shu, X.-o., Li, H.-L., Yang, G., Li, Q., Gao, Y.-T., and Zheng, W. (2007). Influence of exercise, walking, cycling, and overall nonexercise physical activity on mortality in Chinese women. *American journal of epidemiology*, 165(12):1343–1350.

Mayhew, D. R., Simpson, H. M., Wood, K. M., Lonero, L., Clinton, K. M., and Johnson, A. G. (2011). On-road and simulated driving: Concurrent and discriminant validation. *Journal of safety research*, 42(4):267–275.

McFadden, D. and Zarembka, P. (1974). Frontiers in econometrics. *Conditional logit analysis of qualitative choice behavior*, pages 105–142.

Messiah, A., Constant, A., Contrand, B., Felonneau, M.-L., and Lagarde, E. (2012). Risk compensation: a male phenomenon? Results from a controlled intervention trial promoting helmet use among cyclists. *American journal of public health*, 102(2):204–206.

Michon, J. A. (1985). A critical view of driver behavior models: what do we know, what should we do? In *Human behavior and traffic safety*, pages 485–524. Springer, Boston, MA.

Mohr, P. N., Biele, G., and Heekeren, H. R. (2010). Neural processing of risk. *Journal of Neuroscience*, 30(19):6613–6619.

Mummolo, J. and Peterson, E. (2019). Demand effects in survey experiments: An empirical assessment. *American Political Science Review*, 113(2):517–529.

Näher, A.-F. and Krumpal, I. (2012). Asking sensitive questions: the impact of forgiving wording and question context on social desirability bias. *Quality & Quantity*, 46(5):1601–1616.

Naseer, N. and Hong, K.-S. (2015). fNIRS-based brain-computer interfaces: a review. *Frontiers in human neuroscience*, 9:3.

Nayak, C. and Anilkumar, A. (2021). EEG normal waveforms. In *Stat Pearls*. Treasure Island (FL), StatPearls Publishing. URL: https://www.ncbi.nlm.nih.gov/books/NBK539805/ (Accessed: 13/05/2021).

Nazemi, M., van Eggermond, M. A., Erath, A., Schaffner, D., Joos, M., and Axhausen, K. W. (2021). Studying bicyclists' perceived level of safety using a bicycle simulator combined with immersive virtual reality. *Accident Analysis & Prevention*, 151:105943.

Nilsson, D. and Kinateder, M. (2015). Virtual reality experiments-the future or a dead end? In *6th International Symposium Human Behaviour in Fire. Interscience Communications, Cambridge*, pages 319–321.

Nishifuji, S., Sato, M., Maino, D., and Tanaka, S. (2010). Effect of acoustic stimuli and mental task on alpha, beta and gamma rhythms in brain wave. In *Proceedings of SICE Annual Conference 2010*, pages 1548–1554. IEEE.

Nygårdhs, S., Kircher, K., and Johansson, B. J. (2020). Trade-offs in traffic: does being mainly a car driver or a cyclist affect adaptive behaviour while driving and cycling? *European transport research review*, 12(1):1–14.

Oja, P., Titze, S., Bauman, A., De Geus, B., Krenn, P., Reger-Nash, B., and Kohlberger, T. (2011). Health benefits of cycling: a systematic review. *Scandinavian journal of medicine & science in sports*, 21(4):496–509.

Parkin, J., Wardman, M., and Page, M. (2007). Models of perceived cycling risk and route acceptability. *Accident Analysis & Prevention*, 39(2):364–371.

Paschalidis, E., Choudhury, C. F., and Hess, S. (2019). Combining driving simulator and physiological sensor data in a latent variable model to incorporate the effect of stress in car-following behaviour. *Analytic methods in accident research*, 22:100089.

Patterson, P. G. and Mattila, A. S. (2008). An examination of the impact of cultural orientation and familiarity in service encounter evaluations. *International Journal of Service Industry Management*, 19:662–681.

Paulus, M. P., Rogalsky, C., Simmons, A., Feinstein, J. S., and Stein, M. B. (2003). Increased activation in the right insula during risk-taking decision making is related to harm avoidance and neuroticism. *Neuroimage*, 19(4):1439–1448.

Pedroso, R. and Kung'u, J. B. (2019). Tourists' willingness to pay for upstream restoration and conservation measures. *Journal of Sustainable Tourism*, pages 1107–1124.

Philip, P., Sagaspe, P., Taillard, J., Valtat, C., Moore, N., Åkerstedt, T., Charles, A., and Bioulac, B. (2005). Fatigue, sleepiness, and performance in simulated versus real driving conditions. *Sleep*, 28(12):1511–1516.

Rangel, A., Camerer, C., and Montague, P. R. (2008). A framework for studying the neurobiology of value-based decision making. *Nature reviews neuroscience*, 9(7):545–556.

Reason, J., Manstead, A., Stradling, S., Baxter, J., and Campbell, K. (1990). Errors and violations on the roads: a real distinction? *Ergonomics*, 33(10-11):1315–1332.

Reimer, B., D'Ambrosio, L. A., Coughlin, J. F., Kafrissen, M. E., and Biederman, J. (2006). Using self-reported data to assess the validity of driving simulation data. *Behavior Research Methods*, 38:314–324.

Rilling, J. K. and Sanfey, A. G. (2011). The neuroscience of social decision-making. *Annual review of psychology*, 62:23–48.

Risto, M. and Martens, M. H. (2014). Driver headway choice: A comparison between driving simulator and real-road driving. *Transportation Research Part F: Traffic Psychology and Behaviour*, 25:1–9.

Román, C., Martín, J. C., and Espino, R. (2014). Using stated preferences to analyze the service quality of public transport. *International Journal of Sustainable Transportation*, 8(1):28–46.

Rutledge, J. D. (1990). Force-to-motion functions for pointing. In *Proc, INTERACT'90: IFIP Conf. on Human-Computer Interaction*, pages 701–705.

Scanlon, J. E., Redman, E. X., Kuziek, J. W., and Mathewson, K. E. (2020). A ride in the park: Cycling in different outdoor environments modulates the auditory evoked potentials. *International Journal of Psychophysiology*, 151:59–69.

Scanlon, J. E., Sieben, A. J., Holyk, K. R., and Mathewson, K. E. (2017). Your brain on bikes: P3, MMN/N2B, and baseline noise while pedaling a stationary bike. *Psychophysiology*, 54(6):927–937.

Schwartz, L. A. and Cuadros, L. (2017). The effects of the environment on decision-making. *Journal of Financial Education*, 43(2):223–242.

Schwebel, D. C., Ball, K. K., Severson, J., Barton, B. K., Rizzo, M., and Viamonte, S. M. (2007). Individual difference factors in risky driving among older adults. *Journal of safety research*, 38(5):501–509.

Shechtman, O., Classen, S., Awadzi, K., and Mann, W. (2009). Comparison of driving errors between on-the-road and simulated driving assessment: a validation study. *Traffic Injury Prevention*, 10(4):379–385.

Slater, M. and Sanchez-Vives, M. V. (2016). Enhancing our lives with immersive virtual reality. *Frontiers in Robotics and AI*, 3:74.

Slater, M., Usoh, M., and Steed, A. (1994). Depth of presence in virtual environments. *Presence: Teleoperators & Virtual Environments*, 3(2):130–144.

Smith, A., Bernheim, B. D., Camerer, C. F., and Rangel, A. (2014). Neural activity reveals preferences without choices. *American Economic Journal: Microeconomics*, 6(2):1–36.

Solomon Jr, O. (1991). PSD computations using Welch's method. *NASA STI/Recon Technical Report N*, 92:23584.

Steriu, M. (2012). Raising the bar: review of cycling safety policies in the European Union. *European Transport Safety Council*, pages 1–54.

Sun, J. (2019). Research on vocal sounding based on spectrum image analysis. *EURASIP Journal on Image and Video Processing*, 2019(1):1–10.

Sutter, C. and Ziefle, M. (2005). Interacting with notebook input devices: An analysis of motor performance and users' expertise. *Human Factors*, 47(1):169–187.

Tarabay, R. and Abou-Zeid, M. (2021). A dynamic hybrid choice model to quantify stress in a simulated driving environment. *IEEE Transactions on Intelligent Transportation Systems*, pages 1–16.

Teplan, M. et al. (2002). Fundamentals of EEG measurement. *Measurement science review*, 2(2):1–11.

Tuominen, R., Azbel, M., Hemmilä, J., and Möttönen, T. (2011). Willingness to pay for improvement of physical function among rheumatoid arthritis patients as measured by health assessment questionnaire. *Rheumatology international*, 31(3):347–352.

Turner, B. M., Rodriguez, C. A., Norcia, T. M., McClure, S. M., and Steyvers, M. (2016). Why more is better: Simultaneous modeling of EEG, fMRI, and behavioral data. *NeuroImage*, 128:96–115.

Tusche, A., Bode, S., and Haynes, J.-D. (2010). Neural responses to unattended products predict later consumer choices. *Journal of neuroscience*, 30(23):8024–8031.

UK Department of Transport (2016). *Reported casualties in Great Britain: 2016 annual report*. URL: https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/648081/rrcgb2016-01.pdf (Accessed: 17/06/2021).

Wang, Y., Mehler, B., Reimer, B., Lammers, V., D'Ambrosio, L. A., and Coughlin, J. F. (2010). The validity of driving simulation for assessing differences between in-vehicle informational interfaces: A comparison with field testing. *Ergonomics*, 53(3):404–420.

Wen, L. M. and Rissel, C. (2008). Inverse associations between cycling to work, public transport, and overweight and obesity: findings from a population based study in Australia. *Preventive medicine*, 46(1):29–32.

Wilcox, R. R. and Rousselet, G. A. (2018). A guide to robust statistical methods in neuroscience. *Current protocols in neuroscience*, 82(1):8–42.

Witmer, B. G. and Singer, M. J. (1998). Measuring presence in virtual environments: A presence questionnaire. *Presence*, 7(3):225–240.

Wong, K.-F. and Wang, X.-J. (2006). A recurrent network mechanism of time integration in perceptual decisions. *Journal of Neuroscience*, 26(4):1314–1328.

Wynne, R. A., Beanland, V., and Salmon, P. M. (2019). Systematic review of driving simulator validation studies. *Safety Science*, 117:138–151.

Yoon, C., Gonzalez, R., Bechara, A., Berns, G. S., Dagher, A. A., Dubé, L., Huettel, S. A., Kable, J. W., Liberzon, I., Plassmann, H., et al. (2012). Decision neuroscience and consumer decision making. *Marketing Letters*, 23(2):473–485.

Yun, M., Zhao, J., Zhao, J., Weng, X., and Yang, X. (2017). Impact of in-vehicle navigation information on lane-change behavior in urban expressway diverge segments. *Accident Analysis & Prevention*, 106:53–66.

Zhang, Q., Fu, R., Guo, Y., Guo, Y., Yuan, W., Wang, C., Wu, F., and Ma, Y. (2011). Risk attitude, perception, behavior, and personality as indicators of a driver's risk awareness in China. In *3rd International Conference on Road Safety and Simulation*, pages 1–13.

Zimasa, T., Jamson, S., and Henson, B. (2019). The influence of driver's mood on car following and glance behaviour: Using cognitive load as an intervention. *Transportation research part F: traffic psychology and behaviour*, 66:87–100.

Zöller, I., Abendroth, B., and Bruder, R. (2019). Driver behaviour validity in driving simulators–analysis of the moment of initiation of braking at urban intersections. *Transportation research part F: traffic psychology and behaviour*, 61:120–130.

Zuckerman, M., Kolin, E. A., Price, L., and Zoob, I. (1964). Development of a sensation-seeking scale. *Journal of consulting psychology*, 28(6):477.

Chapter 2

Cycling in virtual reality: modelling behaviour in an immersive environment

Martyna Bogacz[1], Stephane Hess[1], Chiara Calastri[1], Charisma F. Choudhury[1], Faisal Mushtaq[2], Muhammad Awais[2], Mohsen Nazemi[3], Michael A.B. van Eggermond[3] & Alexander Erath[3]

Abstract

Nowadays, immersive technologies are gaining popularity as a research tool in transport as they allow for a more dynamic approach to the exploration of road users' behaviour providing at the same time full control over interventions. Nevertheless, their ecological validity is still to be established and therefore their use in the mathematical modelling of human behaviour in a transport setting has been scarce. In the present study, we aim to fill in this gap by conducting a comparative study of cycling behaviour where both, non-immersive and immersive presentation methods are used in a virtual reality setting. Moreover, we developed discrete choice models using the collected data. The results confirm our hypothesis that participants behave differently when shown a choice scenario in non-immersive and immersive settings. In particular, cycling in an immersive setting is characterised by a higher degree of engagement, i.e. more action switches. To gain a more complete understanding of the processes underlying interactions in immersive environments, we also captured neural activity (using electroencephalography recordings) during task performance. We focused on oscillations in the alpha (α) band, a neural signature often associated with the filtering (gating) of sensory information. We found increased suppression in this signal in response

[1]Institute for Transport Studies and Choice Modelling Centre, University of Leeds, UK
[2]School of Psychology & Centre for Immersive Technologies, University of Leeds, UK
[3]Future Cities Laboratory Singapore-ETH Centre, Zürich

to the immersive condition relative to the non-immersive. These results complement the behavioural findings and indicate that immersive environments may increase levels of task-engagement.

1 Introduction

The study of road users' behaviour has direct implications for a number of issues: it is used in road safety, where human factors are a major contributor to traffic accidents (Rothengatter, 1997), policy making aimed at improving transport infrastructures (Cadar et al., 2017; Hood et al., 2011; Leao et al., 2019; Melson et al., 2014), and the study of how travel mode choices affect traffic congestion (Chen et al., 2018; Madhuwanthi et al., 2015) and climate change (Hook, 2007).

In this study we focus on cycling. Many studies have shown the numerous benefits of cycling in terms of sustainability and health; at the same time, existing research has highlighted a number of risks which represent a major obstacle to travelling by bicycle. In particular, unpleasant traffic conditions (Henson et al., 1997), personal security concerns (Davies et al., 1997), stress and danger (Gardner, 1998) and traffic and accidents (Davies and Hartley, 1999) are believed to be related to the low incidence of cycling as a commuting mode.

Nevertheless, data collection is a major challenge in this research area, and researchers have often resorted to experimental approaches when studying cyclist behaviour in risky settings, which give the analyst full control over interventions. Stated preference (SP) methods have been widely used in different formats in transport and beyond, such as SP surveys with visual elements (Wardman et al., 1996), SP web surveys (Auld et al., 2012; Correia and Viegas, 2011), the Lottery Choice Task (Barreda-Tarrazona et al., 2011) or Balloon Analogue Risk Task (Gordon, 2007; Lejuez et al., 2002; Vaca et al., 2013). SP methods allow for the control of factors included in the study design, but their reliability in capturing real-life human behaviour has often been questioned because of the non-commitment bias (Chatterjee et al., 1983) and hypothetical bias due to the lack of consequentiality of actions (Harrison, 2006; Hensher, 2010; Li et al., 2020; Louviere et al., 2000). Moreover, an additional challenge arises in the case of risky situations on the road, as the majority of these SP methods are designed for static settings and fail to account for the dynamic changes in risk and hence potentially also risk perception. Given these limitations, it is important to seek techniques that increase the design realism compared to traditional SP experiments.

A new opportunity to increase the ecological validity of behavioural research, defined as "*the applicability of the results of laboratory analogues to non-laboratory, real-life settings*" (McKechnie, 1977), has arisen in recent years through the increasing prevalence and affordability of virtual reality (VR) technology (Brookes et al., 2020). Virtual reality is typically defined as the computer-generation of three-dimensional interactive environments (Wann and Mon-Williams, 1996) and used to create naturalistic and immersive experiences. Virtual reality experiences are often deployed through head-mounted displays (HMDs), which allow experimenters to tightly control the visual input and track behavioural responses. This approach has been shown to add a level of realism to experiments, even when subjects are aware of the artificial nature of the scenarios (Rovira et al., 2009; Slater et al., 2006). The success of VR in the creation of realistic experiences has been demonstrated in previous studies in a transport context (Farooq et al., 2018; Moussa et al., 2012), transport risk research (Frankenhuis et al., 2010; Underwood et al., 2011), urban design research (Erath et al., 2017) and social context (Patterson et al., 2017).

The aforementioned studies have shed promising light on the elicitation of real behaviour in road situations despite the lack of consequentiality. The findings suggest that participants engage to a greater extent with the presented environment and actively take part in the events, even if in a virtual way. Nonetheless, further verification is advisable, as a recent study by Mai (2017), which compared pedestrians' behaviour at midblock crossings between a PC-based VR and real crosswalk, showed ambiguous findings, where walking speed differed significantly between two environments, however the proportion of decisions to cross were similar. Furthermore, a study by Godley et al. (2002), which examined the validity of driving simulators by comparing driving behaviour in an instrumented car vs a simulator showed similar deceleration activity under both conditions. Yet, on the other hand, individuals tended to drive faster in the instrumented car relative to the simulator. From a technical standpoint, studies which involve the use of simulated environments face the potential problem of artefacts stemming from the limited view field, lagged graphics update or low spatial resolution (Loomis et al., 1999). Studies involving fast motion such as that implied by driving or cycling are particularly prone to such issues due to so-called Simulator Adaptation Syndrome (SAS). This emerges mainly with time discrepancies between the driver's actions (commands) and the simulator's response to the given input. SAS is hypothesised to take place because participants adopt real driving as a reference point, and as a consequence, any delays in the simulator's reaction can lead to headaches, motion sickness, nausea or eye strain (Mollenhauer, 2004). Taken together, extant research shows that VR can be used effectively in road behaviour research, but also highlights the need to establish its ecological validity. We aim to advance this research with a study design that allows for a direct comparison of cycling behaviour as well as risk perception by manipulating the level of immersion participants experience (non-interactive information presented on a two-dimensional display vs interactive, 360-degree virtual environment). Importantly, recent studies by Xu et al. (2017) and Powell (2017) investigated cycling behaviour in virtual environments where the former study was limited to the descriptive analysis of the results while the later was mainly focused on the hardware design of the bicycling simulator.

In addition to using VR to increase ecological validity, we also set out to explore the impact of this presentation method on participants' neural activity as a proxy measure of engagement. We used electroencephalography (EEG), a scalp-recorded measure of electrical activity generated by the brain. Whilst this technique has low spatial resolution (and thus, mapping of observed responses to subcortical structures is a fundamental challenge in contrast to other neuroimaging approaches such as functional magnetic resonance imaging (fMRI) (Glover, 2011)), EEG has a high temporal resolution. As such, it is able to capture brain activity in the order of milliseconds (da Silva, 2013) and it is widely used in the study of risk and decision-making (Gui et al., 2010; Mushtaq et al., 2016). High temporal resolution is particularly important in the context of our experiment, as naturalistic cycling behaviour involves continually monitoring the environment and making fast reactions.

It is also worth noting that, until recently, the use of EEG in an experimental design often involved large bulky equipment with cables connecting a user's scalp directly to an amplifier interfacing with a recording PC, thus limiting its use in experiments designed to examine ecological validity. Recent advances in wireless EEG technology allow for it to be used in conjunction with VR in a relatively unobtrusive manner.

The signal-to-noise ratio of EEG is another factor that has constrained possibilities in applied experimental research: artefacts in EEG data can stem from physiological (e.g. ocular and facial muscle movements) and non-physiological sources (e.g. electric signals generated by nearby equipment (Puce and Hämäläinen, 2017)). Virtual reality experiments which allow a great degree of flexibility in participant head and body movement are more prone to producing artefactual data. Today's wireless systems such as Emotiv Epoc+ (Duvinage et al., 2012) and Enobio (Ratti et al., 2017) are designed for dynamic experimental setups and attempt to mitigate the impact of movement artefacts on the scalp-recorded EEG. However, these systems still require rigorous data pre-processing routines to minimise the influence of artefacts and ensure adequate signal-to-noise ratio.

In the transport literature, the use of EEG has largely focused on the investigation of driver fatigue and drowsiness (Awais et al., 2017; Craig et al., 2012; Eoh et al., 2005; Lal and Craig, 2001), level of alertness, attention or cognitive performance (Klimesch, 1999), except for the studies by Schweizer et al. (2013) and Vorobyev et al. (2015) which combined brain-imaging techniques and risky driving tasks. Although these studies have contributed to a better understanding of brain activity associated with driving in various conditions, the impact of different presentational methods while driving/cycling on human brain processes still remains unclear. In this study, we focused our analysis on a particular pattern of oscillatory brain EEG activity known as occipital alpha (α) – which is quantified through frequency analysis of the signal, focusing on signal power in the 8-14 Hz range. Occipital α is one of the most commonly observed signatures of brain activity, with numerous studies demonstrating a relationship between oscillations in this frequency band and attentional processing (Klimesch, 2012). Current understanding in the field of neuroscience holds that low α power implies increased excitability, and thus an increased response to external stimulation, most likely reflecting neural mechanisms involved in the gating of task-irrelevant information (Jensen and Mazaheri, 2010; Klimesch et al., 2007). As such, the signal presents an ideal candidate to investigate the impact of presentation format on participants' degree of task-relevant engagement.

Additionally, in terms of methodological approach, we develop mathematical models on the collected data to gain in-depth insights into cyclist behaviour beyond the statistical description of the data. The use of models allows us to see the extent to which the behaviour differs between immersive and non-immersive environments and provides new means to evaluate the theory proposed in the hypotheses. Moreover, the mathematical models used in the study give more flexibility in establishing the relationship between cyclists' behaviour and the independent variables and enable us to capture more accurately the complexity of the dynamic process (Cavagnaro et al., 2013).

To summarise, the research objectives of the present paper are threefold. *Firstly*, we aim to compare cycling behaviour under two different elicitation methods, namely non-immersive and immersive videos and validate virtual reality as a research tool. *Secondly*, we measure the stated perceived risk and stated willingness to cycle (SWTC) in the non-immersive and immersive scenarios to compare the stated attitudes towards cycling in these conditions as well as comparing behavioural responses (e.g. in terms of acceleration behaviour). *Finally*, we incorporate a neural perspective with an aim to investigate differences in neural processing of cycling scenarios in non-immersive and immersive presentations.

The remainder of this paper is organised as follows. We present our specific hypotheses guided by the literature in the next section. The data collection design and sample characteristics are presented next, followed by the methodological approach of the study. We next turn to the results section, followed by the discussion section which reviews the insights from the analysis.

2 Hypotheses

Five hypotheses are put forward and tested empirically in our work. They relate to cycling behaviour, risk perception and neural processing, and we now look at these three groups in turn.

Cycling behaviour

- Hypothesis 1A: there is a difference in cycling behaviour between the non-immersive and immersive scenarios;
- Hypothesis 1B: the number of switches between different actions (accelerating, braking and free-wheeling) is higher in the immersive compared to non-immersive scenarios.

These two hypotheses are based on the findings of previous studies, as discussed in the introduction (Erath et al., 2017; Farooq et al., 2018; Frankenhuis et al., 2010; Patterson et al., 2017; Rovira et al., 2009; Slater et al., 2006; Underwood et al., 2011), which show that the immersive environment engaged participants to a larger extent.

Risk perception and willingness to cycle

- Hypothesis 2A: the stated risk is higher in immersive compared to non-immersive setting;
- Hypothesis 2B: the stated willingness to cycle is lower in immersive compared to non-immersive setting.

The immersive representation seeks to elicit behaviour similar to a real-world context and should thus amplify the riskiness compared to the non-immersive presentation, holding everything else the same. Consequently, a higher risk perceived in immersive setting should be associated with lower willingness to cycle under this condition compared to non-immersive one.

Neural processing

- Hypothesis 3: the peak amplitude of the α waves in trials with non-immersive presentations format are higher than in the immersive presentation conditions, reflecting differences in task-relevant attentional processing.

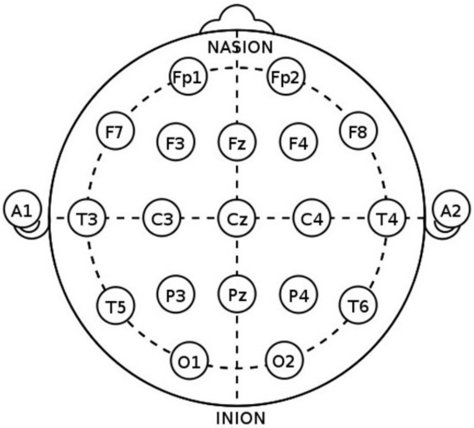
3 Data collection and sample information

This section describes the experimental procedure and its components focusing on the details of the combined research approach employed in this experiment as well as the basic characteristics of the sample.

The single experimental session started with the briefing of the participant who was blinded to the purpose of the experiment. Therefore, the real objectives of the study were not presented to participants and the instructions they were given were worded in such a way as to minimise the experimenter's effect for the exact wording see Participant task instructions in Appendix A). After the introduction, the participant was seated and had an Emotiv Epoc+ EEG headset (EMOTIV, 2018) and an Oculus Rift VR (Oculus.com, 2018) HMD placed on their head. The Emotiv headset uses 14 electrodes (at AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8 and AF4; Figure 2.1) sampling across the scalp. The system was selected as its compact design allowed it to be used jointly with the VR HMD. As a first step, the baseline brain activity was recorded with the sampling rate of 128 Hz, while participants had their eyes opened and focused their gaze on one point on the screen for 15 seconds. The same procedure was then repeated with eyes closed. Power in the α wave band (8-14 Hz) is typically highest during relaxation and low levels of arousal (Lagopoulos et al., 2009) and also increases with the degree of disengagement from the external, visual environment (Ergenoglu et al., 2004; Hawkins et al., 2015; Mathewson et al., 2009; Van Dijk et al., 2008).

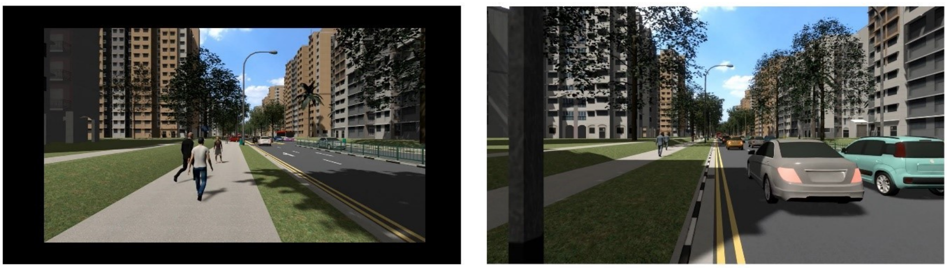
The experiment encompassed two distinct treatments, where we used a within-subject design. Both treatments consisted of a presentation of traffic scenarios from the perspective of the cyclist, however, they differed in the method of presentation: one of them was a non-immersive video, while the other used an immersive virtual reality setting. Both of these conditions were presented using the VR headset in order to avoid potential confounds. The non-immersive video was shown within the boundaries of the static simulation of a screen displayed in front of the participant in the virtual environment. In this condition, a participant observed the simulated scenarios as if they were watching it on a computer screen so that it was not responsive to any movements of the participant (the left pane of Figure 2.2). In contrast, the immersive condition was a 360-degree view of the road which surrounded the

Fig. 2.1: Electrodes position on the scalp (Khazi et al., 2012).



participant and responded to their head movements (the right pane in Figure 2.2). Importantly, based on the feedback received during initial pre-testing of the set-up, sound was included in both the immersive and non-immersive conditions, to capture visual and auditory cues that are available to cyclists in real-life settings. The volume of vehicles was consistent with their distance to the cyclist so that the sound of an approaching car increased as it got closer to the cyclist. We believe that this allowed us to better replicate reality and conduct an analysis where we considered the impact on cycling behaviour of vehicles not only in front of the cyclists that can be seen but we also looked at the impact of cars approaching behind the bicycle which could have been heard.

Fig. 2.2: The non-immersive and immersive views used in the experiment



The visual stimuli in the experiment come from VR road simulations developed by Future Cities Laboratory (Schramka et al., 2017) using Unity 3D Game Engine (Unity, 2017). These stimuli involve pre-programmed environments and they do not respond to the actions of the cyclist. We used two types of traffic scenarios as seen in Figure 2.3, namely, cycling on the pavement (on the left) and cycling on the side of the road (on the right). In the pavement scenarios, the movement of pedestrians was bidirectional ie. they could walk in the same or the opposite direction to the riding cyclist. In contrast, in the road scenarios, all the vehicles were driving in the same direction as the cyclists. The number of people and vehicles differed in the scenarios influencing their riskiness. The risky scenarios were characterized by a higher number of people and more cars passing by as seen in Figure 2.3. The entire experiment comprised of 12 immersive and 12 non-immersive scenarios resulting in the overall number of 24 scenarios and used an orthogonal design where a combination of road/pavement and low/high risk scenarios was shown in non-immersive/immersive environment in random order. Importantly, each participant performed all 24 scenarios and the same scenarios were used in non-immersive and immersive presentations for the same participant, but the order of the treatments (immersive/non-immersive) as well as the scenarios within each treatment were randomised across participants. The number and types of scenarios is summarised in Table 2.1.

Fig. 2.3: A high-risk condition in the pavement and road scenarios

The task for the participant was to cycle through the scenario at the desired pace until the finish line at the end of each scenario (see section 1 in Appendix A for full task description). In order to navigate through the scenario, participants used the keyboard to adjust their speed, but had no ability to turn left or right. They pressed the up arrow to accelerate and the down arrow to brake. The keyboard was placed on the table in front of them, and before the experiment began, they were guided by the experimenter to find the appropriate keys on the keyboard. It is important to note that the use of

Table 2.1: Number and types of scenarios used.

Number of scenarios	Immersion	Scenario riskiness	Road type
3	Immersive	High	Road
3	Immersive	High	Pavement
3	Immersive	Low	Road
3	Immersive	Low	Pavement
3	Non-immersive	High	Road
3	Non-immersive	High	Pavement
3	Non-immersive	Low	Road
3	Non-immersive	Low	Pavement

a keyboard as opposed to an instrumented bicycle has a significant impact on the scope of the study and the modelling approach. For example, due to the use of a keyboard, we decided to model cycling decisions as a discrete (i.e. accelerate vs brake vs freewheel) instead of a continuous choice (e.g. level of acceleration). Moreover, the use of a keyboard makes the cycling experience less realistic because it removes the component of physical effort associated with cycling, and acceleration is more instantaneous when a keyboard is used. On the other hand, the advantages of the use of a keyboard cannot be ignored. Given the exploratory nature of this study, the simpler design contributes to less body movement that could adversely impact the quality of the EEG data in what is already a relatively complex experiment. It results that the use of an instrumented bicycle should be considered for future studies, but the keyboard used in this study provides a benchmark that future studies can build on.

After crossing the finish line, the participant responded verbally to two questions: *"How risky was the scenario?"* and *"How likely are you to cycle in this scenario?"*. The answers were measured on a 7-point Likert scale where 1 was the minimum perceived risk/willingness to cycle and 7 was the maximum perceived risk/willingness to cycle. In addition to the acceleration and braking behaviour, and the stated risk and willingness to cycle answers, the study used the mobile EEG headset to collect the neuroimaging data. After this stage of the experiment, the participants were asked to complete a socio-demographic survey (see Appendix A for the full questionnaire). At the end of the experiment, we conducted a short and informal interview to capture any feedback or comments which were not included in the survey such as which scenario type was riskier or which element within the scenarios was the most hazardous. The entire experiment did not exceed 90 minutes where the duration of each task was between 1- 2 minutes and varied depending on the cycling speed of the participant. Furthermore, the transition time between tasks was approximately 10-15 seconds.

The initial number of recruited participants was 50, from which 4 participants were removed due to failure to complete the whole experiment, leading to a final sample size of 46 participants (18 males, 28 females), comprising staff and students of the University of Leeds as well as the members of the general public. The mean age of the participants was 30.7 years, with 10.88 years standard deviation (see Appendix A for further details on the sample characteristics). Importantly, for the EEG data analysis, an additional 16 participants were dropped due to low quality of the EEG data. The exclusion of participants was decided during the manual cleaning of the EEG data where we removed blocks of continuous signal in which the noise stemming from the body or head movements of the participant (eg. when an individual touched his face, adjusted headset during the experiment, talked or changed his sitting position on the chair) led to a poor connection between the headset and the scalp. If the proportion of the removed signal was larger than the remaining signal, then the whole EEG data for a given participant was discarded to increase the reliability, usability and confidence in the neural inputs on the sample level. The resulting EEG data sample size is small, but this is exploratory work and future studies will be able to add additional evidence with more data. Importantly, this limitation exposes important aspects of experimental design that can prevent or diminish such occurrences in the future. Firstly, when working with novel devices where there is relatively scant literature that can be used for guidance or when the device is used in new circumstances, it is recommended to test the device in various conditions, such as when a person is speaking, mouth breathing, blinking, pulling faces, moving head, walking etc., to be able to assess the impact of those activities on the quality of the signal. Moreover, it is useful to give very detailed instructions to participants before the experiment begins to minimise data loss due to behaviour that can be easily avoided. For example, the participant should be explicitly advised not to touch his head and face or not to talk after the experiment begins. Consequently, before the commencement of the experimental session participant and the experimenter should dedicate sufficient time to adjust the VR headset and EEG device to ensure the comfort of the participant for the duration of the experiment. At the same time, it is important to emphasise that the small sample size is a classic issue faced by researchers working with VR and/or driving simulator data (Di Stasi et al., 2012; Katsis et al., 2011; Moussa et al., 2012) as the experiment durations are much longer and the associated costs are much higher compared to typical SP studies.

4 Methodology

The variety of data collected along the course of this study leads to a multi-stage statistical analysis using behavioural data, stated responses on perceived risk and willingness to cycle and EEG traces, allowing us to address the three research objectives of this study.

4.1 Cycling behaviour data

In terms of the first research objective, we look at the behaviour when cycling through the interactive scenarios, with three possible actions: acceleration, braking and freewheeling (i.e. not accelerating or braking, which is set as a reference category).

We use a multinomial logit model (MNL) (McFadden, 1974) for the choice of the action in every quarter second. The model assumes that the probability of participant n performing action i at time t and in scenario s increases with the value of the deterministic component of utility ($V_{i,n,t,s}$). The utility associated with a particular action is a function of the current state (i.e. accelerating, freewheeling, braking), the attributes of the scenario (e.g. road, pavement), condition type (e.g. non-immersive and immersive), the position of other agents (eg. distance to vehicle/pedestrian in front, distance to the car/pedestrian on the back etc.) and the speed of the cyclists at time *t-1* (i.e. in the previous quarter second). For this last variable, we tested different lag values ranging from 0.25 second to 2 seconds in quarter-second intervals. The speed variable was included in the model in a linear, quadratic and cubic fashion to determine any non-linearity in the relationship between the speed and the dependent variable. The inclusion of polynomials is a common practice in choice models to account for non-linearity (see for example Train (2016)), where it is possible to use polynomials of higher degrees as long as the available degrees of freedom are not exhausted (Ben-Akiva and Lerman, 2018). Nonetheless, this approach results in the polynomial terms being highly correlated, henceforth the coefficients should be interpreted jointly to provide a meaningful measure and the goodness of fit should be compared between models to justify the use of higher-order variables. In the current model, this specific functional form was chosen based on the comparison of model fit and significance of coefficients between models which used lower or higher orders of speed variable. No socio-demographic effects were captured given the small sample size. We use a joint model for the road and the pavement scenarios and for non-immersive and immersive environments but incorporate shift parameters (i.e. additive interaction terms) to allow us to investigate and compare the behaviour undertaken in non-immersive and immersive scenarios and between the two types of scenarios. The utility associated with the decision of a cyclist n to choose one of the three actions (Acc=accelerate, Br=brake, FW=freewheel) at time t in scenario s can, therefore, be expressed as follows, where freewheeling is used as the baseline:

$$
\begin{aligned}
V_{Acc_{n,t,s}} = {} & \delta_{Acc_{t,s}} + (\beta_{distfront_{Acc}} + \Delta_{\beta,distfront_{Acc_I}} \cdot x_{I_{n,s}} \\
& + \Delta_{\beta,distfront_{Acc_{road}}} \cdot x_{road_{n,s}} + \Delta_{\beta,distfront_{Acc_{road_I}}} \\
& \cdot x_{I_{n,s}} \cdot x_{road_{n,s}}) \cdot x_{distfront_{n,t,s}} + (\beta_{distrear_{Acc}} \\
& + \Delta_{\beta,distrear_{Acc_I}} \cdot x_{I_{n,s}} + \Delta_{\beta,distrear_{Acc_{road}}} \cdot x_{road_{n,s}} \\
& + \Delta_{\beta,distrear_{Acc_{road_I}}} \cdot x_{I_{n,s}} \cdot x_{road_{n,s}}) \cdot x_{distrear_{n,t,s}} \\
& + \beta_{speed_{Acc}} \cdot x_{speed_{n,t-1,s}} + \beta_{speed-second_{Acc}} \cdot x^2_{speed_{n,t-1,s}} \\
& + \beta_{speed-third_{Acc}} \cdot x^3_{speed_{n,t-1,s}}
\end{aligned}
\tag{2.1}
$$

$$
\begin{aligned}
V_{Br_{n,t,s}} = {} & \delta_{Br_{t,s}} + (\beta_{distfront_{Br}} + \Delta_{\beta,distfront_{Br_I}} \cdot x_{I_{n,s}} \\
& + \Delta_{\beta,distfront_{Br_{road}}} \cdot x_{road_{n,s}} + \Delta_{\beta,distfront_{Br_{road_I}}} \\
& \cdot x_{I_{n,s}} \cdot x_{road_{n,s}}) \cdot x_{distfront_{n,t,s}} + (\beta_{distrear_{Br}} \\
& + \Delta_{\beta,distrear_{Br_I}} \cdot x_{I_{n,s}} + \Delta_{\beta,distrear_{Br_{road}}} \cdot x_{road_{n,s}} \\
& + \Delta_{\beta,distrear_{Br_{road_I}}} \cdot x_{I_{n,s}} \cdot x_{road_{n,s}}) \cdot x_{distrear_{n,t,s}} \\
& + \beta_{speed_{Br}} \cdot x_{speed_{n,t-1,s}} + \beta_{speed-second_{Br}} \cdot x^2_{speed_{n,t-1,s}} \\
& + \beta_{speed-third_{Br}} \cdot x^3_{speed_{n,t-1,s}}
\end{aligned}
\tag{2.2}
$$

$$
V_{FW} = \quad 0 \tag{2.3}
$$

In Equation 2.1 and 2.2, $\delta_{Acc_{t,s}}$ and $\delta_{Br_{t,s}}$ are alternative specific constants (ASC) which we will look at in more detail below, where the subscripts show the time and scenario dependent nature of these ASCs. The other components look at the impact of the other agents in the scenario and the cyclist's speed at time *t-1* on the utilities, where:

- $x_{distfront_{n,t,s}}$ and $x_{distrear_{n,t,s}}$ are the variables representing the distance (measured in metres) at time t to the nearest car/pedestrian in front and the back of the bicycle respectively, in scenario s for individual n;

- $x_{I_{n,s}}$ and $x_{road_{n,s}}$ are dummy variables indicating whether for individual n, scenario s is an immersive scenario or a road scenario, respectively (equal to 1 if true, 0 otherwise), where the index n reflects the fact that the order was different across participants

- $x_{speed_{n,t-1,s}}$, $x^2_{speed_{n,t-1,s}}$ and $x^3_{speed_{n,t-1,s}}$ are the variables representing the cyclist's speed (measured in km/h) at time *t-1*, for individual n in scenario s. We use polynomials up to degree 3 to allow for non-linear impacts.

We estimate baseline parameters that explain the overall sensitivity to these attributes, along with shifts in these sensitivities for different types of scenarios. In particular:

- $\beta_{distfront_{Acc}}$ and $\beta_{distrear_{Acc}}$ are the baseline parameters representing the impact on the utility for acceleration by the distance to the nearest car/pedestrian in front and behind the bicycle, respectively;

- $\beta_{distfront_{Br}}$ and $\beta_{distrear_{Br}}$ are the baseline parameters representing the impact on the utility for braking by the distance to the nearest car/pedestrian in front and behind the bicycle, respectively; and

- $\beta_{speed_{Acc}}$, $\beta_{speed-second_{Acc}}$ and $\beta_{speed-third_{Acc}}$ are the baseline parameters representing the impact on the utility for acceleration by the speed of the cyclist at the previous time point in first, second and third order, respectively;

- $\beta_{speed_{Br}}$, $\beta_{speed-second_{Br}}$ and $\beta_{speed-third_{Br}}$ are the baseline parameters representing the impact on the utility for braking by the speed of the cyclist at the previous time point in first, second and third order, respectively; and

- The various Δ parameters are interaction terms capturing the shift in the values of the associated β parameters in specific types of scenarios – for example, $\Delta_{\beta,distfront_{Acc_I}}$ and $\Delta_{\beta,distrear_{Acc_I}}$ capture the shift in the values of $\beta_{distfront_{Acc}}$ and $\beta_{distrear_{Acc}}$ for the immersive scenarios. We allow for shifts by cycling environment (road vs base of pavement), by presentation type (immersive vs base of non-immersive) as well as a joint immersive-road shift. Importantly, the non-immersive scenarios did not allow participants to look behind their back although participants were indirectly aware of both the pedestrians and vehicles behind. For the pedestrians, this is because the respondent will have just overtaken them. For the vehicles, though the participants are unlikely to overtake, they are aware of their presence as they could hear the approaching car from behind.

The parameters to represent the impact of the current action on the choice of the next one are included in the utility function via the alternative specific constants (δ) using the expressions below, where we show the full specifications, with some effects dropping out in actual model estimation due to low significance:

$$\begin{aligned}\delta_{Acc_{n,t,s}} = (&\delta_{Acc-current-Acc} + \Delta_{\delta,Acc-current-Acc_I} \cdot x_{I_{n,s}} + \\ &\Delta_{\delta,Acc-current-Acc_{road}} \cdot x_{road_{n,s}} + \Delta_{\delta,Acc-current-Acc_{road_I}} \\ &\cdot x_{road_{n,s}} \cdot x_{I_{n,s}}) \cdot x_{Acc_{t-1}} + (\delta_{Acc-current-Br} + \Delta_{\delta,Acc-current-Br_I} \\ &\cdot x_{I_{n,s}} + \Delta_{\delta,Acc-current-Br_{road}} \cdot x_{road_{n,s}} + \Delta_{\delta,Acc-current-Br_{road_I}} \\ &\cdot x_{road_{n,s}} \cdot x_{I_{n,s}}) \cdot x_{Br_{t-1}} + (\delta_{Acc-current-FW} + \Delta_{\delta,Acc-current-FW_I} \\ &\cdot x_{I_{n,s}} + \Delta_{\delta,Acc-current-FW_{road}} \cdot x_{road_{n,s}} + \Delta_{\delta,Acc-current-FW_{road_I}} \\ &\cdot x_{road_{n,s}} \cdot x_{I_{n,s}}) \cdot x_{FW_{t-1}}\end{aligned} \tag{2.4}$$

$$\begin{aligned}\delta_{Br_{n,t,s}} = (&\delta_{Br-current-Acc} + \Delta_{\delta,Br-current-Acc_I} \cdot x_{I_{n,s}} + \\ &\Delta_{\delta,Br-current-Acc_{road}} \cdot x_{road_{n,s}} + \Delta_{\delta,Br-current-Acc_{road_I}} \\ &\cdot x_{road_{n,s}} \cdot x_{I_{n,s}}) \cdot x_{Acc_{t-1}} + (\delta_{Br-current-Br} + \Delta_{\delta,Br-current-Br_I} \\ &\cdot x_{I_{n,s}} + \Delta_{\delta,Br-current-Br_{road}} \cdot x_{road_{n,s}} + \Delta_{\delta,Br-current-Br_{road_I}} \\ &\cdot x_{road_{n,s}} \cdot x_{I_{n,s}}) \cdot x_{Br_{t-1}} + (\delta_{Br-current-FW} + \Delta_{\delta,Br-current-FW_I} \\ &\cdot x_{I_{n,s}} + \Delta_{\delta,Br-current-FW_{road}} \cdot x_{road_{n,s}} + \Delta_{\delta,Br-current-FW_{road_I}} \\ &\cdot x_{road_{n,s}} \cdot x_{I_{n,s}}) \cdot x_{FW_{t-1}}\end{aligned} \tag{2.5}$$

Where $\delta_{Acc_{n,t,s}}$ and $\delta_{Br_{n,t,s}}$ are the alternative-specific constants for acceleration and braking, respectively, for individual n at time t in scenario s. We have normalized the alternative-specific constant of freewheeling to zero. The estimated values for $\delta_{Acc_{n,t,s}}$ and $\delta_{Br_{n,t,s}}$ capture the influence of the most recently performed action on the choice of the next action. Specifically:

- $\delta_{Acc-current-Acc}$, $\delta_{Acc-current-Br}$ and $\delta_{Acc-current-FW}$ are the baseline parameters that represent the impact of acceleration, braking and free-wheeling, respectively, at time *t-1* and scenario s, on acceleration behaviour at time t;
- $\delta_{Br-current-Br}$, $\delta_{Br-current-Acc}$ and $\delta_{Br-current-FW}$ are the baseline parameters that represent the impact of acceleration, braking and free-wheeling, respectively, at time *t-1* and scenario s, on braking behaviour at time t;

- $x_{Acc_{t-1}}$, $x_{Br_{t-1}}$ and $x_{FW_{t-1}}$ indicate which particular action (acceleration, braking, freewheeling, respectively) was performed at time *t-1*. At time *t-1*, the previous state is set to freewheeling, i.e. do nothing.

- The various Δ parameters are interaction terms capturing the shift in the values of the associated δ parameters in specific types of scenarios - for example, $\Delta_{\delta,Acc-current-Acc_I}$, $\Delta_{\delta,Acc-current-Br_I}$ and $\Delta_{\delta,Acc-current-FW_I}$ are the interaction terms that capture the shift in the values of the baseline parameters $\delta_{Acc-current-Acc}$, $\delta_{Acc-current-Br}$ and $\delta_{Acc-current-FW}$, respectively, for the immersive scenarios. We allow for shifts by cycling environment (road vs base of pavement) and by presentation type (immersive vs base of non-immersive) as well as a joint immersive-road shift.

With this specification, and using a type I extreme value error term, the probability (P) of participant n choosing action i (out of 3 possible actions) at time t in scenario s is given by:

$$P_{i,n,t,s}(\beta) = \frac{e^{V_{i,n,t,s}}}{\sum_{i=1}^{3} e^{V_{i,n,t,s}}}, \tag{2.6}$$

where β is a vector combining all model parameters and $V_{i,n,t,s}$ is the deterministic component of the utility for alternative i, as shown in Equations 2.1-2.3.

4.2 Risk perception and willingness to cycle data

In this section, we look at the modelling of the stated risk and stated willingness to cycle (SWTC) in non-immersive and immersive scenarios. We use an ordered logit model (Greene and Hensher, 2010) as the dependent variables were measured on a 7-point Likert scale, where we do this separately for risk and the SWTC. Consequently, $Y_{n,s}$ is an observed value of perceived risk/SWTC for individual n in scenario s which can take M different possible values, going from m = 1,...,7. The probability of observing value m is expressed as:

$$P_{Y_{n,s=m}} = \frac{e^{\tau_m - V_{n,s}}}{1 + e^{\tau_m - V_{n,s}}} - \frac{e^{\tau_{m-1} - V_{n,s}}}{1 + e^{\tau_{m-1} - V_{n,s}}}, \tag{2.7}$$

The model assumes a deterministic component of utility ($V_{n,s}$) that is a function of scenario attributes and demographic characteristics, controlling for the non-immersive and immersive presentation, and τ are a set of threshold parameters which are to be estimated. Many different effects were tried[1], and the final utility functions for stated risk and SWTC can be seen below:

$$\begin{aligned} V_{stated\ risk_{n,s}} = {} & \Delta_{SR,I} \cdot x_{I_{n,s}} + \Delta_{SR,road} \cdot x_{road_{n,s}} + \Delta_{SR,male} \cdot x_{male_n} \\ & + \Delta_{SR,high\ traffic} \cdot (x_{high\ traffic,pavement_{n,s}} \\ & + x_{high\ traffic,road_{n,s}}) + \Delta_{SR,high\ traffic,road} \\ & \cdot x_{high\ traffic,road_{n,s}} + \Delta_{SR,high\ traffic,I} \\ & \cdot (x_{high\ traffic,pavement_{n,s}} + x_{high\ traffic,road_{n,s}}) \\ & \cdot x_{I_{n,s}} + \Delta_{SR,high\ traffic,road,I} \cdot x_{high\ traffic,road_{n,s}} \cdot x_{I_{n,s}} \end{aligned} \tag{2.8}$$

$$\begin{aligned} V_{SWTC_{n,s}} = {} & \Delta_{SWTC,I} \cdot x_{I_{n,s}} + \Delta_{SWTC,road} \cdot x_{road_{n,s}} + \Delta_{SWTC,male} \cdot x_{male_n} \\ & + \Delta_{SWTC,high\ traffic} \cdot (x_{high\ traffic,pavement_{n,s}} \\ & + x_{high\ traffic,road_{n,s}}) + \Delta_{SWTC,high\ traffic,road} \\ & \cdot x_{high\ traffic,road_{n,s}} + \Delta_{SWTC,high\ traffic,I} \\ & \cdot (x_{high\ traffic,pavement_{n,s}} + x_{high\ traffic,road_{n,s}}) \\ & \cdot x_{I_{n,s}} + \Delta_{SWTC,high\ traffic,road,I} \cdot x_{high\ traffic,road_{n,s}} \cdot x_{I_{n,s}} \end{aligned} \tag{2.9}$$

In an ordered logit model, the probabilities are driven by comparisons between the utility and the thresholds. When all attributes (x) in Equation 2.8 and 2.9 are zero, we have the base scenario for all characteristics (i.e. non-immersive, pavement, female, etc). We then allow for shifts in the utility depending on the user and scenario characteristics. In addition to previously described attributes, we have that $x_{high\ traffic,road_{n,s}}$ and $x_{high\ traffic,pavement_{n,s}}$ are the variables indicating high traffic condition on the road and pavement, respectively, in scenario s, for person n. There are high and low traffic scenarios used in the experiment which differ in the overall traffic volume. The high traffic scenarios used more than 200 pedestrians and 40 cars, on pavement and road respectively.

We estimate parameters that explain the shifts in utility for different types of scenarios. For example, and for ease of notation not showing the sub-

[1] The explanatory variables tested in the model, both with and without interactions, include age groups (18-24, 25-29, 30-39, 40-49, 50-59 years and above 60 years old), education levels (O level, A level, vocational qualifications, undergraduate, Masters and postgraduate doctoral degree), marital status, number of children (zero, one and more than 2 children) and being an active car driver.

scripts SR (for stated risk) and SWTC (for stated willingness to cycle) in the text, $\Delta_{high\ traffic,I}$ captures the shift in the utility (and hence the likely responses) for the high traffic immersive scenarios. We allow for shifts by gender (male vs female), cycling environment (road vs pavement), presentation type (immersive vs non-immersive) as well as a joint immersive-road shift.

4.3 EEG data

For the EEG analyses, we examine differences in peak α power under non-immersive and immersive scenarios. As the EEG readings observed on the scalp are inherently noisy, we undertake a number of steps to eliminate artefacts and improve the signal-to-noise ratio. Prior to undertaking the statistical analysis of the EEG data, we pre-process the data using BESA 6.0 (MEGIS Software GmbH, Gräfelfing, Germany). Specifically, we first apply a 1-20 Hz bandpass filtering (BPF), a linear transformation that retains the components of the data within this specific band of frequencies (Christiano and Fitzgerald, 2003) and removes frequencies outside of this range that may stem from physiological sources such as galvanic skin responses or external environmental sources such as electronic equipment (Repovs, 2010) . Next, we clean the data to remove noise stemming from eyeblinks (movement artefacts were corrected using a multiple source analysis method (Berg and Scherg, 1994; Ille et al., 2002). The head movements and other remaining artefacts are manually marked in BESA by visually inspecting the EEG data. The processed EEG data is imported to MATLAB along with the manually marked artefact events. The artefact events are then removed from the EEG data for further processing. Finally, we compute the power spectrum of the EEG data using Welch's method (Welch, 1967) which estimates the power spectra based on Fast Fourier Transform (FFT) (Shaker, 2007). Because of our interest in occipital α, we perform a region-of-interest analysis and take an average of the activity from electrodes O1, O2, P7, P8, T7 and T8 to increase the stability of the signal (Oken and Chiappa, 1986). The α power is computed every quarter of a second to align with the frequency of behavioral measures, obtained from the MNL model.

5 Results

This section discusses the main findings with respect to the research objectives of the paper. All models were estimated using the Apollo software (Hess and Palma, 2019) where robust t-ratios have been used to account for the repeated choices of the individuals (Daly and Hess, 2011).

5.1 Cycling behaviour data

We used the MNL model to analyse the behavioural data where the dependent variable was the decision of a specific action at each quarter second. The estimation results are summarised in Table 2.2 and, Table 2.3, where significant (95% significance level) or marginally insignificant results are reported. It may be noted that non-immersive pavement scenarios were used as the base, and the effects of the immersive presentation and the impact of the road scenario on behaviour were incorporated in the model in the form of additive interaction variables.

We first look at the alternative specific constants (ASCs) in Table 2.2 and the associated Figure 2.4, where we show the probability of the next action conditional on the current action. To create these plots, we use the average values in the data for all other attributes i.e. the distances and the speed. We can observe that under the non-immersive condition on the pavement, if a person is currently accelerating, he/she is most likely to brake next (estimate = 1.0711; rob.t-ratio = 5.32), followed by free-wheeling and lastly acceleration (estimate = -2.7259). If we look at the interaction parameters for immersive scenarios, which are captured as an added shift to the estimates of the non-immersive base value, we observe that the value for accelerating is now further from freewheeling (-2.7259 - 0.0296). Furthermore, the value for braking is also reduced (1.0711 - 0.2376) in immersive scenarios, albeit that this retains the highest value even after the shift. In a road setting, the value for the ASC for accelerating (when currently accelerating) is further decreased by 0.3802 (-2.7259 - 0.3802 = -3.1061), and acceleration becomes even less likely compared to freewheeling.

In the non-immersive pavement setting, if the person is currently braking, the next most likely action taken is freewheeling, then acceleration (estimate = -1.1032) and lastly braking (estimate = -4.1562). The inclusion of the shift for road scenarios reduces the ASC for braking (if the person is currently braking) by 2.2766 to -6.4328, making consecutive braking actions very unlikely.

If a person is currently free-wheeling in a non-immersive pavement scenario, he/she is most likely to continue freewheeling, followed by acceleration (estimate = -2.7050; rob.t-ratio = -34.93) and braking (estimate = -4.6373; rob.t-ratio = -31.33). Looking at the interaction for immersive scenarios, we observe that freewheeling continues to be the most likely action if currently free-wheeling, followed by acceleration with an estimated shift of -0.1508 (rob.t-ratio = -1.81) which changes the non-immersive scenarios base value from -2.7050 to -2.8558. Following acceleration, the least likely action remains braking albeit that the immersive interaction reduces the gap between braking and freewheeling by 0.3201. In road scenarios, we observe a drop in the value of braking and an increase in the value for acceleration which continues to grow for the immersive road scenarios.

Finally, we have also tested the addition of a dummy variable which takes a value of 1 for cyclists and 0 otherwise but found these effects to be insignificant on both acceleration (estimate = -0.0056; rob. t-ratio = -0.14) and braking behaviour (estimate = 0.1668; rob.t ratio = 0.67). For this reason, we decided to leave out these effects.

Table 2.2: A joint MNL model – action switch (robust t-ratios in brackets).

LL(start): -267,853.8
LL(final): -155,302.1
AIC: 310,664.2
BIC: 310,976.3

			Current action		
		Next action	**Acceleration**	**Braking**	**Free-wheeling**
Base(δ)		Acceleration	-2.7259 (-27.77)	-1.1032 (-6.89)	-2.7050 (-34.93)
		Braking	1.0711 (5.32)	-4.1562(-17.25)	-4.6373 (-31.33)
		Free-wheeling	0	0	0
Shifts in δ ($\Delta\delta$)	for all immersive scenarios	Acceleration	-0.0296 (-1.38)	-	-0.1508 (-1.81)
		Braking	-0.2376 (-3.44)	-	0.3201 (2.01)
		Free-wheeling	0	0	0
	for all road scenarios	Acceleration	-0.3802 (-7.21)	-	0.2614 (3.13)
		Braking	-	-2.2766 (-9.40)	-1.5369 (-9.07)
		Free-wheeling	0	0	0
	for immersive road scenarios	Acceleration	-	-	0.5227 (6.10)
		Braking	-	-	-
		Free-wheeling	0	0	0

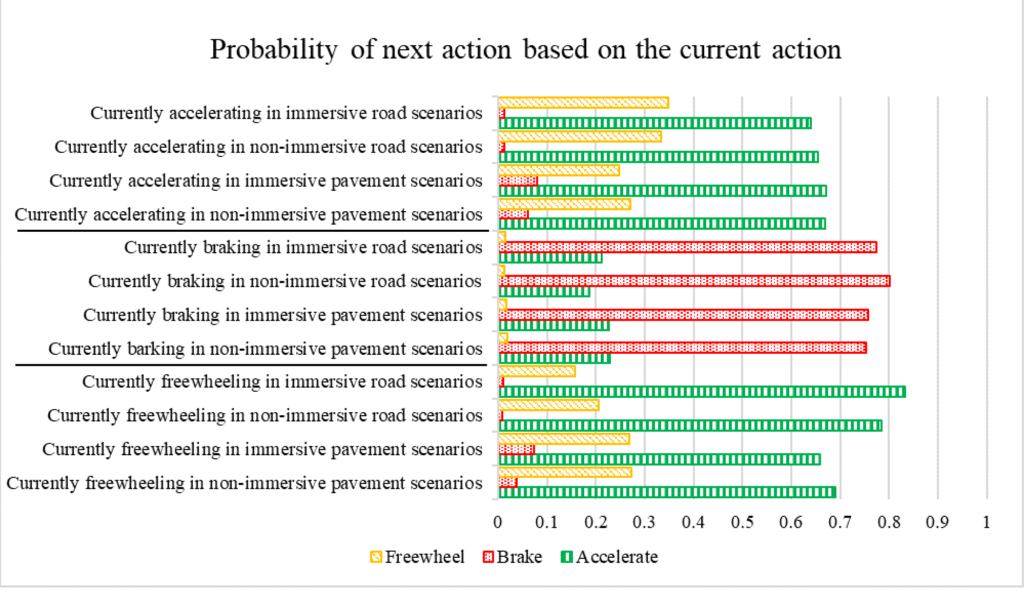
Taken together, these results show that if a person is currently actively cycling (i.e. accelerating or braking) in non-immersive scenario, then he/she is most likely to choose braking or freewheeling, and less likely to accelerate. These differences depending on the current action are visually demonstrated in the top and middle part of Figure 2.4. The immersive interaction reduces the probability of active cycling being undertaken which shows that the person is more inclined to interchange active cycling with freewheeling. On the other hand, current passive cycling (i.e. Free-wheeling) increases the probability of braking and reduces that of acceleration while free-wheeling remains the most likely next action. Overall, these effects could be a result of the increase in attentional resources required to process richer immersive environments resulting in more deliberate and less dynamic cycling behaviour. Furthermore, if a person is currently passively cycling, the results show that in a non-immersive environment, the road setting increases the probability of choosing acceleration as a next action compared to the pavement and this effect is further reinforced in the immersive scenario on the road. These be-

Table 2.3: A joint MNL model – lagged speed (robust t-ratios in brackets).

Impact on utility for	First order lagged speed	Second order lagged speed	Third order lagged speed
Accelerating	1.0356 (43.27)	-0.0657 (-200.53)	0.0011 (23.44)
Braking	0.5869 (14.71)	-0.0222 (-15.42)	-

havioural differences can clearly be observed in the bottom panel of Figure 2.4. Altogether, the results in Table 2.2 highlight differences in cycling be-

Fig. 2.4: Visual representation of probabilities of next actions conditional on the current action.



haviour solely driven by the difference in the presentation format where the immersive setting engages a person to a larger extent. Interestingly, these findings are in accordance with the responses in the post-experiment interviews where a majority of respondents stated that they felt more in control of the bicycle in the immersive scenarios due to the fact that they had a 360-degree view which enabled them to see and experience their surroundings better.

In Table 2.3 we show the effect of speed of the cyclist at the previous time point, i.e. lagged by 0.25 sec, on the utility of acceleration and braking where we observe a significant positive estimate for the first and third order (for acceleration) terms and a negative estimate for the second order terms, hence there is a non-linear relationship between the dependent variable and speed. We interpret these impacts graphically in Figure 2.5, using the immersive scenario on the pavement as our case study and using the average values for the other attributes in the model. We can observe similar patterns in the top and bottom panels (when the person is currently accelerating and freewheeling, respectively) where the probability of acceleration increases as speed goes up from 0 to approximately 10 km/h after which it starts to fall. Conversely, the probability of freewheeling falls considerably as the cyclist starts to move faster until reaching the speed threshold of about 12 km/h. These results are plausible behaviourally as the cyclist needs to gain speed quickly to start moving and after reaching a satisfactory speed, they either try to sustain it or increase further but at much slower rate. Finally, the probability of braking increases with speed, reaching its peak at about 18 km/h. It might suggest that this is the most comfortable cycling speed where at the same time the likelihood of freewheeling sharply increases, and the cyclist is less likely to accelerate, thus transitioning to more passive cycling behaviour. This is in line with findings of naturalistic cycling studies which show that average cycling speed in the real-world is approximately 16.7 km/h with standard deviation of 8.4 km/h (Huertas-Leyva et al., 2018). Finally, the middle graph shows that if person is currently braking, she is most likely to continue braking at different speed levels, highlighting that braking is often a continuous action. Moreover, we can observe that a person is least likely to freewheel where its likelihood falls drastically at low speed which is reasonable from a behavioural perspective as in the real world this would lead to person falling of the bicycle.

Table 2.4 shows the effects of the distance to the nearest passing vehicle or pedestrian on behaviour. Here, it is crucial to note that a negative sign of the estimate means that the further away a vehicle or pedestrian is, the more the utility for that action is reduced and hence the less likely it is that the relevant action is taken. Importantly, the results are very rich and are thus also summarised in graphs which better explain the combined effects.

We observe that in non-immersive scenarios on the pavement (base), as the distance to the vehicle (or pedestrian) in front of the bicycle reduces, the utility for accelerating and braking increases, relative to freewheeling. This is in-line with real world behaviour where cyclists also tend to switch to a more active cycling mode (e.g. accelerate or brake) when they are close to other agents. The non-immersive setting thus successfully captures realistic decisions. In immersive pavement, non-immersive and immersive road settings, the impact of distance on acceleration becomes negligible. The impact of dis-

Fig. 2.5: Impact of speed on the probability of accelerating, braking and freewheeling at different current actions.

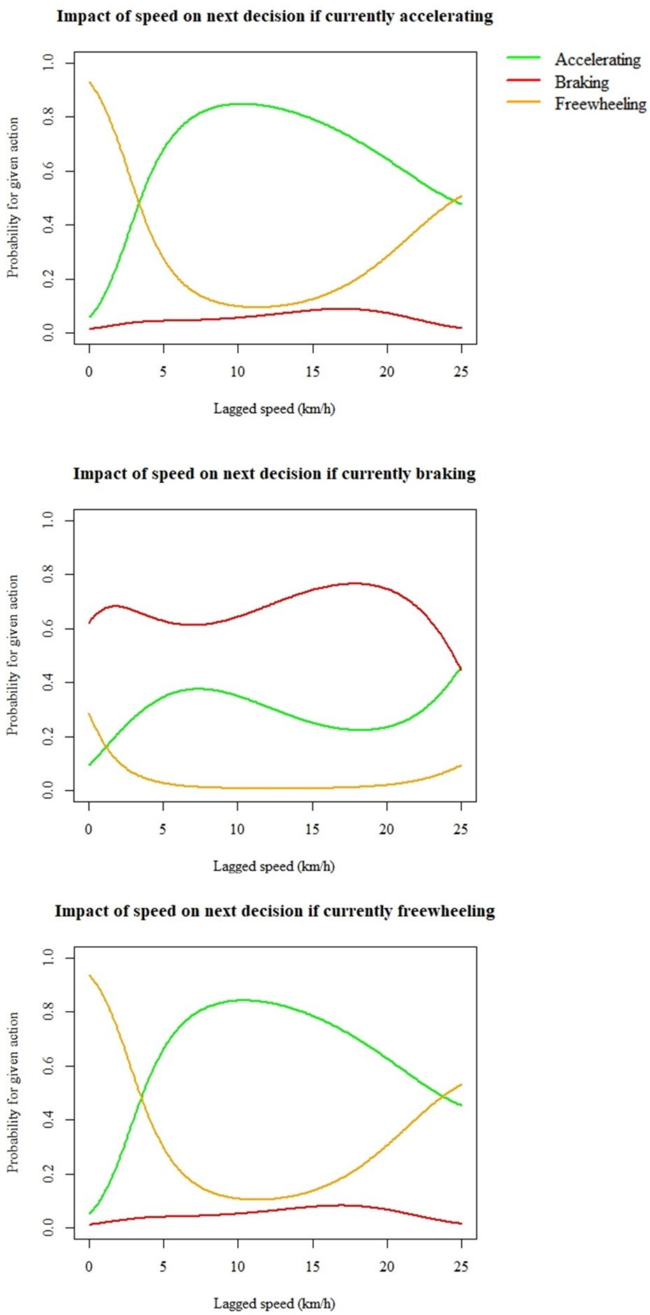


Table 2.4: A joint MNL model – distance variables (robust t-ratios in brackets).

		Distance to nearest vehicle/pedestrian in front (metres)	**Distance to nearest vehicle/pedestrian behind (metres)**
Impact on utility for accelerating	Base(β)	-0.0047 (-4.60)	-0.0029 (-3.28)
	Shift for immersive (Δ_β)	0.0068 (4.64)	-
	Shift for road (Δ_β)	0.0060 (5.37)	0.0024 (2.68)
	Shift for road in immersive (Δ_β)	-0.0088 (-6.03)	-
Impact on utility for braking	Base(β)	-0.0245 (-6.93)	-
	Shift for immersive (Δ_β)	0.0213 (4.53)	-
	Shift for road (Δ_β)	0.0234 (5.76)	-
	Shift for road in immersive (Δ_β)	-0.0187 (-3.66)	-

tance on the utility for braking in immersive scenarios is also much smaller than in non-immersive scenarios, where closer distance still leads to an increase in the utility for braking, however much less so than in non-immersive scenarios. In the case of braking, the utility increases in non-immersive road settings and falls in immersive road setting the closer the vehicle in front becomes but this effect in both cases is much smaller than in the non-immersive pavement setting. In fact, we see that for braking, a sizeable impact remains only in the non-immersive pavement scenarios.

In terms of the impact of vehicles and pedestrians behind the bike, i.e. those already passed by the cyclist or those approaching behind on the road, significant impacts are only observed for accelerating. In the non-immersive setting, a smaller distance increases the utility for accelerating as opposed to freewheeling. Behaviourally, this makes sense, with respondents accelerating more after just having passed a pedestrian. In a non-immersive road setting, the impact on acceleration of vehicles behind the cyclist decreases compared to the pavement scenarios. The effect makes sense as respondents are unlikely to overtake a car (compared to a pedestrian), and less likely to notice a car behind them.

Overall, these results show that both, immersive and road settings reduce the utility for active cycling which may be the result of a lower perceived risk in these scenarios as compared to the pavement scenarios where erratic pedestrians on the pavement were considered more hazardous than passing vehicles and the immersive scenarios increased the impression of control over the bicycle and the environment in comparison to non-immersive simulation.

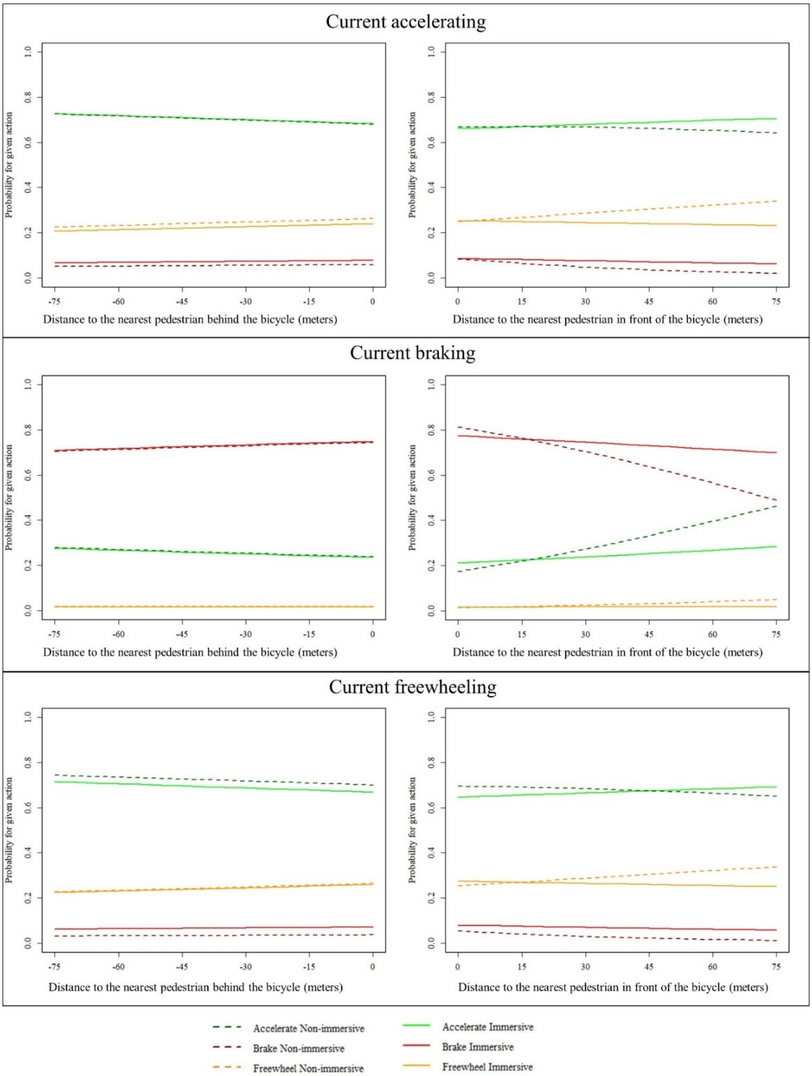
The results in Table 2.4 show the parameters used in the utilities for accelerating and braking. A clearer picture emerges by looking at the resulting probabilities, where of course the probabilities for all three actions are influenced by the utilities for all three actions. This is illustrated in six separate panels in Figure 2.6, where we look only at the pavement scenarios[4]. Here, we look separately at the distance of the closest pedestrian behind (negative distance) and in front (positive distance), where each figure assumes that only one of the two applies while the remaining attributes are fixed at their average levels (e.g. the figure for distance behind assumes the average value in the data for the distance to the pedestrian in front of the bicycle). The figures show the differences in the effect of distance on the probability of the next actions, differentiating between the non-immersive and immersive setting on the pavement. Overall, all of these graphs show cycling trends that are relatable to real-world cycling behaviour. For instance, the top panel demonstrates that if a person is currently accelerating, she is most likely to accelerate next. The distance to the nearest pedestrian behind has a minimal impact on probabilities, with acceleration becoming slightly less likely the closer this pedestrian is. For pedestrians in front, in the non-immersive scenarios braking and acceleration become substantially less likely as the distance increases. Conversely, the middle part of Figure 2.6 demonstrates that current braking is most likely followed by further braking and we observe a strong impact in the non-immersive scenarios for the pedestrians in front where their closer distance to the bicycle increases the probability of braking and decreases that of accelerating. On the other hand, these graphs also clearly show that although these relationships hold, the impact of the distance to the other agents in the scenarios is rather weak in some cases. This is a direct result of the large alternative specific constants showing that behaviour is driven more by the current action than by the surroundings.

Moreover, we compared the frequency of action switches between each time unit which took place in the immersive and non-immersive setting. We found that in the immersive scenarios, participants switch between actions more often as opposed to non-immersive ones (an increase from 36.9% in non-immersive to 54% in immersive scenarios). These findings are in accordance to what was found before, i.e. that the immersive scenarios increase the propensity to switch between subsequent actions and it might suggest higher risk perception in the immersive scenarios although participants felt more in control. This result is consistent with our hypothesis 1B proposed above.

Overall, these results on the behavioural data conform to our hypotheses. We show that behaviour elicited under the non-immersive and immersive scenarios differs significantly, where the immersive presentation leads to more action changes, as a higher level of attention is maintained throughout the cycling scenarios. Differently, in non-immersive scenarios, there is an observed ten-

[4] Similar figures for the road scenarios can be seen in the Appendix A, Fig. A.1.

Fig. 2.6: Example of the impact of distance to pedestrians on the choice of the next action.



dency to perform more abrupt action changes in response to the major events in the environment, which suggest a lower degree of attentional involvement.

5.2 Risk perception and willingness to cycle data

Stated risk and SWTC were modelled using two separate ordered logit models where the explanatory variables were the scenario attributes in the form of the number of pedestrians and vehicles and the presentation method. We did not include any socio-demographic characteristics other than gender due to the small sample size. Table 2.5 shows the results of the estimated model where the dependent variable is the question *"How risky was the scenario?"*, asked at the end of each of the 24 scenarios.

The answer was measured on a 7-point Likert scale, which resulted in six risk thresholds in the model. The classical and robust t-ratios are reported, where, given that we now only have one observation per respondent per scenario, the sample size is so small that lower levels of confidence should not be discarded. We first observe that the high traffic scenarios have a significant impact on risk perception, where the higher number of pedestrians and cars in the scenarios increases perceived risk (estimate = 0.4770; class.t-ratio = 2.27; rob.t-ratio = 3.12). Interestingly, we observe a lower perceived risk for all road scenarios (estimate = -0.3896; class.t-ratio = -1.81; rob.t-ratio = -1.39). Finally, we see a positive shift from the base value for male respondents, i.e. men perceive the risk to be higher. This finding contrasts with a large body of literature which shows that women typically perceive cycling risk as higher, compared to men, see for example Bösehans and Massola (2018) or Prati et al. (2019). This can be the consequence of a relatively small sample where socio-demographic effects may not be fully reliable, especially if we see that in the stated willingness to cycle model this parameter is no longer significant. Nevertheless, some studies point out that the lower participation of females in cycling activity is not only due to higher risk perception and concerns about personal safety but also other factors such as activity preferences or more joint travels with children (Garrard et al., 2012). Further, no differences are observed between the non-immersive and immersive scenarios, nor is the difference between low and high traffic between the pavement and road scenarios. Again, we tested the addition of an effect for cyclists but the coefficient was insignificant (estimate = 0.2218, rob.t-ratio = 0.76). Because of this we decided to not include it in the final model.

Altogether these results indicate that the impact of scenario design is a crucial factor in risk perception but not considerably different under non-immersive and immersive presentations. This further confirms that the risk perceived in these two conditions is effectively similar when captured with a simple question at the end. These results contrast with our hypothesis 2A which states that immersive presentation will lead to higher perceived risk. Our results can be a consequence of the static nature of this question which performs poorly in describing behaviour in a dynamic environment and henceforth emphasises the need for a dynamic approach to risk analysis.

Table 2.5: An ordered logit model for stated risk with interactions (classical and robust t-ratios in brackets).

LL(0): -2,886.306 LL(final): -1,908.386 AIC: 3,844.77 BIC: 3,914.49		
Dependent variable: Stated risk		
		Estimate (classical; rob. t-ratios)
Shifts (Δ)	For male	0.5108 (4.61; 1.59)
	For all immersive scenarios	0.1216 (0.59; 0.77)
	For all road	-0.3896 (-1.81; -1.39)
	For high traffic scenarios	0.4770 (2.27; 3.12)
	For high traffic road scenarios	0.1102 (0.36; 0.48)
	For all immersive road	-0.1572 (-0.52; -0.67)
	For immersive high traffic	-0.0495 (-0.17; -0.28)
	For immersive road high traffic	0.2189 (-0.17; -0.28)
Risk thresholds	1	-1.2265 (-7.41; -5.36)
	2	-0.0138 (-0.09; -0.06)
	3	0.8974 (5.54; 3.05)
	4	1.6295 (9.72; 4.98)
	5	2.5924 (14.15; 7.38)
	6	4.1254 (16.26; 8.35)

Table 2.6 shows the results of a second ordered logit model where the dependent variable is willingness to cycle which was also captured on the 7-point Likert scale with the question *"How likely are you to cycle in this scenario?"*. As in the risk model, we find that the high traffic scenarios significantly influence willingness to cycle (estimate = -0.4553; class.t-ratio = -1.44; rob.t-ratio = -4.24). Hence, as the number of people and cars in the scenario increases, participants are less willing to cycle, which is behaviourally plausible. Again, similarly to our risk model, there is a significant effect (in this case a positive shift) in willingness to cycle for all road scenarios (estimate = 0.6929; class.t-ratio = 2.07; rob.t-ratio = 1.36). We do not find any effects for the remaining variables (including male, all immersive scenarios and high traffic road scenarios) which contrasts with our hypothesis 2B stated above. Nevertheless, the findings summarised in Table 2.6 are consistent with the results for stated risk where the same variables have opposite effects on risk and willingness to cycle, as expected. This suggests that these stated vari-

ables are complementary and consistent with one another. At the same time, they appear to be equally ineffective in describing cycling behaviour under risk, at least if that risk is dynamic and the question is only asked at the end.

Table 2.6: An ordered logit model for stated willingness to cycle with interactions (classical and robust t-ratios in brackets).

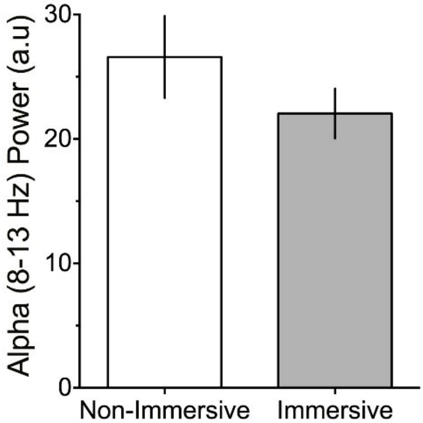
LL(0): -1897.973 LL(final): -811.6235 AIC: 1651.25 BIC: 1708.65		
Dependent variable: Willingness to cycle		
		Estimate (classical; rob. t-ratios)
Shifts (Δ)	For male	0.0324 (0.19; 0.07)
	For all immersive scenarios	0.1692 (0.53; 0.8)
	For all road	0.6929 (2.07; 1.36)
	For high traffic scenarios	-0.4553 (-1.44; -4.24)
	For high traffic road scenarios	0.0483 (0.1; 0.24)
	For all immersive road	0.0422 (0.09; 0.13)
	For immersive high traffic	0.0167 (0.04; 0.07)
	For immersive road high traffic	-0.3712 (-0.55; -0.83)
SWTC thresholds	1	-2.5874 (-8.78; -4.61)
	2	-1.4482 (-5.72; -3.71)
	3	-0.7412 (-3.04; -1.99)
	4	-0.2509 (-1.04; -0.67)
	5	0.423 (1.74; 1.12)
	6	1.0961 (4.41; 2.94)

5.3 EEG data

As a final step, we conducted an exploratory analysis to examine whether the two experimental conditions (immersive vs non-immersive) elicited differences in the occipital α wave. Figure 2.7 shows the mean of the maximum α power in the immersive and non-immersive scenarios in arbitrary units (a.u). We found an increase in α wave power in the non-immersive presentation method where this increase is significant at the 95% level of confidence (t = 2.045, p-value = 0.05).

The results presented here are in line with previous literature showing a robust relationship between increases in α power and relaxed states (Eoh et al., 2005; Lagopoulos et al., 2009) and decreases in α power and increased cognitive workload (Glass and Kwiatkowski, 1970; Osaka, 1984). Finding lower α power in the immersive condition suggests that this condition potentially requires more cognitive engagement than the non-immersive one. The reason for the observed results can be sought in the complexity of the environment

Fig. 2.7: Difference in alpha as a function of condition. Error bars represent standard errors of the mean.



presented to the participant where the non-immersive scenarios which provided a lower level of difficulty resulted in higher occipital α wave, whereas the more complex, immersive scenarios required more attentional resources leading to relatively lower α power. Therefore, we speculate that these findings may be more likely to reflect the cognitive processes involved in performing real-world cycling behaviour.

6 Discussion

The objective of the present paper was to investigate the differences in cycling behaviour and risk perception using behavioural, stated and neural data elicited by a laboratory experiment conducted in virtual reality.

The results of the MNL model on the behavioural data are in line with our hypotheses, showing that there are significant differences in cycling behaviour between the non-immersive and immersive scenarios (Hypothesis 1A). We observe that the immersive scenarios engage participants to a larger extent where less extreme actions are undertaken. At the same time, we observe a higher frequency of action switching compared to the non-immersive ones (Hypothesis 1B). This could suggest that in non-immersive scenarios, lower attentional resources are employed leading to more drastic behaviour in the form of sudden acceleration and braking as well as overall more passive behavioural patterns. One could thus argue that an immersive VR presentation can potentially be a better tool for simulating a cycling environment and safety analyses in the context of cycling behaviour experiments. Of course, the actual proof of this would be the comparison with real world cycling in a comparable setting, and this is an important topic for future work. Either way, our results indicate the importance of the experimental design in research investigating road users' behaviour. Importantly, the remit of the study is only cycling, therefore, based on our results, we are not able to draw conclusions about other modes of transport.

The investigation of the perceived risk and willingness to cycle variables showed that the factors in the estimated ordered logit models that had the most impact were scenario attributes, but we did not find any significant differences in risk perception or SWTC between the non-immersive and immersive presentation methods. These results do not conform to our expectations laid out in the hypotheses (2A and 2B) and suggest that only the most salient elements influencing stated risk and SWTC were captured. Therefore, they do not perform well in detecting more subtle differences in risk perception between the non-immersive and immersive scenarios as the majority of the remaining variables used in the models, including the immersive scenarios dummy variable, were insignificant. Finally, it is important to stress that these variables are coherent with one another as the factors which positively influence risk perception decrease the willingness to cycle.

Lastly, we used the neural data to provide additional insights into processing of risky cycling behaviour. We examined α power in the non-immersive and immersive scenarios and found an increase in this signal in non-immersive scenarios (as proposed in Hypothesis 3). We note that differences were significant at the 95% level, where this is acceptable given the small sample size. Nevertheless, interpretations of these results should be treated with some degree of caution.

It is worth noting that the results are in alignment with a large body of work showing α power to be a well-established correlate of attentional processing with an increase in power found as participants fatigue and attention drifts away from the task (Craig et al., 2012; Hawkins et al., 2015). As described in the introduction, recently, lower α power has been hypothesised to reflect neural mechanisms involved in the gating of task-irrelevant information (Jensen and Mazaheri, 2010; Klimesch et al., 2007) and our results extend this work, through providing empirical evidence which shows that immersive environments elicit lower α power relative to traditional experimental display formats due to higher complexity of the presented environment.

In summary, these results lead us to the conclusion that the immersive presentation improved the design of this experiment that explored dynamic risky cycling behaviour. Additionally, the neural perspective allowed for a further confirmation of the behavioural responses and the verification of the previously identified characteristics of the EEG signal in a more complex context by providing evidence of the application of the neuroimaging technique in a virtual reality study. This experiment serves as a case-study which employs a three-angled approach to explore existing and novel research methods and can be seen as a starting point to more and improved studies of this kind, including with larger sample sizes and in other (non-cycling) settings.

In terms of the practical implications of this study, this work contributes to a better understanding of the factors that influence the behaviour of cyclists and emphasizes the importance of the experimental setup in a VR study. By comparing the behaviour of cyclists in the two different VR environments, the paper provides guidance to researchers investigating cycling behaviour in dynamic settings, which can feed into safety research and/or capacity analyses. The findings also shed light on the level of behavioural congruence of existing VR studies, with clear implications for the interpretation and the level of confidence in their results. This is important not only for researchers, who are directly concerned with improvements to experimental designs to obtain more reliable data, but indirectly for society and policymakers where improved data collection methods will ultimately provide better foundation for more informed decision-making. Cycling is particularly relevant because of the multidimensional advantages of this mode of transport, which, at the same time, is characterised by underdeveloped infrastructure and therefore perceived as too dangerous by many travellers. Previous research shows that cycling is one of the least safe modes of transport with 5.5 times more deaths per kilometre travelled when compared to car (Hartog et al., 2011). Further research needs to be done to generalize these findings for which we recommend testing more scenarios in transport and beyond and potentially comparing the behaviour with real-world decisions.

Moreover, our study provides insights into potential cycling solutions: based on the results of the ordered logit models, it can be concluded that cycling on the road is perceived to be less risky compared to cycling on the pavement amongst pedestrians. Similarly, the MNL model shows that participants indeed brake more often while cycling on the pavement. This can be a result of higher unpredictability of pedestrians movement as compared to cars, where the flow of vehicles is less erratic. Pedestrians are more likely to suddenly stop or change walking direction which significantly increases the possibility of collision with the cyclist, especially if the pedestrian is facing away from the cyclist and is unaware of the approaching bicycle. On the other hand, although the consequences of an accident with the vehicle are more severe compared to a collision with a pedestrian, the probability of crashing is lower because vehicles that drive along the lane are less likely to change their behaviour unexpectedly, which makes them more predictable and gives more time for a cyclist to react. These findings have been further confirmed in the anecdotal evidence gathered through the post-experimental interviews where the majority of respondents claimed that cycling among walking pedestrians was more challenging. The findings are expected to be useful for planners who are interested in deploying VR to more realistically test the impact of different urban designs on propensity to cycle, indicating, for example, the road and pavement features which contribute to the higher perception of safety among cyclists. The research findings can hence help transport and urban planners in making more informed choices regarding urban infrastructure. In closing, the findings thus demonstrate the value-added by immersive technologies in the detailed modelling of cycling behaviour and our work paves the way for further research on factors that can lead to wider adoption and utilization of this sustainable transport mode.

References

Auld, J., Sokolov, V., Fontes, A., and Bautista, R. (2012). Internet-based stated response survey for no-notice emergency evacuations. *Transportation Letters*, 4(1):41–53.

Awais, M., Badruddin, N., and Drieberg, M. (2017). A hybrid approach to detect driver drowsiness utilizing physiological signals to improve system performance and wearability. *Sensors*, 17(9):1991.

Barreda-Tarrazona, I., Jaramillo-Gutiérrez, A., Navarro-Martínez, D., and Sabater-Grande, G. (2011). Risk attitude elicitation using a multi-lottery choice task: Real vs. hypothetical incentives. *Spanish Journal of Finance and Accounting/Revista Española de Financiación y Contabilidad*, 40(152):613–628.

Ben-Akiva, M. and Lerman, S. R. (2018). *Discrete Choice Analysis: theory and application to travel demand.* MIT Press, Cambridge MA.

Berg, P. and Scherg, M. (1994). A multiple source approach to the correction of eye artifacts. *Electroencephalography and clinical neurophysiology*, 90(3):229–241.

Bösehans, G. and Massola, G. M. (2018). Commuter cyclists' risk perceptions and behaviour in the city of São Paulo. *Transportation Research Part F: Traffic Psychology and Behaviour*, 58:414–430.

Brookes, J., Warburton, M., Alghadier, M., Mon-Williams, M., and Mushtaq, F. (2020). Studying human behavior with virtual reality: The Unity experiment framework. *Behavior research methods*, 52:455–463.

Cadar, R. D., Boitor, R. M., and Petrelli, M. (2017). Urban mobility and road user behavior assessment. *Procedia engineering*, 181:116–122.

Cavagnaro, D. R., Myung, J. I., Pitt, M. A., and Myung, J. (2013). Mathematical modeling. *The Oxford handbook of quantitative methods*, 1:438–453.

Chatterjee, A., Wegmann, F. J., and McAdams, M. A. (1983). Noncommitment bias in public opinion on transit usage. *Transportation*, 11(4):347–360.

Chen, J., Li, Z., Wang, W., and Jiang, H. (2018). Evaluating bicycle–vehicle conflicts and delays on urban streets with bike lane and on-street parking. *Transportation letters*, 10(1):1–11.

Christiano, L. J. and Fitzgerald, T. J. (2003). The band pass filter. *International Economic Review*, 44(2):435–465.

Correia, G. and Viegas, J. M. (2011). Carpooling and carpool clubs: Clarifying concepts and assessing value enhancement possibilities through a stated preference web survey in Lisbon, Portugal. *Transportation Research Part A: Policy and Practice*, 45(2):81–90.

Craig, A., Tran, Y., Wijesuriya, N., and Nguyen, H. (2012). Regional brain wave activity changes associated with fatigue. *Psychophysiology*, 49(4):574–582.

da Silva, F. L. (2013). EEG and MEG: relevance to neuroscience. *Neuron*, 80(5):1112–1128.

Daly, A. and Hess, S. (2011). Simple approaches for random utility modelling with panel data. In *90th annual meeting of the transportation research board, Washington, DC*.

Davies, D., Halliday, M., Mayes, M., and Pocock, R. (1997). *Attitudes to cycling: a qualitative study and conceptual framework*. Transport Research Laboratory Crowthorne, Wokingham.

Davies, D. and Hartley, E. (1999). New cycle owners: Expectations and experience. *TRL REPORT 369*.

Di Stasi, L. L., Renner, R., Catena, A., Cañas, J. J., Velichkovsky, B. M., and Pannasch, S. (2012). Towards a driver fatigue test based on the saccadic main sequence: A partial validation by subjective report data. *Transportation research part C: emerging technologies*, 21(1):122–133.

Duvinage, M., Castermans, T., Dutoit, T., Petieau, M., Hoellinger, T., Saedeleer, C. D., Seetharaman, K., and Cheron, G. (2012). A P300-based quantitative comparison between the Emotiv Epoc headset and a medical EEG device. *Biomedical Engineering*, 765(1):2012–2764.

EMOTIV (2018). *14 Channel Wireless EEG Headset*. URL: https://www.emotiv.com/epoc (Accessed: 13/05/2019).

Eoh, H. J., Chung, M. K., and Kim, S.-H. (2005). Electroencephalographic study of drowsiness in simulated driving with sleep deprivation. *International Journal of Industrial Ergonomics*, 35(4):307–320.

Erath, A., Maheshwari, T., Joos, M., Kupferschmid, J., and van Eggermond, M. A. (2017). Visualizing transport futures: the potential of integrating procedural 3D modelling and traffic micro-simulation in virtual reality applications. *Arbeitsberichte Verkehrs-und Raumplanung*, 1185:1–24.

Ergenoglu, T., Demiralp, T., Bayraktaroglu, Z., Ergen, M., Beydagi, H., and Uresin, Y. (2004). Alpha rhythm of the EEG modulates visual detection performance in humans. *Cognitive Brain Research*, 20(3):376–383.

Farooq, B., Cherchi, E., and Sobhani, A. (2018). Virtual immersive reality for stated preference travel behavior experiments: A case study of autonomous vehicles on urban roads. *Transportation research record*, 2672(50):35–45.

Frankenhuis, W. E., Dotsch, R., Karremans, J. C., and Wigboldus, D. H. (2010). Male physical risk taking in a virtual environment. *Journal of Evolutionary Psychology*, 8(1):75–86.

Gardner, G. (1998). *Transport implications of leisure cycling*. Transport Research Laboratory Crowthorne, Wokingham.

Garrard, J., Handy, S., and Dill, J. (2012). *Women and cycling*, volume 2012. MIT Press, Cambridge MA.

Glass, A. and Kwiatkowski, A. (1970). Power spectral density changes in the EEG during mental arithmetic and eye-opening. *Psychologische Forschung*, 33(2):85–99.

Glover, G. H. (2011). Overview of functional magnetic resonance imaging. *Neurosurgery Clinics*, 22(2):133–139.

Godley, S. T., Triggs, T. J., and Fildes, B. N. (2002). Driving simulator validation for speed research. *Accident analysis & prevention*, 34(5):589–600.

Gordon, M. A. (2007). *Evaluating the Balloon Analogue Risk Task (BART) as a Predictor of Risk Taking in Adolescent and Adult Male Drivers.* PhD thesis, The University of Waikato.

Greene, W. H. and Hensher, D. A. (2010). *Modeling ordered choices: A primer.* Cambridge University Press, Cambridge.

Gui, X., Chuansheng, C., Zhong-Lin, L., and Qi, D. (2010). Brain imaging techniques and their applications in decision-making research. *Xin li xue bao. Acta psychologica Sinica*, 42(1):120.

Harrison, G. W. (2006). Making choice studies incentive compatible. In *Valuing environmental amenities using stated choice studies*, pages 67–110. Springer.

Hartog, J. J. d., Boogaard, H., Nijland, H., and Hoek, G. (2011). Do the health benefits of cycling outweigh the risks? *Ciência & Saúde Coletiva*, 16(12):4731–4744.

Hawkins, G., Mittner, M., Boekel, W., Heathcote, A., and Forstmann, B. U. (2015). Toward a model-based cognitive neuroscience of mind wandering. *Neuroscience*, 310:290–305.

Hensher, D. A. (2010). Hypothetical bias, choice experiments and willingness to pay. *transportation research part B: methodological*, 44(6):735–752.

Henson, R., Skinner, A., and Georgeson, N. (1997). Analysis of cycling deterrence factors in Greater Manchester. In *Velo City'97: redescubrir la bicicleta-estrategias para una nueva movilidad (Barcelona, 15-19 septiembre 1997)*, pages 223–226.

Hess, S. and Palma, D. (2019). Apollo: A flexible, powerful and customisable freeware package for choice model estimation and application. *Journal of choice modelling*, 32:100170.

Hood, J., Sall, E., and Charlton, B. (2011). A GPS-based bicycle route choice model for san francisco, california. *Transportation Letters*, 3(1):63–75.

Hook, W. (2007). Reducing transport-related greenhouse gas emissions in developing countries: The role of the global environmental facility. In *Driving climate change*, pages 165–188. Elsevier.

Huertas-Leyva, P., Dozza, M., and Baldanzini, N. (2018). Investigating cycling kinematics and braking maneuvers in the real world: e-bikes make cyclists move faster, brake harder, and experience new conflicts. *Transportation Research Part F: Traffic Psychology and Behaviour*, 54:211 – 222.

Ille, N., Berg, P., and Scherg, M. (2002). Artifact correction of the ongoing EEG using spatial filters based on artifact and brain signal topographies. *Journal of Clinical Neurophysiology*, 19:113–124.

Jensen, O. and Mazaheri, A. (2010). Shaping functional architecture by oscillatory alpha activity: Gating by inhibition. *Frontiers in Human Neuroscience*, 4:186.

Katsis, C., Goletsis, Y., Rigas, G., and Fotiadis, D. (2011). A wearable system for the affective monitoring of car racing drivers during simulated conditions. *Transportation research part C: emerging technologies*, 19(3):541–551.

Khazi, M., Kumar, A., and Vidya, M. (2012). Analysis of EEG using 10: 20 electrode system. *International Journal of Innovative Research in Science, Engineering and Technology*, 1(2):185–191.

Klimesch, W. (1999). EEG alpha and theta oscillations reflect cognitive and memory performance: a review and analysis. *Brain research reviews*, 29(2-3):169–195.

Klimesch, W. (2012). Alpha-band oscillations, attention, and controlled access to stored information. *Trends in cognitive sciences*, 16(12):606–617.

Klimesch, W., Sauseng, P., and Hanslmayr, S. (2007). EEG alpha oscillations: the inhibition–timing hypothesis. *Brain research reviews*, 53(1):63–88.

Lagopoulos, J., Xu, J., Rasmussen, I., Vik, A., Malhi, G. S., Eliassen, C. F., Arntsen, I. E., Sæther, J. G., Hollup, S., Holen, A., et al. (2009). Increased theta and alpha EEG activity during nondirective meditation. *The Journal of Alternative and Complementary Medicine*, 15(11):1187–1192.

Lal, S. K. and Craig, A. (2001). A critical review of the psychophysiology of driver fatigue. *Biological psychology*, 55(3):173–194.

Leao, S. Z., Lieske, S. N., and Pettit, C. J. (2019). Validating crowdsourced bicycling mobility data for supporting city planning. *Transportation letters*, 11(9):486–497.

Lejuez, C. W., Read, J. P., Kahler, C. W., Richards, J. B., Ramsey, S. E., Stuart, G. L., Strong, D. R., and Brown, R. A. (2002). Evaluation of a behavioral measure of risk taking: the Balloon Analogue Risk Task (BART). *Journal of Experimental Psychology: Applied*, 8(2):75.

Li, Z., Hensher, D. A., and Ho, C. (2020). An empirical investigation of values of travel time savings from stated preference data and revealed preference data. *Transportation Letters*, 12(3):166–171.

Loomis, J. M., Blascovich, J. J., and Beall, A. C. (1999). Immersive virtual environment technology as a basic research tool in psychology. *Behavior research methods, instruments, & computers*, 31(4):557–564.

Louviere, J. J., Hensher, D. A., and Swait, J. D. (2000). *Stated choice methods: analysis and applications*. Cambridge University Press, Cambridge.

Madhuwanthi, R., Marasinghe, A., Rpc, J., Dharmawansa, A. D., and Nomura, S. (2015). Factors influencing to travel behavior on transport mode choice. *International Journal of Affective Engineering*, 15(2):63–72.

Mai, K. L. (2017). *Evaluation of PC-Based Virtual Reality as a Tool to Analyze Pedestrian Behavior at Midblock Crossings*. Faculty of California Polytechnic State University, San Luis Obispo.

Mathewson, K. E., Gratton, G., Fabiani, M., Beck, D. M., and Ro, T. (2009). To see or not to see: prestimulus α phase predicts visual awareness. *Journal of Neuroscience*, 29(9):2725–2732.

McFadden, D. (1974). The measurement of urban travel demand. *Journal of public economics*, 3(4):303–328.

McKechnie, G. E. (1977). Simulation techniques in environmental psychology. In *Perspectives on environment and behavior*, pages 169–189. Springer.

Melson, C. L., Duthie, J. C., and Boyles, S. D. (2014). Influence of bridge facility attributes on bicycle travel behavior. *Transportation letters*, 6(1):46–54.

Mollenhauer, M. A. (2004). Simulator adaptation syndrome literature review. Technical report, Realtime Technologies Inc Royal Oak Mi.

Moussa, G., Radwan, E., and Hussain, K. (2012). Augmented reality vehicle system: Left-turn maneuver study. *Transportation research part C: emerging technologies*, 21(1):1–16.

Mushtaq, F., Wilkie, R. M., Mon-Williams, M. A., and Schaefer, A. (2016). Randomised prior feedback modulates neural signals of outcome monitoring. *NeuroImage*, 125:868–879.

Oculus.com (2018). *Oculus*. URL: https://www.oculus.com (Accessed: 17/03/2019).

Oken, B. S. and Chiappa, K. H. (1986). Statistical issues concerning computerized analysis of brainwave topography. *Annals of neurology*, 19(5):493–494.

Osaka, M. (1984). Peak alpha frequency of EEG during a mental task: Task difficulty and hemispheric differences. *Psychophysiology*, 21(1):101–105.

Patterson, Z., Darbani, J. M., Rezaei, A., Zacharias, J., and Yazdizadeh, A. (2017). Comparing text-only and virtual reality discrete choice experiments of neighbourhood choice. *Landscape and Urban Planning*, 157:63–74.

Powell, J. (2017). Hardware design for an electro-mechanical bicycle simulator in an immersive virtual reality environment. *International Journal of Virtual Reality*, 18(2):1–18.

Prati, G., Fraboni, F., De Angelis, M., Pietrantoni, L., Johnson, D., and Shires, J. (2019). Gender differences in cycling patterns and attitudes towards cycling in a sample of European regular cyclists. *Journal of transport geography*, 78:1–7.

Puce, A. and Hämäläinen, M. S. (2017). A review of issues related to data acquisition and analysis in EEG/MEG studies. *Brain sciences*, 7(6):58.

Ratti, E., Waninger, S., Berka, C., Ruffini, G., and Verma, A. (2017). Comparison of medical and consumer wireless EEG systems for use in clinical trials. *Frontiers in human neuroscience*, 11:398.

Repovs, G. (2010). Dealing with noise in EEG recording and data analysis. In *Informatica Medica Slovenica*, volume 15, pages 18–25.

Rothengatter, T. (1997). Psychological aspects of road user behaviour. *Applied Psychology: An International Review: Special Issue-Traffic Psychology*, 46(3):223–234.

Rovira, A., Swapp, D., Spanlang, B., and Slater, M. (2009). The use of virtual reality in the study of people's responses to violent incidents. *Frontiers in behavioral neuroscience*, 3:59.

Schramka, F., Arisona, S., Joos, M., and Erath, A. (2017). Development of virtual reality cycling simulator. *Journal of Computers*, 13:603–615.

Schweizer, T. A., Kan, K., Hung, Y., Tam, F., Naglie, G., and Graham, S. (2013). Brain activity during driving with distraction: an immersive fMRI study. *Frontiers in human neuroscience*, 7:53.

Shaker, M. M. (2007). EEG waves classifier using wavelet transform and Fourier transform. *International Journal of Medical, Health, Biomedical, Bioengineering and Pharmaceutical Enineering*, 1(3):1–6.

Slater, M., Antley, A., Davison, A., Swapp, D., Guger, C., Barker, C., Pistrang, N., and Sanchez-Vives, M. V. (2006). A virtual reprise of the Stanley Milgram obedience experiments. *PloS one*, 1(1):e39.

Train, K. (2016). Mixed logit with a flexible mixing distribution. *Journal of choice modelling*, 19:40–53.

Underwood, G., Crundall, D., and Chapman, P. (2011). Driving simulator validation with hazard perception. *Transportation research part F: traffic psychology and behaviour*, 14(6):435–446.

Unity (2017). *Unity - Game Engine*. URL: https://unity3d.com (Accessed: 10/11/2018).

Vaca, F. E., Walthall, J. M., Ryan, S., Moriarty-Daley, A., Riera, A., Crowley, M. J., and Mayes, L. C. (2013). Adolescent balloon analog risk task and behaviors that influence risk of motor vehicle crash injury. *Annals of advances in automotive medicine*, 57:77–88.

Van Dijk, H., Schoffelen, J.-M., Oostenveld, R., and Jensen, O. (2008). Prestimulus oscillatory activity in the alpha band predicts visual discrimination ability. *Journal of Neuroscience*, 28(8):1816–1823.

Vorobyev, V., Kwon, M. S., Moe, D., Parkkola, R., and Hämäläinen, H. (2015). Risk-taking behavior in a computerized driving task: brain activation correlates of decision-making, outcome, and peer influence in male adolescents. *PLoS one*, 10(6):e0129516.

Wann, J. and Mon-Williams, M. (1996). What does virtual reality need?: Human factors issues in the design of three-dimensional computer environments. *International Journal of Human-Computer Studies*, 44(6):829–847.

Wardman, M., Bonsall, P. W., and Shires, J. (1996). *Stated preference analysis of driver route choice reaction to variable message sign information*. (Working paper 475). Institute for Transport Studies, University of Leeds.

Welch, P. (1967). The use of fast Fourier transform for the estimation of power spectra: a method based on time averaging over short, modified periodograms. *IEEE Transactions on audio and electroacoustics*, 15(2):70–73.

Xu, J., Lin, Y., and Schmidt, D. (2017). Exploring the influence of simulated road environments on cyclist behavior. *International Journal of Virtual Reality*, 17(3):15–26.

Chapter 3

A Comparison of Cycling Behaviour between Keyboard-Controlled and Instrumented Bicycle Experiments in Virtual Reality

Martyna Bogacz[1], Stephane Hess[1], Chiara Calastri[1], Charisma F. Choudhury[1], Faisal Mushtaq[2], Muhammad Awais[2], Mohsen Nazemi[3], Michael A.B. van Eggermond[3] & Alexander Erath[3]

Abstract

The use of virtual reality (VR) in transport research offers the opportunity to collect behavioural data in a controlled dynamic setting. VR settings are useful in the context of hypothetical situations where real-world data does not exist and/or in situations which involve risk and safety issues making real-world data collection infeasible. Nevertheless, VR studies can contribute to transport-related research only if the behaviour elicited in a virtual environment closely resembles real-world behaviour. Importantly, as VR is a relatively new research tool, the best-practice in terms of the experimental design is still to be established. In this paper, we contribute to a better understanding of the implications of the choice of the experimental setup by comparing cycling behaviour in VR between two groups of participants in similar immersive scenarios – the first group controlling the manoeuvres using a keyboard and the other group riding an instrumented bicycle. We critically compare the speed, acceleration, braking and head movements of the participants in the two

[1]Institute for Transport Studies and Choice Modelling Centre, University of Leeds (UK)
[2]School of Psychology & Centre for Immersive Technologies, University of Leeds, UK
[3]Future Cities Laboratory Singapore-ETH Centre Zurich

experiments. We also collect electroencephalography (EEG) data to compare the alpha wave amplitudes and assess the engagement levels of participants in the two settings. The results demonstrate the ability of VR to elicit behavioural patterns in line with those observed in the real-world and indicate the importance of the experimental design in a VR environment beyond the choice of audio-visual stimuli. The findings will be useful for researchers in designing the experimental setup of the VR for behavioural data collection.

1 Introduction

Virtual reality (VR) has become an increasingly popular tool for travel behaviour research. This is because in the transport domain, it is often inherently difficult to collect real-life data in hazardous road circumstances. VR provides a high degree of experimental control, safety and ease of data collection, while at the same time allowing to collect data in a dynamic setting. Further, as in other domains, VR makes it possible to collect data in hypothetical future scenarios allowing to pre-test behavioural responses in the context of new modes and novel urban design. Consequently, it has been widely used in previous studies in a transport context. For example, Mai (2017) evaluated VR as a tool to analyse pedestrian behaviour at midblock crossings and Frankenhuis et al. (2010) explored male risk-taking behaviour while crossing a bridge in an immersive environment. Finally, Moussa et al. (2012) tried to apply the Augmented Reality Vehicle system to left-turn manoeuvres at two-way stop-controlled intersections.

Nevertheless, the potential disadvantages of VR include motion sickness, high costs and most importantly, the risk of an unrealistic representation of reality. The ecological validity of VR experiments is one of its main issues, as it is widely known that experimental designs which have a different degree of immersion or employ different equipment can elicit distinct behavioural responses. For example, Farooq et al. (2018) elicited preferences over Connected and Autonomous Vehicles comparing three methods: an immersive reality technology, a conventional visual presentation and text-only descriptions. The findings showed that preference for autonomous vehicles increased from 50% in text-only case, through 40% in a visual presentation to 70% if VR was used. It was concluded that preferences elicited with immersive equipment were more consistent with real world preferences and the understanding of scenarios improved. Furthermore, Bogacz et al. (2019), which looked at the differences in risk processing between 2D and 3D cycling scenarios in VR, showed that the behavioural patterns from the experiments were similar to the actual behaviour of cyclists on the roads. Moreover, the study found that the propensity to brake was higher in the 3D presentations compared to the 2D scenarios. Patterson et al. (2017) conducted two experiments to investigate the influence of the presentation method on neighbourhood choice. The first one was based on the textual description of the living area, while the second used VR simulations of the neighbourhood. The results showed that preferences elicited with text-only surveys reflected participants' subjective, imagined illustration of the described place, whereas, in the case of the visualizations, the preferences were based on the observed material. It suggests that VR technology allows for constructing experimental scenarios that give the researcher more control over factors that affect the respondents' choices, but at the same time these studies clearly exhibit the fact that preferences are highly dependent on the presentation format. This effect is expected to be even stronger within immersive technology experiments, as they engage individuals to a larger extent than traditional survey methods. However, as VR is still an innovative and relatively new research tool, the best practices are yet to be established especially in the light of mixed evidence in the existing literature.

In contrast, the domain of driving simulators represents an exception, as there has been extensive research on the factors that affect the behavioural congruence in simulated driving. For instance, Underwood et al. (2011), who assessed the comparability of driving on a road and in a simulator, concluded that driving simulators can demonstrate similar patterns of differences across drivers as observed on actual roads. However, this was only relative, in the sense that they were unable to create the same hazardous situations on a road as can be designed in a simulator. Furthermore, Godley et al. (2002) examined the validity of driving simulators by comparing driving behaviour in an instrumented car vs a simulator. They showed similar deceleration activity under both conditions. Yet, on the other hand, individuals tended to drive faster in the instrumented car relative to the simulator. To the best of our knowledge, there has not been any similar in-depth investigation on the factors that affect the behavioural congruence in the context of different variants of immersive cycling environments. In this paper, we address this research gap and contribute to a better understanding of the implications of the choice of the experimental setup by comparing the cycling behaviour in VR between two groups of participants in similar immersive scenarios – the first group controlling the manoeuvres using a keyboard and the other group riding an instrumented bicycle.

These two types of equipment both have their advantages and drawbacks. The use of a keyboard significantly reduces the cost of the experiment as well as the setup time but diminishes the realism of the experiment. The employment of an instrumented bicycle in the experiment is more effort consuming and requires novel engineering design (e.g. measuring wheel and pedal rotation, braking force etc.) and is not portable. Nevertheless, the latter provides participants with an experience which resembles reality to a larger extent and allows analysts to obtain richer data from the sensors installed on the bicycle. This is also likely to be reflected in their neural activity, which can be used as an indicator of the level of engagement.

There are several studies in cognitive psychology which have looked at the effects of the use of different input devices on the neural processing and the elicited behaviours. For example, key presses can be considered discrete decisions and while they have been widely used in PC-based experiments before (Szul et al., 2020) many studies have shown a continuous flow of information between the brain systems involved in motor processes as opposed to previous assumptions about sequential stages in motor outputs (Cisek and Kalaska, 2005; Spivey et al., 2005). These findings suggest that devices which allow for continuous rather than discrete input in terms of motor decisions better mimic the neural processing of such decisions. Moreover, a study by Rupp et al. (2015) demonstrated that the use of a joystick, as opposed to a keyboard, resulted in lower mental workload in a difficult task, which could suggest that keyboards are unsuitable input devices in complex control tasks. Finally, a study by Chung et al. (2018) investigated online shopping experience and purchase patterns using both mouse-controlled and touch interface settings. They found that shoppers who used a touch interface to browse products (vs. mouse) have a significantly higher engagement with their shopping experience. The studies mentioned above show that there are possible differences in behaviour resulting from the type of input device adopted, making the search for and testing of alternative solutions in dynamic experiments a research priority.

In addition to comparing cycling behaviour in VR when using different devices to elicit preferences, we also set out to explore the latter's impact on participants' neural activity as a proxy measure of engagement. For this reason, we employed electroencephalography (EEG), a scalp-recorded measure of the electrical activity generated by the brain. Typically, in the transport literature, the use of EEG has largely focused on the investigation of driver fatigue and drowsiness (Awais et al., 2017; Craig et al., 2012; Eoh et al., 2005; Lal and Craig, 2001), level of alertness/attention or cognitive performance (Klimesch, 1999). However, little has been done to evaluate the engagement of participants in the immersive environment from a neural perspective. In particular, the use of neuroimaging devices in applied experimental research has been heavily constrained by the signal-to-noise ratio of EEG, where artefacts in the data can stem from physiological (e.g. ocular, facial and body muscle movements) and non-physiological sources (e.g. electric signals generated by nearby equipment, as shown by Puce and Hämäläinen (2017)). Therefore, VR experiments which allow a great degree of flexibility in participants' head and body movements are more prone to producing artefactual data. However, recent wireless systems such as Emotiv EPOC+ (EMOTIV, 2018) and Enobio (Ratti et al., 2017) are designed for dynamic experimental setups and attempt to mitigate the impact of movement artefacts on the scalp-recorded EEG.

In this paper, we compare a particular pattern of oscillatory brain activity known as occipital alpha (α) to infer participant's engagement in the task. Occipital α, which is quantified through frequency analysis of the signal ranging from 8 to 14 Hz, is one of the most commonly observed signatures of brain activity, with numerous studies demonstrating a relationship between oscillations in this frequency band and attentional processing (Klimesch, 2012; Klimesch et al., 1998; Sauseng et al., 2005; Thut et al., 2006). As such, the signal presents an ideal candidate to investigate the impact of presentation format on participants' degree of task-relevant engagement.

The remainder of this paper is organized as follows. We present our specific hypotheses in the next section. The survey design and sample characteristics for the two experiments are discussed next, followed by the methodological approach of the study. We next turn to the results section, followed by the discussion that reviews the insights from the analysis.

2 Hypotheses

Five hypotheses are put forward based on the evidence from the existing literature presented above and tested empirically using our data. They relate to cycling speed, head movements (an indicator of engagement with the surroundings beyond peripheral vision), acceleration and braking behaviour as well as neural processing. We now look at these five in turn.

2.1 Cycling speed

Hypothesis 1A: The average speed is higher in the keyboard-controlled experiment as opposed to instrumented bicycle one.

Hypothesis 1B: There is more variance in speed in the instrumented bicycle experiment than in the keyboard experiment.

It is hypothesized that the average speed will be higher in the keyboard-controlled experiment as it requires less physical effort to accelerate compared to an instrumented bicycle. Moreover, the acceleration is more instantaneous when using the keyboard. For the same reason, we expect that there will be more variation in the speed observed in the instrumented bicycle experiment, as more physical effort is needed to move through the scenarios, making it more difficult to maintain constant speed levels.

2.2 Head movement

Hypothesis 2: The average head movement is higher in the instrumented bicycle experiment than in the keyboard experiment.

We expect that the use of the instrumented bicycle will induce participants to inspect the environment, resulting in more head movement (Hu et al., 2017; Sitzmann et al., 2018). This would be due to the higher level of immersion in the environment, due to the improved design compared to the keyboard, and due to the fact that braking in case of any hazardous circumstances on the road will take longer on the instrumented bike compared to instantaneous reaction while pressing the arrows on the keyboard.

2.3 Acceleration & Braking

Hypothesis 3: There is more variance in the acceleration behaviour in the instrumented bicycle experiment than in the keyboard experiment.

Hypothesis 4: There is more variance in the braking behaviour in the instrumented bicycle experiment than in the keyboard experiment.

Hypotheses 3 and 4 stem from the fact that the use of the instrumented bicycle provides more scope to control behaviour, as participants intertwine acceleration and deceleration more often compared to a keyboard. Cycling on the bike requires more physical effort and time to switch between subsequent actions or respond to changing conditions on the road, whereas acceleration and braking are more instantaneous with the keyboard.

2.4 Neural processing

Hypothesis 5: The mean amplitude of the alpha wave is higher in keyboard-controlled experiment compared to that of the instrumented bicycle.

Hypothesis 5 is based on the evidence from a large body of work showing the α wave to be a well-established correlate of attentional processing with an increase in amplitude found as participants' attention drifts away from the task (Craig et al., 2012; Hawkins et al., 2015). On the other hand, current understanding in neuroscience holds that a low α wave implies increased excitability, and thus an increased response to external stimuli (Jensen and Mazaheri, 2010; Klimesch et al., 2007). Therefore, we hypothesize that if the keyboard-controlled experiment engages participants to a lower extent, the mean α amplitude is expected to be higher as opposed to the instrumented bicycle data.

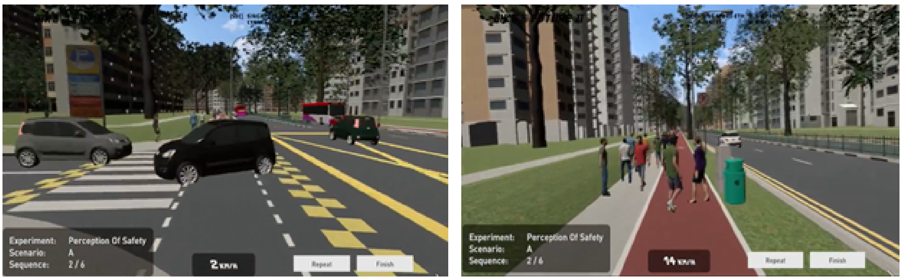
3 Experimental design

This section describes the common experimental procedure used for the two experiments. It also discusses the components that were different between keyboard-controlled and instrumented bike experiment as well as the basic characteristics of the two samples.

3.1 Keyboard-controlled experimental setup

The experimental session started with the participant being seated on a chair and having an Emotiv Epoc+ EEG headset (EMOTIV, 2018) and an Oculus Rift VR (Oculus.com, 2018) head mounted display (HMD) placed on their head. The Emotiv headset uses 14 electrodes (at AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8 and AF4) sampling across the scalp. The system was selected as its compact design allowed it to be used jointly with the VR HMD. As a first step, the baseline brain activity was recorded with the sampling rate of 128 Hz, while participants had their eyes open and focused their gaze on one point on the screen for 15 seconds. The same procedure was then repeated with their eyes closed. Importantly, before the main part of the experiment started, the participants had an opportunity to familiarise themselves with the equipment in a trial run. The experiment used six sce-

Fig. 3.1: The immersive scenarios used in the experiment.



narios with an immersive presentation of traffic from the perspective of the cyclist. All the scenarios had a number of common elements. Firstly, the cyclist was riding on the pavement. Secondly, in each scenario, there were four locations where a potential collision with other road users could occur, namely, two junctions and two points along the cycling lane where pedestrians could cross to reach the bin on the right side of the bike lane, as seen in Figure 3.1. Thirdly, all the scenarios featured pedestrians as well as cars and the percentage of pedestrians and cars which would cross the bike lane or turn at the junction was constant. At the same time, there were also random components in each scenario which stemmed from the fact that in each scenario, the specific movements of crossing pedestrians and turning cars were presented randomly, while keeping their overall percentage the same across all the scenarios. This resulted in differences between scenarios in terms of the actual number of pedestrians or cars at the "*collision locations*" when the cyclist was passing by these points. This was clearly also influenced by the speed of the cyclist, and hence the point in time at which the "*collision locations*" were reached. Altogether, these elements gave basis for the complex traffic scenarios which participants were required to navigate. The scenarios encompassed a 360-degree view of the road which surrounded the participant and responded to their head movements. Importantly, based on the feedback received during initial pre-testing of the set-up, sound was also included to capture both visual and auditory cues that are available to cyclists in real-life settings. The volume of vehicles was consistent with their distance to the cyclist so that the sound of an approaching car increased as it got closer to the cyclist.

The experiment comprised the same six scenarios. The repetition was used because we also collected neural data which required a higher number of trials in order to obtain more stability in the EEG signal. The task for the participant was to cycle through the scenario at the desired pace until the finish line at the end of each scenario. In order to navigate through the scenario, participants used the keyboard to adjust their speed but had no ability to turn left or right. They pressed the up arrow to accelerate and the down arrow to brake. The keyboard was placed on the table in front of them, and before the experiment began, they were guided by the experimenter to find the appropriate keys on the keyboard. The experimental setup of a keyboard-controlled experiment can be seen on right-hand side of Figure 3.2.

The visual stimuli in the experiment come from VR road simulations developed by Future Cities Laboratory (Schramka et al., 2017) using Unity 3D Game Engine (Goldstone, 2009). These stimuli involve pre-programmed environments where the cars and pedestrian movements do not respond to the actions of the cyclist. That is to say, other road users do not accelerate or decelerate in reaction to the chosen action of the cyclist (participant), therefore collisions between the cyclist and cars/pedestrians were possible. Collisions were detected if a cyclist overlapped visually with any other agent. Even though participants were specifically instructed to avoid any collisions, there were 19 instances (3.2 % of all scenarios by all participants) of collisions with other road users. When this happened, the experiment was interrupted, and the participant was asked to start again from the beginning of that scenario.

The initial number of recruited participants was 50, from which 4 participants were removed due to failure to complete the whole experiment, leading to a final sample size of 46 participants (18 males, 28 females), comprising staff and students of the University of Leeds as well as members of the general public. The mean age of the participants was 30.7 years, with a standard deviation of 10.88 years.

3.2 Instrumented bike experimental setup

The experimental design for the instrumented bicycle data collection was similar to the keyboard counterpart in terms of the audio and visual stimuli used and number and types of cycling scenarios. The experimental session commenced by familiarizing the participant with the instrumented bicycle, including demonstrating how to use a hand brake (all the participants could ride a bike in reality). Subsequently, the participant mounted the bike and the HTC Vive head mounted display (HMD) (Borrego et al., 2018) and Enobio (Riera et al., 2008) devices were placed on their head. The Enobio headset uses 8 electrodes (at FP1, FP2, Fz, C3, Cz, C4, P3 and P4) sampling across the scalp. The system allowed joint use with HTC Vive HMD. As a first step, the baseline brain activity was recorded with the sampling rate of 128 Hz, while participants had their eyes open and focused their gaze on one point on the screen for one minute. The same procedure was then repeated with eyes closed. Before the main part of the experiment started, participants could familiarise themselves with the use of the bicycle and the environment in a trial session.

The experiment consisted of six immersive presentations of traffic scenarios from the perspective of the cyclists, shown in random order. The visual stimuli proceeded from the same source as before. Similarly, the participant was asked to cycle through the scenario at the desired pace until the finish line at the end of each scenario. In order to navigate through the scenario, the participant used the pedals of the bicycle and had no ability to turn left or right. To brake, the participant used a hand brake positioned on the right side of the handlebar. For the exact instructions see Participant task instructions in Appendix B. The instrumented bike can be observed on the left-hand side of Figure 3.2. The instrumented bike belongs to Future Cities Laboratories in Singapore. The scenarios used in these experiments

Fig. 3.2: Instrumented bicycle (FCL Singapore) and keyboard-controlled experiments (University of Leeds)

allowed for recording of cycling behaviour with respect to changing traffic environment. The specific variables of interest, which are described in detail in the next section, included the cycling speed, braking activity, acceleration, horizontal head movements as well as the EEG signal. We put forward several hypotheses based on these variables, as specified in the section above.

Fifty participants were recruited for the experiment, however two of them were removed due to failure to complete the whole experiment, leading to a final sample size of 48 participants (29 males, 19 females), comprising staff and students of the National University of Singapore as well as the members of the general public. The mean age of the participants was 26.5 years, with 6.7 years standard deviation (for more details regarding the sample see Appendix B). The socio-demographic characteristics of the sample were collected using a PC-based survey, see Appendix B for the full questionnaire. It is important to emphasize that the small sample size in both experiments is a typical issue faced by researchers working with VR and/or driving simulator data (Di Stasi et al., 2012; Katsis et al., 2011; Moussa et al., 2012) as the experiment duration is much longer and the associated cost much higher compared to typical stated preference (SP) studies.

4 Methods

In this section, we present the methodology used to test our hypotheses. We conducted a between-subject comparison of the behaviour in two samples, where one sample used a keyboard and the other used the instrumented bike to cycle through the scenarios. As a result of this experimental design, none of the participants took part in both treatments. To compare the behaviour, we analysed the following variables: acceleration, braking, speed and head movement. We also looked at the difference in mean α amplitude in the two experiments. The sampling rate for all variables except EEG was 4 Hz. To test the proposed hypotheses, we conduct a Welch's t-test (Welch, 1947) on the mean values of *Speed*, sideways movements of the head (*Head Yaw*) as well as α-wave amplitude. This test was chosen due to the slightly unequal sample sizes, where keyboard sample contains 46 participants and the instrumented bicycle sample includes 48 participants. Furthermore, the F-test (Johnston, 1972) was used to make inferences about the variances in *Speed, Acceleration* and *Braking* between two experiments. The individual variables produced during the experiments were the following:

Acceleration
The acceleration variable (a) is the rate of velocity gain and is measured in metre per squared second (m/s^2). The formula used to calculate acceleration can be seen in Equation 3.1 :

$$a = \frac{\Delta v}{\Delta t}, \tag{3.1}$$

Where Δ denotes changes in velocity (v) and time (t), respectively.

Braking
In the instrumented bicycle experiment, braking is measured as the degree of deviation of the braking pad from its default position. It ranges from 0 to 15^o. In the keyboard setting, the braking variable recorded the degree to which the down-arrow key was pressed, and the values range from 0 to 1. In order to be able to compare these values, we performed a min-max normalization on the values of *Braking* for the instrumented bicycle.

Speed
The speed is expressed in kilometres per hour (km/h). In the keyboard-controlled experiment, the maximum speed was capped at 25 km/h. This level was chosen based on the previous literature which showed that the average speed of cycling in the real world is between 13.5-16 km/h with standard deviation ranging from 3.2 - 8.4 km/h (Dozza and Werneke, 2014; Huertas-Leyva et al., 2018; Schleinitz et al., 2017). Differently, in the instrumented

bicycle experiment, there was no limit on the maximum speed. The restriction on the keyboard-controlled experiment was imposed in order to avoid unreasonable speeds, which could have been easily achieved with the constant pressing of the key, and to minimize the risk of motion sickness.

Head movement
The head movement is based on head yaw - the sideways movement of the head. It is measured in degrees from the default position (looking straight ahead), and can range from -180^o to $+180^o$, where turning the head (as well as the torso) to the left produces negative values while a movement to the right results in positive scores.

EEG
For the EEG analyses, we examined differences in mean α amplitude in keyboard-controlled and instrumented bicycle experiments. As the EEG signal collected through the scalp are inherently noisy, we undertook a number of steps to eliminate artefacts and improve the signal-to-noise ratio. Specifically, we first applied a 1-20 Hz bandpass filtering (BPF), a linear transformation that retains the components of the data within this specific band of frequencies (Christiano and Fitzgerald, 2003) and removes frequencies outside of this range that may stem from physiological sources such as galvanic skin responses or external environmental sources such as electronic equipment (Repovs, 2010). Next, we cleaned the data to remove noise stemming from eyeblinks (movement artefacts were corrected using a multiple source analysis method (Berg and Scherg, 1994; Ille et al., 2002). Finally, we computed the power spectrum of the EEG data using Welch's method (Welch, 1967) which estimates the power spectra based on the Fast Fourier Transform (FFT) (Shaker, 2007). Because of our interest in occipital α, we performed a region-of-interest analysis and took an average of the activity from electrodes O1, O2, P7, P8, T7 and T8 in the keyboard-experiment and electrodes P7, P8, C3, C4 in the instrumented bicycle to increase the stability of the signal (Oken and Chiappa, 1986).

5 Results

In this section, we present visual profiles of *Speed* and *Braking* for the two experiments and an overview of the descriptive statistics in Table 3.1. The table highlights clear differences between the mean values of the variables of interest in the two samples. Next, these differences are tested more rigorously using t-test and F-test, and the results are reported for each variable.

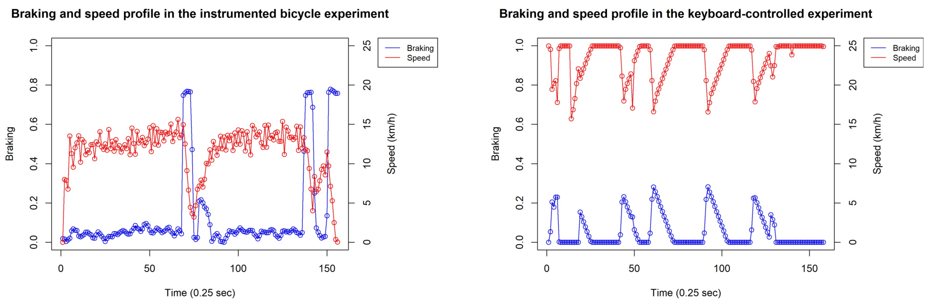
In Figure 3.3, we plot the profiles of the variables *Speed* and *Braking* for

Table 3.1: Summary statistics of the variables of interest.

Variable	Units of measurement	Mean values in the keyboard-controlled experiment	Standard deviation values in the keyboard-controlled experiment	Mean values in instrumented bicycle experiment	Standard deviation values in instrumented bicycle experiment
Speed	km/h	22.90	4.93	14.32	7.03
Head Yaw	degrees	1.76	8.52	4.93	27.71
Break	degrees	0.03	0.10	0.23	0.25
Acceleration	m/s^2	0.11	1.29	0.02	2.68

two randomly chosen participants cycling in similar immersive scenarios but in the two different experimental settings. The graphs highlight that both experiments captured participants' behaviour correctly, as higher values of *Braking* are associated with lower *Speed*. At the same time, it is clear that the employment of the instrumented bike resulted in a considerably higher amount of variation in *Speed* and *Braking* compared to the keyboard experiment, where the profiles are smoother and less dynamic.

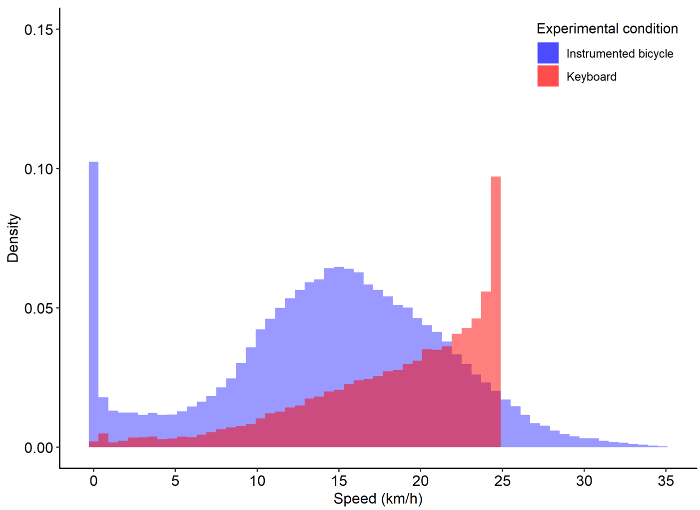
Fig. 3.3: Profiles of Braking and Speed in the two experiments for two randomly chosen participants.



5.1 Speed

The one-sided Welch's t-test performed on the mean values of *Speed* at the individual level showed that the mean *Speed* is significantly higher in the keyboard-controlled experiment (t = -16.163, df = 70.134, p-value $\sim$ 0). This result is in line with our Hypothesis 1A, where we expected that the lack of physical effort and consequently relative easiness in developing higher speed would result in higher average speed in the keyboard-controlled experiment. Moreover, when we compared the variances in mean *Speed*, we found that the variance in the instrumented bicycle experiment was significantly higher compared to the keyboard-controlled counterpart ($F(47,45) = 3.9252$, p-value ~ 0). Again, this result conforms to our Hypothesis 1B. We show that the use of the bicycle induces people to adjust their speed more often. It is also interesting to look at the density histogram of *Speed* in these two experiments (Figure 3.4). We can see the near bell-shaped distribution of *Speed* in the experiment using the bicycle, where the values are centred around the mean and there is more variation observed in contrast with the keyboard-controlled experiments. A peak near zero can be observed in the instrumented-bicycle setting: this relates to small movements when participants slowed down to stop (while waiting to cross the street or give priority to pedestrians who crossed their bike lane). In contrast, in the keyboard experiment, we observe a skewed distribution of *Speed* where the majority of observations correspond with the maximum possible level, equal to 25 km/h. This suggests that the removal of physical effort and the use of a keyboard contributes to the choice of maximum speed regardless of the scenario conditions.

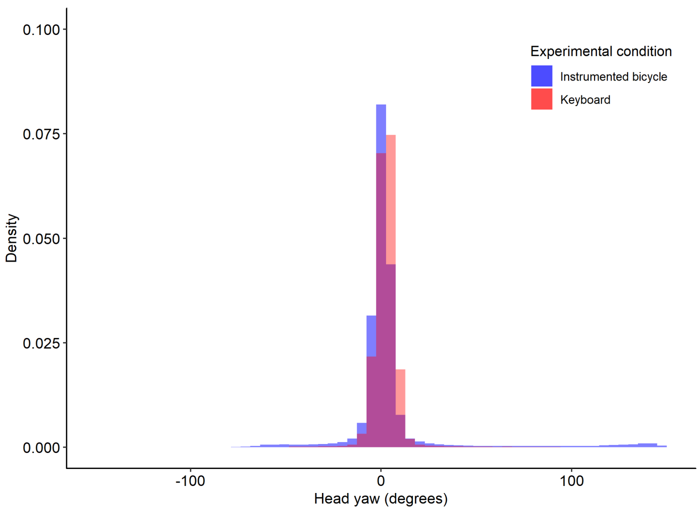
Fig. 3.4: Histograms of Speed in the two experimental settings.



5.2 Head movement

Head movement is an indication that the participant is making an effort to gather information beyond the peripheral vision. The one-sided Welch's t-test of *Head Yaw* demonstrated that the average head movement is significantly higher in the instrumented bicycle experiment as opposed to the keyboard-controlled setting (t = 2.3944, df = 89.987, p-value = 0.009362). This is in line with our Hypothesis 2, where we expected more head movement to the sides in the instrumented bicycle experiment due to more complex mechanism of control over the bicycle compared to keyboard, which in turn required participants to explore the environment to a larger extent in order to be able to react more quickly. The density histogram of the *Head Yaw* values (Figure 3.5) shows this trend, as it includes a wider range of values for instrumented bicycle compared to the keyboard experiment. It suggests that the use of the instrumented bicycle induces participants to inspect the environment more than a keyboard due to the higher level of immersion in the environment and due to the fact that braking in case of any hazardous circumstances on the road will take longer on the instrumented bike compared to instantaneous reaction while pressing the arrow on the keyboard.

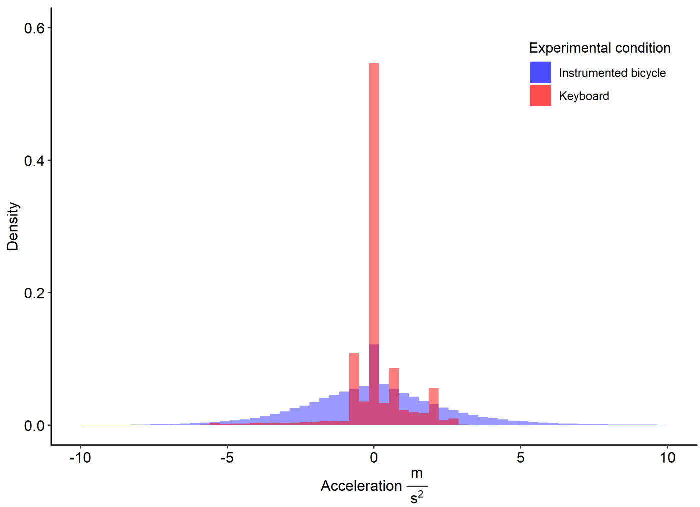
Fig. 3.5: Histograms of Head Yaw in the two experimental settings



5.3 Acceleration

The results of the one-sided F-test showed that the variance of *Acceleration* is significantly larger in the instrumented-bike experiment (F (47,45) = 3.1474, p-value = 0.00008789). This is in line with our Hypothesis 3: we expected higher variation in acceleration due to the presence of physical effort and higher difficulty in maintaining constant speed. The density histogram for *Acceleration* presented in Figure 3.6 reflects the results of the test, as we observe that the *Acceleration* values are accumulated near the mean with little variation in the keyboard-controlled experiment and have a near bell-shape distribution in the other experiment.

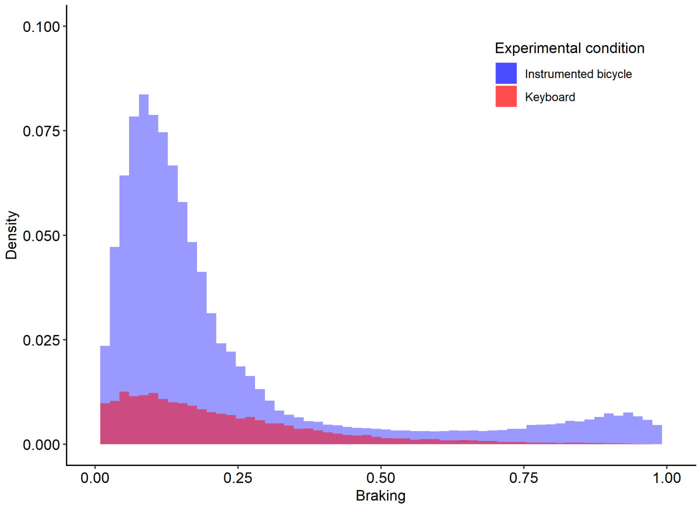
Fig. 3.6: Histograms of Acceleration in the two experimental settings.



5.4 Braking

The result of one-sided F-test showed that the variance of *Braking* is significantly larger in the instrumented-bike experiment (F (47,45) = 3.8141, p-value = 0.000007114). This result conforms to our Hypothesis 4 that more variance is present in the instrumented-bicycle experiment. Again, the density histogram of *Braking* in Figure 3.7 visually reflects the results of the test, as there is more variation in an experiment that used an instrumented bicycle. Importantly, as mentioned in section 4, *Braking* variables had different scales in the two experiments, hence, data from the instrumented-bicycle experiment was normalised (using min-max normalisation function) to be able to compare them and present jointly in a single figure.

Fig. 3.7: Histograms of Braking in the two experimental settings.



5.5 Amplitude of α wave

The one-sided Welch's t-test demonstrated that the mean α amplitude is lower in the instrumented bicycle experiment as opposed to the keyboard-controlled at the 90 % confidence level (t = 1.35, df = 40.79, p-value = 0.09), which is in line with our Hypothesis 5, where we expected a lower α amplitude in instrumented bicycle experiment due to the more immersive setting and higher cognitive engagement compared to the keyboard.

6 Discussion

VR experiments can effectively contribute to transport research only if the behaviour elicited in a virtual environment closely resembles real-world behaviour. Hence, it is important to be able to discriminate between different experimental designs that employ immersive technologies. The objective of the present paper was to compare the cycling behaviour elicited in two separate experiments which used the same visual stimuli but different devices to control the navigation through the simulated scenarios. The first one employed a keyboard and the second one an instrumented bicycle. In order to draw conclusions about the behaviour, we analysed participants' speed, acceleration, braking and head movements, along with data about their neural activity. The results are summarized in Table 3.2, where we also show examples from the existing literature which reached similar results in different experimental contexts. This highlights not only that our findings are in line with the literature, but that we confirm these results for the context of cycling and for the joint use of immersive technology and EEG.

Overall, the results show significant differences in behaviour. A more active and varied behaviour is observed in the instrumented bicycle experiment as compared to the keyboard-controlled study. For instance, the average speed is lower and more heterogeneous in the instrumented bicycle experiment, suggesting that participants dedicate more time to explore the environment. Moreover, the average speed in the instrumented bicycle experiment of 14.32 km/h is closer to the average speed of cycling in reality, which ranges between 13.5-16 km/h, in contrast to the keyboard counterpart where average speed was considerably higher in spite of the cap of 25km/h. It suggests that the use of the instrumented bicycle instead of the keyboard allows for better approximation of the real cycling kinematics.

More variation in acceleration and braking, as well as more head movement is also observed in the instrumented bicycle setting, implying a higher degree of engagement with the environment. This is further confirmed by the analysis of the EEG data, where a lower amplitude of the α wave in the instrumented bicycle experiment suggests higher mental engagement in the task compared to the keyboard-controlled one.

Our work provides evidence that the instrumented bicycle is more effective than the keyboard controls in eliciting behavioural patterns demonstrated by previous naturalistic studies of cycling behaviour. We use these studies as a benchmark due to the lack of evidence in the previous literature with regard to typical, real-life cycling behaviour in absolute terms. Moreover, our results are consistent with previous studies conducted in other contexts that investigated the effects of the use of various input devices on behaviour, as presented in the introduction and in Table 3.2. In particular, the use of a keyboard, or in fact any other input device such as a joystick or touchpad, makes the cycling experience clearly less realistic as the user does not need to exert physical effort, a crucial component associated with cycling. It, then, follows that changes in action could be seen as less consequential as they do not have impact on physical fatigue. This relates, both, to the actual action (e.g. accelerate) as well as the degree thereof. Existing literature shows similar patterns, where a previous study by Tran et al. (2018) compared the

Table 3.2: Summary of results.

No.	**Hypotheses**	**Result**	**Similar conclusions in the literature**
1A	Average speed is higher in the keyboard-controlled experiment than in instrumented bicycle one.	True	Bella (2008) and Changbin et al. (2015) with driving simulators
1B	There is more variance in speed in the instrumented bicycle experiment than in the keyboard experiment.	True	Bhise and Bhardwaj (2008) with two driving simulators
2	The average head movement is higher in the instrumented bicycle experiment than in the keyboard experiment.	True	Sitzmann et al. (2018) focusing on head movement in VR; Underwood et al. (2011) with driving simulator context
3	There is more variance in the acceleration behaviour in the instrumented bicycle experiment than in the keyboard experiment.	True	Reymond et al. (2001) with driving simulator
4	There is more variance in the braking behaviour in the instrumented bicycle experiment than in the keyboard experiment.	True	Zöller et al. (2019) focusing on braking behaviour in driving simulator
5	The mean amplitude of α wave is higher in the keyboard-controlled experiment compared to an instrumented bicycle.	True	Argento et al. (2017) in the context of brainwave entertainment in VR

perception of speed in VR between instrumented bicycle that was powered by throttling (electric-based power) or participant pedalling. They found that when pedalling, participants' perception of speed was more accurate and the perception of presence in the virtual environment was higher. Similarly, in pedestrian research, a study by Boletsis and Cedergren (2019) compared the performance of walking simulator, VR controller and VR teleportation (in which the user's viewpoint is instantaneously moved to a predefined location through visual 'jumps') when navigating through a simulated city. The results showed that the walking simulator provided the highest level of immersion relative to other methods, but also resulted in the highest level of physical fatigue.

Beyond the physical effort, hand-held motion recognition devices lack the appropriate kinematics associated with cycling and, therefore, constrain natural body movement used to modulate cycling behaviour. This, in turn, reduces the immersion in the virtual experience. Consequently, in recent years, the number of cycling simulators, developed for research purposes, increased significantly (Michahelles and Wintersberger, 2021; O'Hern et al., 2017; Ranky et al., 2010; Schramka et al., 2017; Shepherd et al., 2018; Tran et al., 2018). In other contexts, this trend is also noticeable, where, for example, a study by Kreimeier et al. (2020) focused only on the walking simulators based on walk-in-place locomotion technique, namely, Vive Trackers, Virtux Omni and Cyberith Virtualizer to explore their relative performance.

Finally, in terms of functional considerations, the use of a keyboard jointly with a head-mounted display is simply impractical, when participants are not able to see the physical world around them (LaViola Jr et al., 2017). This is particularly difficult in the case of cycling because the movement with the keyboard is not as intuitive compared to the instrumented bicycle.

On the other hand, the advantages of the employment of a keyboard or other simple devices cannot be ignored. Their use is cheaper and less time consuming than the employment of the stationary bicycle, where the design and manufacturing of custom-built bike takes approximately nine to twelve months and is about twenty times more costly relative to controllers readily available on the market.

Keyboard and other standardised input devices should also be considered during study design, given the findings of a large body of literature which shows that, in certain scenarios, these commercial devices perform equally well as more advanced ones. For example, a study by Fund (2015) showed that mouse and keyboard outperformed Xbox controller and joystick in steering task. Similarly, Ardito et al. (2009) demonstrated that keyboard and mouse were faster and more efficient than Xbox and Nintendo Wii controllers in the task that required moving objects in the virtual environment. Therefore, researchers can exploit the fact that the majority of participants is familiar with these devices which allows them to perform certain tasks easier and faster (Cabral et al., 2005)

Further, the hand-held motion recognition devices are also more portable which makes it more convenient to collect data in different locations. This may be particularly beneficial if specific segments of the population are of interest. For example, Syed-Abdul et al. (2019) studied the acceptance and use of virtual reality among the elderly population. The data collection was conducted in an ageing centre with HTC Vive controllers because the portability of VR devices was an absolute priority.

Moreover, the emergence of movement artefacts in the EEG signal is a widely recognised issue in current literature (Hertweck et al., 2019; Li et al., 2020; Tauscher et al., 2019; Tremmel et al., 2019). Hence, if VR is used jointly with neuroimaging devices, then a simpler input device offers a more static approach, reducing the extent of potential noise in the neural data stemming from body movements.

Overall, the choice of input device for VR experiments is not an arbitrary decision and should be aligned with the objectives of the study to not constrain the spectrum of behaviour which can be captured and minimise the potential biases resulting from the mere choice of the controller. Moreover, the decision of an appropriate input tool also has to be weighed against technical capabilities such the budget, duration of the experiment and comfort of the participants as well as a possibility of joint use with other equipment employed in the study. In this paper, we compare only two devices. However, it is important to take into consideration other available appliances such as a 3D mouse, joystick, steering wheel, gamepad or hybrid controller which may offer different benefits depending on the design of the study.

The results thus emphasize the importance of the experimental setup in a VR experiment beyond the choice of appropriate visual stimulus. The findings extend understanding of the effects of the use of distinct input devices within the VR domain by demonstrating that the use of an instrumented bicycle increases the realism of the cycling simulations by influencing the manoeuvring decisions. These results were further reinforced by the analysis of neural data. Further research needs to be conducted to generalize these findings. In particular, we recommend testing different cycling scenarios as well as experiments focusing on different aspects of travel behaviour to compare participants' actions in the experimental setting with real-world decisions. The findings shed light on the level of behavioural congruence of the state-of-the-art VR studies which will be valuable in the interpretation and the level of confidence in the results of different VR studies. It is also expected to be a valuable resource to researchers and practitioners planning to administer VR-based data collection and help them to better design the experimental setup as there has been a significant interest in using VR for modelling cycling behaviour (Nazemi et al., 2018, 2021). By comparing and contrasting the behaviour of cyclists in the two VR environments, the paper is expected to provide guidance to researchers investigating cycling behaviour in dynamic setting and hence improve the modelling of speed and acceleration of cyclists which can feed into safety research or capacity analyses for instance. The findings are also expected to be useful for planners who are interested in deploying VR to more realistically test the impact of different urban designs on the propensity to cycle, indicating, for example, the road and pavements features which contribute to the higher perception of safety among cyclists. The research findings can hence help transport and urban planners in making more informed choices regarding urban infrastructure. Finally, VR tools are increasingly being used in designing vehicles of the future – the interaction between connected and automated vehicles (CAVs) and other road users. The findings can help researchers modelling the interaction between cyclists and CAVs in designing their experiments and better interpreting the results by giving an idea about the comparative realism of the collected data.

References

Ardito, C., Buono, P., Costabile, M. F., Lanzilotti, R., and Simeone, A. L. (2009). Comparing low cost input devices for interacting with 3D virtual environments. In *2009 2nd Conference on Human System Interactions*, pages 292–297. IEEE.

Argento, E., Papagiannakis, G., Baka, E., Maniadakis, M., Trahanias, P., Sfakianakis, M., and Nestoros, I. (2017). Augmented cognition via brainwave entrainment in virtual reality: An open, integrated brain augmentation in a neuroscience system approach. *Augmented Human Research*, 2(1):3.

Awais, M., Badruddin, N., and Drieberg, M. (2017). A hybrid approach to detect driver drowsiness utilizing physiological signals to improve system performance and wearability. *Sensors*, 17(9):1991.

Bella, F. (2008). Driving simulator for speed research on two-lane rural roads. *Accident Analysis & Prevention*, 40(3):1078–1087.

Berg, P. and Scherg, M. (1994). A multiple source approach to the correction of eye artifacts. *Electroencephalography and clinical neurophysiology*, 90(3):229–241.

Bhise, V. D. and Bhardwaj, S. (2008). *Comparison of driver behavior and performance in two driving simulators.* SAE Technical Paper: 2008-01-0562.

Bogacz, M., Calastri, C., Choudhury, C. F., Hess, S., Erath, A., van Eggermond, M. A., and Mushtaq, F. (2019). Processing cycling risk under different elicitation methods: comparing 2D and 3D in virtual reality choice environments. In *2019 TRB Annual Meeting Online*, pages 19–02604. Transportation Research Board.

Boletsis, C. and Cedergren, J. E. (2019). VR locomotion in the new era of virtual reality: an empirical comparison of prevalent techniques. *Advances in Human-Computer Interaction*, 2019:1–15.

Borrego, A., Latorre, J., Alcaniz, M., and Llorens, R. (2018). Comparison of Oculus Rift and HTC vive: feasibility for virtual reality-based exploration, navigation, exergaming, and rehabilitation. *Games for health journal*, 7(3):151–156.

Cabral, M. C., Morimoto, C. H., and Zuffo, M. K. (2005). On the usability of gesture interfaces in virtual reality environments. In *Proceedings of the 2005 Latin American conference on Human-computer interaction*, pages 100–108.

Changbin, C., Junhua, W., and Yangming, L. (2015). Driving simulator validation for research on driving behavior at entrance of urban underground road. In *2015 International Conference on Transportation Information and Safety (ICTIS)*, pages 147–150. IEEE.

Christiano, L. J. and Fitzgerald, T. J. (2003). The band pass filter. *International Economic Review*, 44(2):435–465.

Chung, S., Kramer, T., and Wong, E. M. (2018). Do touch interface users feel more engaged? The impact of input device type on online shoppers' engagement, affect, and purchase decisions. *Psychology & Marketing*, 35(11):795–806.

Cisek, P. and Kalaska, J. F. (2005). Neural correlates of reaching decisions in dorsal premotor cortex: specification of multiple direction choices and final selection of action. *Neuron*, 45(5):801–814.

Craig, A., Tran, Y., Wijesuriya, N., and Nguyen, H. (2012). Regional brain wave activity changes associated with fatigue. *Psychophysiology*, 49(4):574–582.

Di Stasi, L. L., Renner, R., Catena, A., Cañas, J. J., Velichkovsky, B. M., and Pannasch, S. (2012). Towards a driver fatigue test based on the saccadic main sequence: A partial validation by subjective report data. *Transportation research part C: emerging technologies*, 21(1):122–133.

Dozza, M. and Werneke, J. (2014). Introducing naturalistic cycling data: What factors influence bicyclists' safety in the real world? *Transportation research part F: traffic psychology and behaviour*, 24:83–91.

EMOTIV (2018). *14 Channel Wireless EEG Headset*. URL: https://www.emotiv.com/epoc (Accessed: 13/05/2019).

Eoh, H. J., Chung, M. K., and Kim, S.-H. (2005). Electroencephalographic study of drowsiness in simulated driving with sleep deprivation. *International Journal of Industrial Ergonomics*, 35(4):307–320.

Farooq, B., Cherchi, E., and Sobhani, A. (2018). Virtual immersive reality for stated preference travel behavior experiments: A case study of autonomous vehicles on urban roads. *Transportation research record*, 2672(50):35–45.

Frankenhuis, W. E., Dotsch, R., Karremans, J. C., and Wigboldus, D. H. (2010). Male physical risk taking in a virtual environment. *Journal of Evolutionary Psychology*, 8(1):75–86.

Fund, I. (2015). *Usability of Various Input Devices on a Steering Task*. University of Central Florida, Orlando.

Godley, S. T., Triggs, T. J., and Fildes, B. N. (2002). Driving simulator validation for speed research. *Accident analysis & prevention*, 34(5):589–600.

Goldstone, W. (2009). *Unity game development essentials*. Packt Publishing Ltd, Birmingham.

Hawkins, G., Mittner, M., Boekel, W., Heathcote, A., and Forstmann, B. U. (2015). Toward a model-based cognitive neuroscience of mind wandering. *Neuroscience*, 310:290–305.

Hertweck, S., Weber, D., Alwanni, H., Unruh, F., Fischbach, M., Latoschik, M. E., and Ball, T. (2019). Brain activity in virtual reality: Assessing signal quality of high-resolution EEG while using head-mounted displays. In *2019 IEEE Conference on Virtual Reality and 3D User Interfaces (VR)*, pages 970–971. IEEE.

Hu, B., Johnson-Bey, I., Sharma, M., and Niebur, E. (2017). Head movements during visual exploration of natural images in virtual reality. In *2017 51st Annual Conference on Information Sciences and Systems (CISS)*, pages 1–6. IEEE.

Huertas-Leyva, P., Dozza, M., and Baldanzini, N. (2018). Investigating cycling kinematics and braking maneuvers in the real world: E-bikes make cyclists move faster, brake harder, and experience new conflicts. *Transportation research part F: traffic psychology and behaviour*, 54:211–222.

Ille, N., Berg, P., and Scherg, M. (2002). Artifact correction of the ongoing EEG using spatial filters based on artifact and brain signal topographies. *Journal of clinical neurophysiology*, 19(2):113–124.

Jensen, O. and Mazaheri, A. (2010). Shaping functional architecture by oscillatory alpha activity: Gating by inhibition. *Frontiers in Human Neuroscience*, 4:186.

Johnston, J. (1972). *Econometric methods-2.* McGraw-Hill Book, New York.

Katsis, C., Goletsis, Y., Rigas, G., and Fotiadis, D. (2011). A wearable system for the affective monitoring of car racing drivers during simulated conditions. *Transportation research part C: emerging technologies*, 19(3):541–551.

Klimesch, W. (1999). EEG alpha and theta oscillations reflect cognitive and memory performance: a review and analysis. *Brain research reviews*, 29(2-3):169–195.

Klimesch, W. (2012). Alpha-band oscillations, attention, and controlled access to stored information. *Trends in cognitive sciences*, 16(12):606–617.

Klimesch, W., Doppelmayr, M., Russegger, H., Pachinger, T., and Schwaiger, J. (1998). Induced alpha band power changes in the human EEG and attention. *Neuroscience letters*, 244(2):73–76.

Klimesch, W., Sauseng, P., and Hanslmayr, S. (2007). EEG alpha oscillations: the inhibition–timing hypothesis. *Brain research reviews*, 53(1):63–88.

Kreimeier, J., Ullmann, D., Kipke, H., and Götzelmann, T. (2020). Initial evaluation of different types of virtual reality locomotion towards a pedestrian simulator for urban and transportation planning. In *Extended Abstracts of the 2020 CHI Conference on Human Factors in Computing Systems*, pages 1–6.

Lal, S. K. and Craig, A. (2001). A critical review of the psychophysiology of driver fatigue. *Biological psychology*, 55(3):173–194.

LaViola Jr, J. J., Kruijff, E., McMahan, R. P., Bowman, D., and Poupyrev, I. P. (2017). *3D user interfaces: theory and practice*. Addison-Wesley Professional, Atlanta.

Li, J., Jin, Y., Lu, S., Wu, W., and Wang, P. (2020). Building environment information and human perceptual feedback collected through a combined virtual reality (VR) and electroencephalogram (EEG) method. *Energy and Buildings*, 224:110259.

Mai, K. L. (2017). *Evaluation of PC-Based Virtual Reality as a Tool to Analyze Pedestrian Behavior at Midblock Crossings*. Faculty of California Polytechnic State University, San Luis Obispo.

Michahelles, F. and Wintersberger, P. (2021). The eternity bike-bringing active safety to the bicycle. In *Cycling@CHI: Towards a Research Agenda for HCI in the Bike Lane at CHI '21, May 8–13, 2021, Yokohama, Japan*, pages 1–5. ACM, New York, NY, USA.

Moussa, G., Radwan, E., and Hussain, K. (2012). Augmented reality vehicle system: Left-turn maneuver study. *Transportation research part C: emerging technologies*, 21(1):1–16.

Nazemi, M., van Eggermond, M. A., Erath, A., and Axhausen, K. W. (2018). Studying cyclists' behavior in a non-naturalistic experiment utilizing cycling simulator with immersive virtual reality. *Arbeitsberichte Verkehrs-und Raumplanung*, 1383:1–20.

Nazemi, M., van Eggermond, M. A., Erath, A., Schaffner, D., Joos, M., and Axhausen, K. W. (2021). Studying bicyclists' perceived level of safety using a bicycle simulator combined with immersive virtual reality. *Accident Analysis & Prevention*, 151:105943.

Oculus.com (2018). *Oculus*. URL: https://www.oculus.com (Accessed: 30/07/2019).

O'Hern, S., Oxley, J., and Stevenson, M. (2017). Validation of a bicycle simulator for road safety research. *Accident Analysis & Prevention*, 100:53–58.

Oken, B. S. and Chiappa, K. H. (1986). Statistical issues concerning computerized analysis of brainwave topography. *Annals of neurology*, 19(5):493–494.

Patterson, Z., Darbani, J. M., Rezaei, A., Zacharias, J., and Yazdizadeh, A. (2017). Comparing text-only and virtual reality discrete choice experiments of neighbourhood choice. *Landscape and Urban Planning*, 157:63–74.

Puce, A. and Hämäläinen, M. S. (2017). A review of issues related to data acquisition and analysis in EEG/MEG studies. *Brain sciences*, 7(6):58.

Ranky, R., Sivak, M., Lewis, J., Gade, V., Deutsch, J. E., and Mavroidis, C. (2010). Vrack—virtual reality augmented cycling kit: Design and validation. In *2010 IEEE Virtual Reality Conference (VR)*, pages 135–138. IEEE.

Ratti, E., Waninger, S., Berka, C., Ruffini, G., and Verma, A. (2017). Comparison of medical and consumer wireless EEG systems for use in clinical trials. *Frontiers in human neuroscience*, 11:398.

Repovs, G. (2010). Dealing with noise in EEG recording and data analysis. In *Informatica Medica Slovenica*, volume 15, pages 18–25.

Reymond, G., Kemeny, A., Droulez, J., and Berthoz, A. (2001). Role of lateral acceleration in curve driving: Driver model and experiments on a real vehicle and a driving simulator. *Human factors*, 43(3):483–495.

Riera, A., Dunne, S., Cester, I., and Ruffini, G. (2008). Starfast: A wireless wearable EEG/ECG biometric system based on the enobio sensor. In *Proceedings of the International workshop on wearable micro and nanosystems for personalised health*, pages 1–4.

Rupp, M. A., Oppold, P., and McConnell, D. S. (2015). Evaluating input device usability as a function of task difficulty in a tracking task. *Ergonomics*, 58(5):722–735.

Sauseng, P., Klimesch, W., Stadler, W., Schabus, M., Doppelmayr, M., Hanslmayr, S., Gruber, W. R., and Birbaumer, N. (2005). A shift of visual spatial attention is selectively associated with human EEG alpha activity. *European Journal of Neuroscience*, 22(11):2917–2926.

Schleinitz, K., Petzoldt, T., Franke-Bartholdt, L., Krems, J., and Gehlert, T. (2017). The German naturalistic cycling study–comparing cycling speed of riders of different e-bikes and conventional bicycles. *Safety Science*, 92:290–297.

Schramka, F., Arisona, S., Joos, M., and Erath, A. (2017). Development of virtual reality cycling simulator. *Journal of Computers*, 13(6):603–615.

Shaker, M. M. (2007). EEG waves classifier using wavelet transform and Fourier transform. *International Journal of Medical, Health, Biomedical, Bioengineering and Pharmaceutical Enineering*, 1(3):1–6.

Shepherd, J., Carter, L., Pepping, G.-J., and Potter, L.-E. (2018). Towards an operational framework for designing training based sports virtual reality performance simulators. In *Multidisciplinary Digital Publishing Institute Proceedings*, volume 2, page 214.

Sitzmann, V., Serrano, A., Pavel, A., Agrawala, M., Gutierrez, D., Masia, B., and Wetzstein, G. (2018). Saliency in VR: How do people explore virtual environments? *IEEE transactions on visualization and computer graphics*, 24(4):1633–1642.

Spivey, M. J., Grosjean, M., and Knoblich, G. (2005). Continuous attraction toward phonological competitors. *Proceedings of the National Academy of Sciences*, 102(29):10393–10398.

Syed-Abdul, S., Malwade, S., Nursetyo, A. A., Sood, M., Bhatia, M., Barsasella, D., Liu, M. F., Chang, C.-C., Srinivasan, K., Raja, M., et al. (2019). Virtual reality among the elderly: a usefulness and acceptance study from Taiwan. *BMC geriatrics*, 19(1):1–10.

Szul, M. J., Bompas, A., Sumner, P., and Zhang, J. (2020). The validity and consistency of continuous joystick response in perceptual decision-making. *Behavior research methods*, 52(2):681–693.

Tauscher, J.-P., Schottky, F. W., Grogorick, S., Bittner, P. M., Mustafa, M., and Magnor, M. (2019). Immersive EEG: Evaluating electroencephalography in virtual reality. In *2019 IEEE Conference on Virtual Reality and 3D User Interfaces (VR)*, pages 1794–1800. IEEE.

Thut, G., Nietzel, A., Brandt, S. A., and Pascual-Leone, A. (2006). α-band electroencephalographic activity over occipital cortex indexes visuospatial attention bias and predicts visual target detection. *Journal of Neuroscience*, 26(37):9494–9502.

Tran, T. Q., Tran, T. D. N., Nguyen, T. D., Regenbrecht, H., and Tran, M.-T. (2018). Can we perceive changes in our moving speed: a comparison between directly and indirectly powering the locomotion in virtual environments. In *Proceedings of the 24th ACM Symposium on Virtual Reality Software and Technology*, pages 1–10.

Tremmel, C., Herff, C., and Krusienski, D. J. (2019). EEG movement artifact suppression in interactive virtual reality. In *2019 41st Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, pages 4576–4579. IEEE.

Underwood, G., Crundall, D., and Chapman, P. (2011). Driving simulator validation with hazard perception. *Transportation research part F: traffic psychology and behaviour*, 14(6):435–446.

Welch, B. L. (1947). The generalization of student's problem when several different population variances are involved. *Biometrika*, 34(1/2):28–35.

Welch, P. (1967). The use of fast Fourier transform for the estimation of power spectra: a method based on time averaging over short, modified periodograms. *IEEE Transactions on audio and electroacoustics*, 15(2):70–73.

Zöller, I., Abendroth, B., and Bruder, R. (2019). Driver behaviour validity in driving simulators–analysis of the moment of initiation of braking at urban intersections. *Transportation research part F: traffic psychology and behaviour*, 61:120–130.

Chapter 4

Modelling risk perception using a dynamic hybrid choice model and brain-imaging data: application to virtual reality cycling

Martyna Bogacz[1], Stephane Hess[1], Chiara Calastri[1], Charisma F. Choudhury[1], Faisal Mushtaq[2], Muhammad Awais[2], Mohsen Nazemi[3], Michael A.B. van Eggermond[3] & Alexander Erath[3]

Abstract

Road risk analysis is one of the key research areas in the transport, where the impact of perceived risk on choices, especially in a dynamic setting, has been long recognised. However, due to the lack of dynamic data and the difficulty in capturing risk perception, the existing studies typically resort to static and stated approaches to infer the experienced level of risk of individuals. In this paper, we aimed to address this research gap through developing a hybrid choice model that jointly employed dynamic data on cycling behaviour in virtual reality and neural data to evaluate how the fluctuations in momentary risk perception influence the behaviour of cyclists. The results of the developed model confirm our hypotheses, demonstrating that the cyclists reduce their speed when approaching a junction as the potential for a collision with passing cars increases. Moreover, the latent component allowed us to establish a link between the neural data, the amplitude of alpha brainwaves, and objective risk measures. In line with our hypothesis, we found that de-

[1]Institute for Transport Studies and Choice Modelling Centre, University of Leeds, UK
[2]School of Psychology & Centre for Immersive Technologies, University of Leeds, UK
[3]Future Cities Laboratory Singapore-ETH Centre Zurich

creased alpha amplitude is associated with higher perceived risk which in turn increases the likelihood of braking. The implications of our study are manifold. On the one hand, it shows the ability of virtual reality to elicit complex cyclists' behaviour and the feasibility of a joint collection of dynamic neural and choice data. On the other hand, we demonstrate the potential of the employment of neural data in a hybrid model framework as an indicator of risk that allows us to gain a better understanding of cycling behaviour and associated neural processing. These promising findings pave the way for future studies that would explore the advantages of neuroscientific inputs in the choice models.

1 Introduction

Modelling risk perception in the transport context plays a critical role in the prediction of individuals' behaviour in a risky situation on the road. Traditionally, perceived risk and its effect on choices have been explored by means of paper or web-based stated preference (SP) surveys or simple laboratory experiments. In particular, direct questionnaires and attitudinal scales have been widely used in the transport context (Ram and Chand, 2016; Rundmo and Iversen, 2004; Ulleberg and Rundmo, 2003).The major issue associated with this approach is the possible incongruence between the stated and experienced risk and between the stated and actual actions. For instance, Andersson (2013) found a significant discrepancy between stated and observed willingness to pay for traffic safety, with Svensson (2009) also showing an inconsistency between the willingness to pay for risk reduction and the precautionary behaviour actually used to reduce it.

Additionally, a limitation arises from the lack of dynamic data on risk, where attitudinal questions provide only a static indication of the inherently dynamic risk perception. While the experimental techniques may not capture the experience of risk to the same degree as real-life settings, some headway can be made with augmented and virtual reality (VR) technologies. These have been previously used, mostly in psychology research, to measure risk perception (Dixit et al., 2015) as well as physiological responses (Chirico et al., 2017; Johnson et al., 2011; Shechtman et al., 2009). A key advantage is the dynamic nature of the VR experiments, where many studies, focussed on risk, have adopted such a dynamic approach to improve realism and better capture the reactions to momentary changes in risk perception on the road (Frankenhuis et al., 2010; Mai, 2017; Underwood et al., 2011).

Virtual reality provides an alternative to the established methods of measuring risk perception and associated stress levels. Crucially for the present work, it also enables a joint use with physiological devices and neuroimaging techniques such as electroencephalography (EEG), where the signal can be a proxy for risk perception. Therefore, a major opportunity arises with the greater accessibility to neuroimaging equipment to provide a new perspective on behaviour in risky and stressful conditions. Studies in neuropsychology have established that α waves[4] are a reliable stress marker (Lewis et al., 2007; Nishifuji et al., 2010; Seo and Lee, 2010; Vanitha and Krishnan, 2016; Verona et al., 2009) and links have been made between α wave variations and its role in attention and perception (Cooper et al., 2006; Magosso et al., 2019; Ray and Cole, 1985). In particular, a study by Brouwer et al. (2011) looked at neural correlates of stress evoked by the use of virtual reality. They found that simulated stressful conditions significantly influenced several physiological stress indicators used in the study, including frontal α power. Finally, Magosso et al. (2019) used virtual reality simulations and electroencephalography to detect changes in attention. The results of the study demonstrated that the α power decreased during tasks which required high attention to the external environment and conversely, α amplitude increased when the attentional demands of the task diminished. The results of these studies provide a promising basis for using α wave data as an indicator for the perceived risk, in the transport context, which increases the attentional demands. In particular, its usefulness in modelling of the perceived risk on the road could be explored if continuous EEG and behavioural data are collected jointly.

In a choice modelling context, previous attempts to combine neuroscientific concepts with mathematical models resulted in the emergence of decision field theory (DFT) (Hancock et al., 2018), which allowed for an adoption of a new, underlying decision rule in the models. However, in the current study, a model based on the random utility maximisation (RUM) theory is used to incorporate neural data. It was chosen because, on one hand, RUM is sufficiently flexible and powerful to allow for the incorporation of neural inputs, while at the same time being a relatively simple and well-understood method. For this reason, it has been selected for the first attempts to use jointly with novel data. Beyond the model's decision rule, there are different possible approaches to include neural data as indicators in the model. For example, structural equation modelling (SEM) allows accounting for the fact that both, the choice and the indicators are driven by the same underlying latent variable. However, SEM produces inefficient estimates, where they

[4]Brain patterns form sinusoidal waves that are measured from peak to peak, with amplitude ranging from 0.5 to 100 μV. The brainwaves are measured in cycles per second (Hertz) which are also known as a frequency of brain wave activity. There are five major brainwaves identified: beta, alpha, theta, delta and gamma. The frequency of alpha brainwaves ranges between 8-13 Hz (Ambekar and Achrekar, 2014; Isa et al., 2014; Teplan et al., 2002).

only use the information provided by the indicators and the information on the choices made by the respondent is not accounted for (Civelek, 2018). Further, indicators could be directly incorporated into the choice model as explanatory variables. However, this approach can give rise to the endogeneity bias, if some unobserved factors influence both choices and indicators. Then, treating indicators as a direct, error-free measure of the latent variable can lead to inconsistent estimates. Finally, this method assumes causality between the indicators and the observed behaviour, which is particularly problematic because we cannot safely assume that a certain response to the indicator has a causal relationship with the observed choice (Hensher et al., 2005). For this reason, Hybrid Choice Models (HCM) are the most suitable framework to incorporate neural data into the model because they do not assume causality between the indicators and the dependent variable. Instead, they allow capturing simultaneously the impact of the exogenous variables on the choices and the indicators of the latent variable to create a link between them (Vij and Walker, 2016). HCMs have been previously used mostly to combine latent constructs such as attitudes, opinions or perceptions together with observed choices in a single model structure by the means of measurable indicators (Abou-Zeid and Ben-Akiva, 2014; Ben-Akiva et al., 2002; Bolduc and Alvarez-Daziano, 2010). More recently, Paschalidis et al. (2019) applied a hybrid framework with heart rate and skin conductance as indicators of unobserved stress to investigate its impact on driving behaviour.

The present paper addresses the shortcoming of past work by exploiting these novel opportunities in terms of an experiment that employs neuroimaging techniques to explore cycling risk perception in virtual reality simulation. We employ a dynamic HCM with an unobserved risk as a latent variable and we use α wave data as an indicator of the perceived risk to better explain the behavioural responses of the cyclist in the simulated environment. This approach allows us to achieve better understanding of cyclists' choices and make inferences about their neural background.

The remainder of this paper is organised as follows. We present our specific hypotheses guided by the literature in the next section. The data collection design and sample characteristics are presented next, followed by the model structure and specification. We next turn to the results section, followed by the discussion section which reviews the insights from the analysis.

2 Hypotheses

In this section, we propose a number of hypotheses related to the changes in cyclists' behaviour with respect to fluctuations in the perceived level of risk due to dynamic traffic conditions and associated neural processing of their choices.

2.1 Behavioural data

- Hypothesis 1a: The presence of a passing car at the junction increases perceived risk, which in turn increases cyclists' propensity to reduce speed.

- Hypothesis 1b: The increase (or decrease) in perceived risk and hence the propensity to reduce (or increase) speed is a function of the remaining distance to reach the junction. That is, a shorter distance until the potential collision with the car at the junction increases cyclists' propensity to reduce speed.

These hypotheses are driven by the fact that junctions are parts of the road in our experiment where accidents with cars are possible, while speed reduction is the most common avoidance manoeuvre among cyclists (Johnson et al., 2010). Therefore, closer proximity to the junction and the presence of a car are expected to make cyclists brake more often in order to avoid collisions with other agents on the road or to gain more time to assess the dynamic situation at the junction, similarly to how we expect cyclists to react in reality when approaching a dangerous road.

2.2 Neural data - α amplitude

- Hypothesis 2: The α wave decreases (or increases) with increased (or reduced) risk.

This hypothesis draws on the existing literature which links α wave to stress, visual attention, task performance and information processing relevant to the task (Borghini et al., 2014; Fairclough et al., 2005; Fournier et al., 1999; Slobounov et al., 2000; Verona et al., 2009). In particular, multiple previous studies have shown that the changes of α activity were related to the strength of attention to external stimuli required by the task (Lei and Roetting, 2011; Mann et al., 1996; Simon et al., 2019; Vanni et al., 1997). In other words, the presence of a dangerous element in the scenario (car crossing at the junction) is considered to increase the task complexity, and consequently, higher attentional demands lead to a decrease in the α power. Therefore, it is hypothesised that α power is negatively associated with perceived risk.

3 Experimental design and sample information

This section explains the experimental procedure, technical details of the data collection and describes the equipment employed in the experiment i.e. the instrumented bicycle, virtual reality goggles and the EEG device. Beyond, we present the basic characteristics of the sample.

The experiment used six scenarios with an immersive presentation of traffic from the perspective of the cyclist. All the scenarios had a number of common elements. Firstly, the cyclist was riding on the pavement. Secondly, in each scenario, there were two locations where a potential collision with cars could occur, namely two junctions, as seen in Figure 4.1. Thirdly, all the scenarios featured pedestrians as well as cars and the percentage of pedestrians and cars which would cross the bike lane or turn at the junction was constant. At the same time, there were also random components in each scenario which stemmed from the fact that in each scenario, the specific movements of crossing pedestrians and turning cars were presented randomly, while keeping their overall percentage the same across all the scenarios. This resulted in differences between scenarios in terms of the actual number of cars at the "*collision locations*" when the cyclist was passing by these points. This was clearly also influenced by the speed of the cyclist, and hence the point in time at which the "*collision locations*" were reached. Altogether, these elements gave basis for the complex traffic scenarios which a participant was required to navigate. The microsimulation of traffic used in the scenarios was designed using PTV Vissim software (PTV-Group, 2021) and later developed in Unity as a 3D, virtual reality scenario (Unity, 2017). Therefore, the scenarios encompassed a 360-degree view of the road which surrounded the participant and responded to their head movements. Importantly, based on the feedback received during initial pre-testing of the set-up, sound was also included to capture both visual and auditory cues that are available to cyclists in real-life settings. The volume of noise generated by the vehicles was consistent with their distance to the cyclist so that the sound of an approaching car increased as it got closer to the cyclist.

Several scenarios were used because we collected neural data which requires a higher number of trials in order to obtain more stability in the EEG signal. The task for the participant was to cycle through the scenario at the desired pace until the finish line at the end of each scenario. In order to navigate through the scenario, the participant used the pedals of the bicycle and had no ability to turn left or right. To brake, the participant used a hand brake positioned on the right side of the handlebar. The instrumented bike can be observed in Figure 4.2. The instrumented bike belongs to Future Cities

Fig. 4.1: An example of collision point - a junction.

Laboratories in Singapore.

Each experimental session started with familiarising the participant with the instrumented bicycle, including demonstrating how to use the hand brake (all participants could ride a bike in reality). Subsequently, the participant mounted the bike and the HTC Vive head mounted display (HMD) (Borrego et al., 2018) and the EEG recording device Enobio (Riera et al., 2008) were placed on their head. The Enobio headset used 8 electrodes (at FP1, FP2, Fz, C3, Cz, C4, P3 and P4) sampling across the scalp. The system allowed for a joint use with HTC Vive HMD. As a first step, the baseline brain activity was recorded with the sampling rate of 128 Hz[5], while participants had their eyes open and focussed their gaze on one point on the screen for 1 minute. The same procedure was then repeated with eyes closed. Before the main part of the experiment started, participants had a trial session to familiarise themselves with the use of the bicycle and the virtual environment. The summary of the data collected in the experiment is presented in Table 4.1.

Fifty individuals participated in the experiment, comprising of staff and students of the National University of Singapore as well as members of the general public. Nonetheless, two of them failed to complete the whole experiment hence the final sample size was 48 individuals. The mean age of the participants was 26.5 years, with 6.7 years standard deviation. It is im-

[5]Hertz (Hz) is a unit of temporal frequency which denotes the number of occurrences of an event per one second. For example, a recording resolution of 128 Hz means that the data has been collected 128 times per one second.

Fig. 4.2: Instrumented bicycle used in the experiment

Table 4.1: Summary of data collected in the experiment.

Data type	**Variable**	**Resolution of recording**	**Unit of measurement**
Behavioural	Speed	4 Hz	km/h
Behavioural	Acceleration	4 Hz	m/s^2
Neural	α wave amplitude	128 Hz	μV (microvolt)

portant to emphasize that the small sample size is a typical issue faced by researchers working with VR and/or driving simulator data (Di Stasi et al., 2012; Katsis et al., 2011; Moussa et al., 2012) as the experiment duration is much longer and the associated cost much higher compared to typical stated preference studies.

4 Methods for EEG data cleaning and extraction

The EEG signals collected through the scalp are inherently noisy and we thus applied a number of steps to eliminate artefacts and improve the signal-to-noise ratio. Specifically, we first applied a 1-20 Hz bandpass filtering (BPF), a linear transformation that retains the components of the data within this specific band of frequencies (Christiano and Fitzgerald, 2003) and removes frequencies outside of this range that may stem from physiological sources such as galvanic skin responses or external environmental sources such as electronic equipment. Next, we cleaned the data to remove noise stemming from eyeblinks (movement artefacts were corrected using a multiple source analysis method) (Berg and Scherg, 1994; Ille et al., 2002). We next computed the power spectrum of the EEG data using Welch's method (Welch, 1967) which estimates the power spectra based on the Fast Fourier Transform (FFT) (Shaker, 2007), before we averaged the EEG data from 128 Hz to 4 Hz to match the resolution of the behavioural data. Finally, we normalized the logarithm of α wave so that for each individual α values have mean of 0 and the standard deviation of 1.

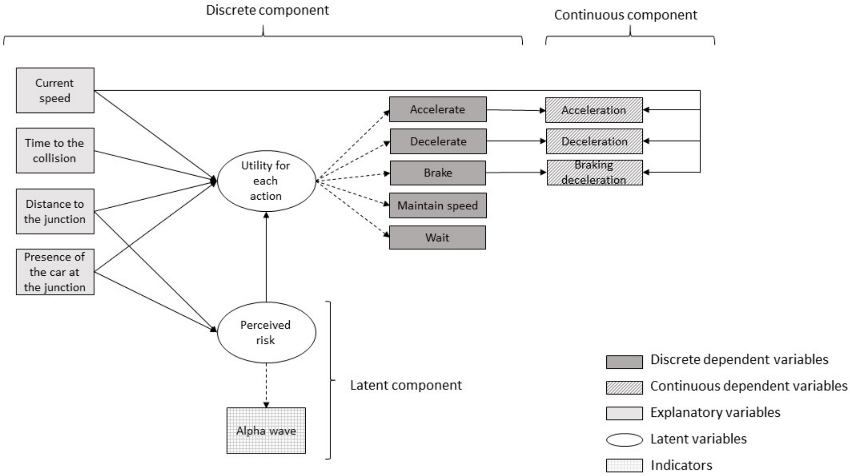
5 Modelling framework

In this section we describe the modelling framework used in this study, where we developed a hybrid choice model with discrete and continuous choice components and a latent variable. Cyclists' choices of action in the virtual environment were recorded every quarter of a second. In Figure 4.3, the latent variables are presented in ovals and the observed variables are presented in rectangles. The utility of each of the discrete actions (i.e. accelerate, brake, decelerate, maintain speed and wait) is influenced by the different exogenous variables related to the situation in the scenario and latent perceived risk. The latent component of the model consists of the latent risk with α wave as its indicator and two explanatory variables. If the cyclist chooses to accelerate, brake, or decelerate, then the continuous component for a given action is considered. Importantly, in the continuous part, the acceleration is split into two cases, namely acceleration when previously stopped and when previously in motion. We present a more detailed description of each model component in turn.

5.1 Specification of latent risk

The developed hybrid choice model encompasses a latent component that seeks to capture the impact of risk on cyclist's actions, where it is believed that in real life the individuals also adjust their cycling in response to observed level of risk. Based on the existing literature, it is assumed that the perceived risk is influenced by a cyclist's distance to the junction (Carter et al., 2007; Landis et al., 2003; Wang and Akar, 2018) and the presence of a car at the junction (Chaurand and Delhomme, 2013; Griffin et al., 2020). The latter

Fig. 4.3: A model structure



was included as an additive interaction term. The structural equation for the latent variable can be seen in Equation 4.1.

$$\theta_{latent-risk} = (\gamma_{dist-to-junction} + \gamma_{car-present} \cdot x_{car-present}) \cdot x_{dist-to-junction} + \epsilon \tag{4.1}$$

Where:

- $x_{dist-to-junction}$ is the variable representing the cyclist's distance to the junction (measured in meters);
- $x_{car-present}$ is a dummy variable, taking value 1 if a car is present at the junction at current point in time and 0, otherwise;
- ϵ is an error term.

Further, the corresponding parameters:

- $\gamma_{dist-to-junction}$ is the parameter representing the influence of the cyclist's distance to the junction on the perceived risk;
- $\gamma_{car-present}$ is the interaction parameter representing the additive shift in the perceived risk if a car is present at the junction.

Importantly, different forms of structural equations for the latent variable were tested, including for example, discrete levels of time to collision, however the final specification was chosen as described above because the analysis of the data showed that the level of risk that the cyclist perceives in each time point is related to their distance to the hazardous part of the scenario, i.e. the junction. This particular relationship can possibly be explained by the fact that distance is an easier feature to be judged by the cyclist compared to, for example, time until arrival to the junction. Then, we included the presence of the car at the junction which undoubtedly amplifies the perceived risk since it materialises the potential hazard.

5.2 Specification of discrete component

5.2.1 Dependent variable

The choice variable for the discrete part of the model allows for five possible actions, namely, *accelerate*, *brake*, *decelerate*, *maintain speed*, and *wait*. These actions are linked to the changes in cycling speed, where *accelerate* refers to an increase in speed, *brake* encompasses cases of an abrupt decline in speed, while *decelerate* covers instances where a person slows down at a slower rate than when braking. This distinction was made to account for different underlying reasons for these actions. For example, braking may be the result of a sudden emergence of a car at the junction leading to an increase in the risk of collision; while deceleration may be chosen when there are no imminent risks of collision, but the need for increased caution (e.g. when the cyclist is still far from the junction) or it is possible that deceleration arises simply when the cyclist stops or reduces pedalling due to physical exhaustion. Cases where a person is moving while keeping a constant speed are classified as *maintain speed*. Finally, *wait* refers to instances where a cyclist has stopped and remains still. Importantly, *wait* is not available when the cyclist is currently moving. On the other hand, when the cyclist in not in motion, the only two available actions are *wait* and *accelerate*. *Wait* was included as an alternative because we observed in the data that cyclists chose it close the junction to allow for the traffic to clear and cross the junction at an appropriate time.

To summarise, when the cyclist is moving, the available actions are: *accelerate*, *brake*, *decelerate*, *maintain speed*, whereas when the cyclist is not moving, he can either *wait* or *accelerate*. For this reason, the reference category in the model is *accelerate* because this is the only action which is always available, whether moving or not. Finally, this categorisation of actions was chosen because it allows us to capture a cyclist's reactions to the dynamic environment in the scenario by the degree to which he adjusts his current speed, similarly to individuals cycling in the real world. In other words, we are interested in the instances when the changes in the external environment induce the cyclist to switch his currently chosen action to a different one.

5.2.2 Utility functions

As a result of our approach described in the previous section, the utility associated with each action is a function of:

- the cyclist's distance to the junction;
- the cyclist's speed;
- the presence of a car at the junction and the time until the collision with the given car (if there is one), considering current speed of the cyclist.

In order to account for the potential non-linear effects of distance and speed, we included the polynomials of distance to the junction and cyclist's speed up to the third order. Furthermore, the impact of a car being present at the junction is captured by a dummy which indicates a potential collision with a car, given the cyclist's current distance to the junction and his current speed, which are recorded every quarter second. The reason for using the attribute on a possible collision in the future is that it allows us to capture how a cyclist adjusts his current behaviour to avoid colliding with the car. We did not use the presence of the car at the junction, because, while it increases the perceived risk, it does not automatically require acting upon. In other words, it would not enable us to observe how a cyclist changes his behaviour as a result of increase in situation riskiness. Moreover, we included a variable that accounts for the time remaining until collision (again with the resolution of a quarter second) if a car is present at the junction. This time component allows us to consider the impact of the remaining time to the collision on the choice of different actions. Finally, we also included a random variable to account for individuals' heterogeneity in preferences for different actions.

Therefore, below we present the utility functions associated with the decision of a cyclist n to choose one of the five actions (Acc=accelerate, Br=brake, Dec=decelerate, Maintain=maintain speed, Wait=wait) at time t, where accelerate is used as the baseline. Importantly, Equations 4.2 - 4.5 show full specification but some components were removed during the actual estimation of the model because they were insignificant, or they were not relevant explanators for that given alternative[6]. For instance, in the actual utility

[6]Beyond, there were other variables such as cyclist's distance to the junction after crossing it, which were tested as well but not included in the final models due to non-intuitive sign and statistical insignificance.

function for *Wait*, we did not retain the speed or distance to the junction as they were not meaningful components when the cyclist was not moving.

$$\begin{aligned}V_{Maintain_{n,t}} = {} & \delta_{Maintain} + \sigma_{Maintain} \cdot \xi_{Maintain} \\ & + \beta_{dist-to-junction_{Maintain}} \cdot x_{dist-to-junction_{n,t}} \\ & + \beta_{dist-second_{Maintain}} \cdot x^2_{dist-to-junction_{n,t}} \\ & + \beta_{dist-third_{Maintain}} \cdot x^3_{dist-to-junction_{n,t}} \\ & + \beta_{speed_{Maintain}} \cdot x_{speed_{n,t}} + \beta_{speed-second_{Maintain}} \cdot x^2_{speed_{n,t}} \\ & + \beta_{speed-third_{Maintain}} \cdot x^3_{speed_{n,t}} + \beta_{collision_{Maintain}} \\ & \cdot x_{collision_{n,t}} \cdot x_{time-collision_{n,t}}^{\lambda_{time-collision_{Maintain}}} + \beta_{risk_{Maintain}} \cdot \theta_{latent-risk}\end{aligned} \tag{4.2}$$

$$\begin{aligned}V_{Br_{n,t}} = {} & \delta_{Br} + \sigma_{Brake} \cdot \xi_{Br} \\ & + \beta_{dist-to-junction_{Br}} \cdot x_{dist-to-junction_{n,t}} + \beta_{dist-second_{Br}} \\ & \cdot x^2_{dist-to-junction_{n,t}} + \beta_{dist-third_{Br}} \cdot x^3_{dist-to-junction_{n,t}} \\ & + \beta_{speed_{Br}} \cdot x_{speed_{n,t}} \\ & + \beta_{speed-second_{Br}} \cdot x^2_{speed_{n,t}} + \beta_{speed-third_{Br}} \cdot x^3_{speed_{n,t}} \\ & + \beta_{collision_{Br}} \cdot x_{collision_{n,t}} \cdot x_{time-collision_{n,t}}^{\lambda_{time-collision_{Br}}} + \beta_{risk_{Br}} \cdot \theta_{latent-risk}\end{aligned} \tag{4.3}$$

$$\begin{aligned}V_{Dec_{n,t}} = {} & \delta_{Dec} + \sigma_{Dec} \cdot \xi_{Dec} \\ & + \beta_{dist-to-junction_{Dec}} \cdot x_{dist-to-junction_{n,t}} + \beta_{dist-second_{Dec}} \\ & \cdot x^2_{dist-to-junction_{n,t}} + \beta_{dist-third_{Dec}} \cdot x^3_{dist-to-junction_{n,t}} \\ & + \beta_{speed_{Dec}} \cdot x_{speed_{n,t}} \\ & + \beta_{speed-second_{Dec}} \cdot x^2_{speed_{n,t}} + \beta_{speed-third_{Dec}} \cdot x^3_{speed_{n,t}} \\ & + \beta_{collision_{Dec}} \cdot x_{collision_{n,t}} \cdot x_{time-collision_{n,t}}^{\lambda_{time-collision_{Dec}}} + \beta_{risk_{Dec}} \cdot \theta_{latent-risk}\end{aligned} \tag{4.4}$$

$$
\begin{aligned}
V_{Wait_{n,t}} = \delta_{Wait} + \sigma_{Wait} \cdot \xi_{Wait} \\
&+ \beta_{dist-to-junction_{Wait}} \cdot x_{dist-to-junction_{n,t}} + \beta_{dist-second_{Wait}} \\
&\cdot x^2_{dist-to-junction_{n,t}} + \beta_{dist-third_{Wait}} \cdot x^3_{dist-to-junction_{n,t}} \\
&+ \beta_{speed_{Wait}} \cdot x_{speed_{n,t}} \\
&+ \beta_{speed-second_{Wait}} \cdot x^2_{speed_{n,t}} + \beta_{speed-third_{Wait}} \cdot x^3_{speed_{n,t}} \\
&+ \beta_{collision_{Wait}} \cdot x_{collision_{n,t}} \cdot x_{time-collision_{n,t}}^{\lambda_{time-collision_{Wait}}} + \beta_{risk_{Wait}} \cdot \theta_{latent-risk}
\end{aligned}
\tag{4.5}
$$

$$
V_{Acc_{n,t}} = 0 \tag{4.6}
$$

The δ_i parameters in Equations 4.2 to 4.5 above represent the alternative specific constants (ASC), where the subscripts refer to each action. We allowed for random heterogeneity in these preferences through the additional terms σ_i, which multiply a standard Normal variate ξ_i.

Also, there are several other components which look at the impact of different variables in the scenarios on the utilities, as seen in Table 4.2.

The Equations 4.2 to 4.5 also have parameters for each action, where for the ease of notation we use subscript i in the text that can denote *Accelerate*, *Brake*, *Decelerate*, *Maintain speed* and *Wait*:

- δ_i represent the alternative specific constant (ASC) for each action;
- σ_i captures the heterogeneity in the alternative specific constant (ASC) for each action;
- $\beta_{dist-to-junction_i}$, $\beta_{dist-second_i}$ and $\beta_{dist-third_i}$ are parameters which represent the impact of the distance to the junction on the utility for each action, first, second and third order, respectively;
- β_{speed_i}, $\beta_{speed-second_i}$ and $\beta_{speed-third_i}$ are parameters which represent the impact of the cyclist's speed on the utility for each action, first, second and third order, respectively;
- $\beta_{collision_i}$ are the parameters which show the impact of the potential presence of the car at the junction on the utility for each action;
- β_{risk_i} are the parameters that represent the impact of latent risk on different actions;

Table 4.2: Variables used in the utility functions.

Variable name	**Variable meaning**	**Units**
$x_{dist-to-junction}$	cyclist's distance to the junction; used also in polynomial form: $x_{dist-to-junction^2}$ and $x_{dist-to-junction^3}$ to capture the non-linear impacts	metres
x_{speed}	cyclist's speed; used also in polynomial form: x_{speed^2}, x_{speed^3} to capture the non-linear impacts	km/h
$x_{collision}$	dummy variables which denote if there would be a collision with the car at the junction when the cyclist would arrive there, given his current speed and distance to the junction	equal to 1 if true, 0 otherwise
$x_{time-collision}$	remaining time to collision between cyclist and the car given cyclists current speed and distance to the junction	seconds
$\theta_{latent-risk}$	latent risk variable	-
ξ_i	random variable that represent the individual's heterogeneity for different actions	-

- $\lambda_{time-collision_i}$ are the parameters which represent the impact of the time left until the collision on each action.

5.3 Specification of continuous component

The continuous component of the model was developed to give an additional level of detail on cycling behaviour, providing information on the magnitude of the actions chosen in the discrete component. This not only allows to achieve higher level of understanding of modelled behaviour, but its also helps to validate further the adopted methodological approach. Consequently, in the continuous component of the model, the dependent variables are the continuous values of accelerate, decelerate and brake (called acceleration, deceleration and braking deceleration, respectively, in the continuous part), chosen by the cyclist. The model assumes that the cyclist firstly chooses one of these three actions in the discrete part of the model and subsequently he decides on the acceleration/deceleration associated with the chosen decision in the continuous part. The continuous decision is thus conditional on the discrete choice. In the case of acceleration in the continuous part, it differentiates between accelerating when the cyclist was moving in the previous time point and when he was waiting (i.e. was stopped). For the former, the current cycling speed is expected to affect the chosen value of acceleration while for the latter, the current speed is zero. Guided by the shapes of the distributions of the observed acceleration and deceleration values, the dependent variable is assumed to follow a log-normal distribution with the mean being a function of explanatory variables (e.g. current speed).

5.4 Specification of measurement component

The final component of the hybrid structure is the measurement model which is used to link the latent variable with its indicators. In our model, the risk is not observed or measured directly, but instead it is manifested in its indicator, the alpha (α) brain activity, derived from the EEG data. To account for the heterogeneity in the α ranges across the respondents, normalized values of α have been employed (as used by Paschalidis et al. (2019) for physiological indicators and Makeig and Jung (1995) for the EEG signal). Multiple previous studies showed that the changes of α activity were related to the strength of attention to external stimuli required by the task, where naturally more hazardous elements increase these attention demands. The measurement model can be seen in Equation 4.7.

$$\alpha = \zeta_{\alpha}\theta_{latent-risk} + \nu_{\alpha} \tag{4.7}$$

Where,

- $\theta_{latent-risk}$ is latent risk variable;
- ν_{α} is an independent error term,

and the corresponding parameter:

- ζ_{α} is a parameter relating the latent risk to its indicator, the α wave.

6 Results

This section presents the full results of the hybrid model in Table 4.3 and the different components of the modelling approach developed in this paper are described in turns. The model was estimated using the Apollo software (Hess and Palma, 2019).

Table 4.3: A discrete-continuous model (robust standard errors and t-ratios in brackets).

LL(start): -152236.00
LL(final, whole model): -149642.40
AIC: 299370.70
BIC: 299752.40
LL(final, choice component): -45129.09
LL(final, acceleration when static): 464.95
LL(final, acceleration when moving): -14384.50
LL(final, deceleration): -7492.83
LL(final, braking deceleration): -8338.87
LL(final, α): -74790.59

		Action	Estimate (rob. std.err.; rob.t-ratios)
ASC (δ)		Maintain	-0.2644 (0.0797; -3.32)
		Brake	-2.4598 (0.1256; -19.58)
		Decelerate	-2.9847 (0.1183; -25.23)
		Wait	4.1069 (0.1869; 21.98)
		Accelerate	0
Individual's heterogeneity (σ)		Maintain	0.2241 (0.0217; 10.34)
		Brake	0.0363 (0.0397; 0.92)
		Decelerate	-0.1051 (0.0445; -2.36)
Collision ($\beta_{collision}$)		Maintain	0.2031 (0.0384; 5.28)
		Brake	0.7535 (0.1542; 4.89)
		Decelerate	0.3616 (0.1185; 3.05)
		Wait	0.6292 (0.1758; 3.58)
Time to collision ($\lambda_{time-collision}$)		Brake	-0.5280 (0.0905; -5.83)
		Decelerate	-0.1612 (0.1508; -1.07)
Distance to junction ($\beta_{dist-to-junction}$)	1^{st} order	Maintain	0.0444 (0.0038; 11.68)
	2^{nd} order	Maintain	-0.0835 (0.0085; -9.86)
	1^{st} order	Brake	0.1900 (0.0138; 13.78)
	2^{nd} order	Brake	-0.2708 (0.0604; -4.48)
	3^{rd} order	Brake	0.0195 (0.0080; 2.44)
	1^{st} order	Decelerate	0.0850 (0.0125; 6.78)
	2^{nd} order	Decelerate	-0.2446 (0.0621; -3.94)
	3^{rd} order	Decelerate	0.0166 (0.0078; 2.12)
Speed (β_{Speed})	1^{st} order	Maintain	0.0605 (0.0062; 9.80)
	2^{nd} order	Maintain	-0.0026 (0.0004; -5.79)
	1^{st} order	Brake	0.0458 (0.0141; 3.26)
	2^{nd} order	Brake	0.0014 (0.0006; 2.25)
	1^{st} order	Decelerate	0.1931 (0.0270; 7.16)
	2^{nd} order	Decelerate	-0.0058 (0.0019; -3.09)
	3^{rd} order	Decelerate	0.0001 (0.0000; 3.06)
Continuous acceleration when stopped		μ	-3.0631 (0.1386; -22.10)
		σ	2.2931 (0.0795; 28.84)
Continuous acceleration when in motion		μ	-0.3722 (0.0336; -11.09)
		σ	1.0912 (0.0144; 75.58)
		Speed	0.0518 (0.0022; 23.90)
Continuous deceleration		μ	-0.2864 (0.0435; -6.59)
		σ	1.1047 (0.0196; 56.38)
		Speed	0.0394 (0.0026; 15.15)
Continuous braking deceleration		μ	-0.4394 (0.0639; -6.87)
		σ	1.1958 (0.0253; 47.32)
		Speed	0.0602 (0.0038; 15.97)
Latent risk (θ)		Brake ($\beta_{risk_{Br}}$)	0.3285 (0.0774; 4.24)
		Distance to the junction ($\gamma_{dist-to-junction}$)	-0.0762 (0.0058; -13.11)
		Presence of the car at the junction ($\gamma_{car-present}$)	0.0041 (0.0015; 2.72)
		ζ_α	-0.0937 (0.0187; -5.01)

6.1 Latent component

We start by looking at the latent variable since it is a key component of the model, where we see that higher risk significantly increases the propensity to brake (estimate = 0.3285), whereas for the other actions the effect is not significantly different from that to accelerate. The result for brake is plausible because higher risk induces more braking.

6.1.1 Measurement model

Then, looking at the results of the measurement model, we observe a negative and significant ζ_α coefficient, which suggests that increased risk decreases the amplitude of α wave, which is in line with the existing literature.

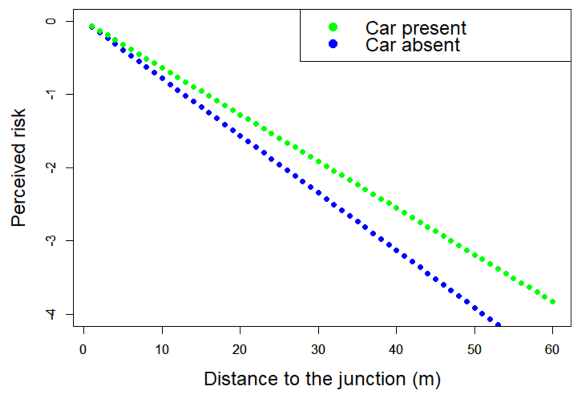
6.1.2 Structural model

Furthermore, in the structural model within the latent component we observe a negative relationship between distance to the junction and perceived risk (estimate = -0.0762), which again makes sense where higher distance to the hazardous area decreases perceived risk. Then, the *presence of the car at the junction* dummy variable is an additive shift for when there is a car present at the junction regardless of the cyclist's distance to the junction. The effect (of a car being present) on risk perception is visualised in the Figure 4.4, where we see that the presence of the car results in an upward shift in the perceived risk. To clarify, the negative sign of the perceived risk is not relevant here because it only shows us the relationship within the latent construct where the plot allows us to understand how the explanatory variables (here the distance and presence of the car) influence the unobserved risk.

6.2 Discrete component

We, then, turn to the discrete component of the model, where the ASCs represent the impact of different actions on utility, all else being equal. In the current model, the ASCs are highly significant which may partly be caused by some relevant explanatory variables being omitted from the model or due to an intrinsic bias towards one of the alternatives. For example, the latter can be observed in the large positive ASC for *Wait* which suggests that cyclists have an inherent preference for waiting (being stopped) relative to *Accelerate*. Moreover, in the case of dynamic data, such as the one used in the current model, it is not unexpected because the individuals perform some actions significantly more often than others (Lorenzo Varela, 2018). Nonetheless, to alleviate this issue, beyond scenario related variables, additional parameters for random heterogeneity were included in the model. In particular, the σ

Fig. 4.4: Risk perception plot.



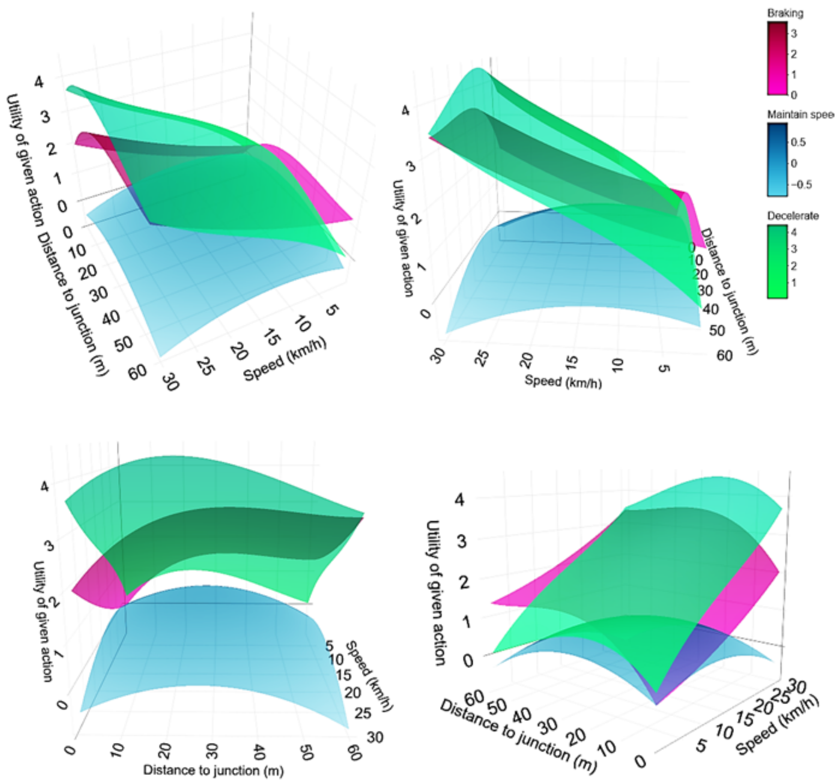
estimated for *maintain speed* and *decelerate* are statistically significant showing the individual's heterogeneity for these two actions, while σ for *wait* and *brake* was not significantly different from zero. It suggests that individuals differ in their propensity to maintain speed and decelerate regardless of their perceived risk, which may be related to other factors such as the level physical fitness, personal traits or cycling style.

Next, the dummy *collision* variables demonstrate that the potential presence of a car at the junction when cyclists arrive at the junction increases the propensity to brake. The next more likely actions are *wait* and *decelerate* and finally *maintain speed* (all relative to accelerate, which is therefore the least likely action). These again show realistic cycling behaviour which we would observe in real life situation when cyclists approach a junction in the presence of a car.

Moreover, the *time to collision* parameters for *brake* and *decelerate* allowed us to factor in the time left to the collision given a cyclist's speed and distance to the junction. These show us that less time left to the collision increases the probability of braking and decelerating relative to accelerating. Again, these results are plausible where closeness to a potential accident with a car at the junction increases the likelihood of reaction by decreasing the speed. Further, for *maintain speed* and *wait*, the effect was not significantly different compared to *accelerate*.

Then, we see a number of *distances to junction* variables, where the results of these variables are demonstrated in the Figure 4.5. We can see the graphs

Fig. 4.5: 3D graphs of the utilities for each action given cyclist's current speed and distance to the junction.



of utility for *decelerate*, *maintain speed* and *brake* depending on the cycling speed and distance to the junction. The same graph is shown from different angles to make the interpretation easier.

Looking at the graph for *brake*, we observe that the utility for this action is the highest at high speed levels and it decreases as the cycling speed falls. In particular, it increases 10 to 20 meters from the junction which is an area where cyclists tend to slow down (or stop) to assess the situation at the junction. On the other hand, utility for braking is lower when the cyclist is far away from the junction or very close to it because he has no reason to brake far away and he wants to cross quickly when at the junction.

Next, looking at the graph for *decelerate*, we see that the utility for decelerating is the highest at the high speed levels where there is the biggest scope for physical exhaustion to emerge, and it falls with speed. Similar to brake, utility for decelerate increases between 10-20 meters from the junction.

Finally, looking at the graph for *maintain speed*, we see that the utility for this action is the highest when cyclists are going at low to medium speed levels and decreases as the cycling speed goes up, independently of the distance to the junction. Moreover, it also increases up to about 30 meters away from the junction, where it starts falling, as the cyclists becomes closer to the junction.

6.3 Continuous component

Finally, the continuous part of the model shows us that all the estimates are significant. Importantly, the dependent variables in all four cases are derived from the absolute values of acceleration but for each of them, the values are only considered when the given action is chosen in the discrete part, as described above. Therefore, for correct interpretation of the parameter estimates, it should be noted that the acceleration refers to increasing velocity in the case of *accelerate* as a discrete choice and decrease in velocity for deceleration and braking deceleration. The μ and σ in the model denote the means and standard deviations of the logarithm of the dependent variables.

Firstly, comparing the values of μ for acceleration when static and moving we see a considerably more negative value in case of stationary acceleration. This suggests that, on average, the acceleration rates are smaller when cyclists only start accelerating after being stopped, than when already moving, which can be expected as cyclist is only gaining speed from a standstill.

Next, looking at the values of σ for acceleration when static and when in motion, we see that the standard deviation of acceleration from static position is twice as high, which can be attributed to the higher variability of individual strength input when starting the bicycle. Whereas when moving, the level of force required to accelerate is more homogenous because individuals benefit from momentum leading to smaller standard deviation of acceleration. Notably, the σ for acceleration when previously moving, deceleration and braking deceleration are similar in magnitude.

Further, the estimated parameters for speed are positive in all three cases (it has been dropped from the model for acceleration when previously waiting because in this case the cycling speed is zero) and they show that at higher current speed, the magnitude of acceleration changes more. In the case of braking deceleration and deceleration, it shows that the scope for reducing the speed is larger if cyclist is going at a higher speed. While, in case of acceleration, we see that it becomes easier to accelerate.

6.4 Hybrid choice model efficiency gain

Finally, to assess the impact of the inclusion of the neural data in the hybrid model, we compare the model results between our model as showed in Table 4.3, and a reduced model, where the measurement component in the latent part was dropped (see Appendix C, Table B.1 for the full model output). Hence, the role of the latent variable is explained only by the choice data. We, then, see that removing a measurement model changes the magnitude of distance variable in the structural equation and it becomes less significant (change from t-ratio = -13.11 to t-ratio = -1.72). Moreover, in the reduced model, the standard errors of variables increased from 0.0058 to 0.0305 for distance variable and from 0.0015 to 0.0021 for car presence variable. Therefore, the inclusion of the measurement model not only increases the efficiency of the parameters, but also confirms the directionality of the link between risk and α wave amplitude as demonstrated in the previous literature.

7 Discussion

The aim of the current paper was to jointly model behavioural and neural data in the hybrid choice model framework to gain insights into cycling behaviour and associated neural processing and consequently, deepen our understanding achieved with the previous models. Therefore, we proposed three hypotheses with respect to observed behaviour and the α amplitude.

The results of the developed hybrid model are in line with our hypotheses. The model estimates indicate that the cyclists in the virtual scenarios are indeed more likely to reduce their speed when approaching the junction where passing cars are present (Hypothesis 1a). They also demonstrate that the reaction to the passing cars becomes stronger as the cyclists get closer to the potential collision (Hypothesis 1b). Further, the model allowed us to quantify the relative impact of a range of influencing variables (such as a cyclist's current speed or distance relative to the junction) on the cyclist's responses. Together, they build a complex picture of cyclist's behaviour where we observe that among them, the most impactful on the choice of current action is the possibility of collision with other road users, providing evidence that our experiment was able to elicit realistic reactions to the traffic events.

Further, the employment of the instrumented bicycle allowed us to capture the physical effort exerted by the cyclists, where we observe that high speed levels increase the physical tiredness and results in a gradual loss of speed. We could also observe that typical speed level developed by the cyclists in our experiment is in line with that observed in other studies and that cyclists naturally converged to that desired level by increasing or decreasing acceleration rate accordingly. In particular, cyclists were more inclined to accelerate or maintain speed if their current speed was below or within the range of average speed developed by the cyclists in reality (Schleinitz et al., 2017).

The inclusion of the continuous element showed the magnitudes of the performed actions allowing us to reach additional levels of detail with respect to how cyclists behave. This in turn allowed us to expand current knowledge of cyclists' choices in a dynamic environment. Moreover, these behavioural results provide evidence that VR can be a reliable equipment in transport safety research provided that the experimental design is suitable to capture wide range of potential behaviour and encourages natural responses rather than hinders the extent to which participants can represent their reactions.

Furthermore, the latent component in the model showed that the decreased α amplitude is associated with the increased perceived risk and elevated complexity of the task faced by the cyclist which in turn increases the propensity to brake which confirmed our hypothesis (Hypothesis 2). The benefits of incorporating the neural data in explaining the behaviour are reflected in the improvement in the efficiency (i.e. smaller standard errors) of variables included in the structural equation (in comparison with a model that does not use the neural data). These results, taken together, demonstrate a behavioural and neural congruence. In this sense, the neural data could be seen as an alternative or at least an addition to attitudinal scales, frequently used in the latent constructs. As these are claimed to be prone to bias of the respondent (conscious or unconscious), heavily dependent on the choice of scale or be susceptible to the experimenter effect. Therefore, neural data, seen as an unfiltered response, could help offsetting these effects and provide a validation tool if used jointly in the models. The results also demonstrate the feasibility of successful incorporation of neural data into mathematical models in general through the hybrid structure.

Nonetheless, it is crucial to be aware of the potential constraints of this type of work. Even though, in this study we chose α power, which is a relatively well-understood brainwave with a broad spectrum of studies which explored it in different conditions, it is important to take our results with a degree of caution because this is an exploratory work. It attempts to marry difficult disciplines, therefore the promising results presented here are only a small step forward where undoubtedly more research is required to build a strong case.

Another potential limitation of this work are the aspects in the scenario such as the elements of urban infrastructure or features of other agents that also influence cyclists' behaviour, as suggested by the significant alternative specific constants in the model output, but which are not accounted for in the model. Future work should, thus, consider the inclusion of other variables to fully capture the physical changes in the scenarios, such as walking pedestrians, as well as more random variables to account for inter-individual (between different respondents) and intra-individual (across observations within the same person) heterogeneity (Hess and Train, 2011).

Overall, the practical implications of this study are three-fold. *Firstly*, this study extends the practical knowledge on the VR study design for those researchers who plan to implement it in the future, where we were able to capture the complex behaviour and reactions of the cyclists depending on the changing situation on the road. This, builds and increases the confidence in the validity of VR studies in transport context. *Secondly*, we provide evidence that behavioural and neural data can be collected jointly using state-of-art equipment currently available on the market with respect to HDMs and neuroimaging. *Thirdly*, we demonstrate how neural data can be incorporated into the mathematical models and provide an example of an integrative approach to understanding human choices in the dynamic context. This serves as the first step in bridging the gap between mathematical modelling and neuroscience and is expected to encourage further research in this direction.

References

Abou-Zeid, M. and Ben-Akiva, M. (2014). *Hybrid choice models*. Edward Elgar Publishing, Cheltenham.

Ambekar, A. and Achrekar, V. (2014). Real time EEG measurement. *International Journal of Innovative Research in Advanced Engineering*, 1(5):20–25.

Andersson, H. (2013). Consistency in preferences for road safety: An analysis of precautionary and stated behavior. *Research in transportation economics*, 43(1):41–49.

Ben-Akiva, M., McFadden, D., Train, K., Walker, J., Bhat, C., Bierlaire, M., Bolduc, D., Boersch-Supan, A., Brownstone, D., Bunch, D. S., et al. (2002). Hybrid choice models: Progress and challenges. *Marketing Letters*, 13(3):163–175.

Berg, P. and Scherg, M. (1994). A multiple source approach to the correction of eye artifacts. *Electroencephalography and clinical neurophysiology*, 90(3):229–241.

Bolduc, D. and Alvarez-Daziano, R. (2010). On estimation of hybrid choice models. In *Choice Modelling: The State-of-the-Art and the State-of-Practice: Inaugural International Choice Modelling Conference*, page 259.

Borghini, G., Astolfi, L., Vecchiato, G., Mattia, D., and Babiloni, F. (2014). Measuring neurophysiological signals in aircraft pilots and car drivers for the assessment of mental workload, fatigue and drowsiness. *Neuroscience & Biobehavioral Reviews*, 44:58–75.

Borrego, A., Latorre, J., Alcaniz, M., and Llorens, R. (2018). Comparison of Oculus Rift and HTC vive: feasibility for virtual reality-based exploration, navigation, exergaming, and rehabilitation. *Games for health journal*, 7(3):151–156.

Brouwer, A.-M., Neerincx, M. A., Kallen, V., van der Leer, L., and ten Brinke, M. (2011). EEG alpha asymmetry, heart rate variability and cortisol in response to virtual reality induced stress. *Journal of Cybertherapy & Rehabilitation*, 4(1):21–34.

Carter, D. L., Hunter, W. W., Zegeer, C. V., Stewart, J. R., and Huang, H. (2007). Bicyclist intersection safety index. *Transportation Research Record*, 2031(1):18–24.

Chaurand, N. and Delhomme, P. (2013). Cyclists and drivers in road interactions: A comparison of perceived crash risk. *Accident Analysis & Prevention*, 50:1176–1184.

Chirico, A., Cipresso, P., Yaden, D. B., Biassoni, F., Riva, G., and Gaggioli, A. (2017). Effectiveness of immersive videos in inducing awe: an experimental study. *Scientific Reports*, 7(1):1–11.

Christiano, L. J. and Fitzgerald, T. J. (2003). The band pass filter. *International Economic Review*, 44(2):435–465.

Civelek, M. E. (2018). *Essentials of structural equation modeling.* Zea Books, Lincoln.

Cooper, N. R., Burgess, A. P., Croft, R. J., and Gruzelier, J. H. (2006). Investigating evoked and induced electroencephalogram activity in task-related alpha power increases during an internally directed attention task. *Neuroreport*, 17(2):205–208.

Di Stasi, L. L., Renner, R., Catena, A., Cañas, J. J., Velichkovsky, B. M., and Pannasch, S. (2012). Towards a driver fatigue test based on the saccadic main sequence: A partial validation by subjective report data. *Transportation research part C: emerging technologies*, 21(1):122–133.

Dixit, V. V., Harb, R. C., Martínez-Correa, J., and Rutström, E. E. (2015). Measuring risk aversion to guide transportation policy: Contexts, incentives, and respondents. *Transportation Research Part A: Policy and Practice*, 80:15–34.

Fairclough, S. H., Venables, L., and Tattersall, A. (2005). The influence of task demand and learning on the psychophysiological response. *International Journal of Psychophysiology*, 56(2):171–184.

Fournier, L. R., Wilson, G. F., and Swain, C. R. (1999). Electrophysiological, behavioral, and subjective indexes of workload when performing multiple tasks: manipulations of task difficulty and training. *International Journal of Psychophysiology*, 31(2):129–145.

Frankenhuis, W. E., Dotsch, R., Karremans, J. C., and Wigboldus, D. H. (2010). Male physical risk taking in a virtual environment. *Journal of Evolutionary Psychology*, 8(1):75–86.

Griffin, W., Haworth, N., and Twisk, D. (2020). Patterns in perceived crash risk among male and female drivers with and without substantial cycling experience. *Transportation research part F: traffic psychology and behaviour*, 69:1–12.

Hancock, T. O., Hess, S., and Choudhury, C. F. (2018). Decision field theory: Improvements to current methodology and comparisons with standard choice modelling techniques. *Transportation Research Part B: Methodological*, 107:18–40.

Hensher, D. A., Rose, J. M., Rose, J. M., and Greene, W. H. (2005). *Applied choice analysis: a primer*. Cambridge University Press, Cambridge.

Hess, S. and Palma, D. (2019). Apollo: A flexible, powerful and customisable freeware package for choice model estimation and application. *Journal of choice modelling*, 32:100–170.

Hess, S. and Train, K. E. (2011). Recovery of inter-and intra-personal heterogeneity using mixed logit models. *Transportation Research Part B: Methodological*, 45(7):973–990.

Ille, N., Berg, P., and Scherg, M. (2002). Artifact correction of the ongoing EEG using spatial filters based on artifact and brain signal topographies. *Journal of clinical neurophysiology*, 19(2):113–124.

Isa, I. S., Zainuddin, B. S., Hussain, Z., and Sulaiman, S. N. (2014). Preliminary study on analyzing EEG alpha brainwave signal activities based on visual stimulation. *Procedia Computer Science*, 42:85–92.

Johnson, M., Charlton, J., Oxley, J., and Newstead, S. (2010). Naturalistic cycling study: identifying risk factors for on-road commuter cyclists. In *Annals of advances in automotive medicine/annual scientific conference*, volume 54, page 275. Association for the Advancement of Automotive Medicine.

Johnson, M. J., Chahal, T., Stinchcombe, A., Mullen, N., Weaver, B., and Bedard, M. (2011). Physiological responses to simulated and on-road driving. *International journal of Psychophysiology*, 81(3):203–208.

Katsis, C., Goletsis, Y., Rigas, G., and Fotiadis, D. (2011). A wearable system for the affective monitoring of car racing drivers during simulated conditions. *Transportation research part C: emerging technologies*, 19(3):541–551.

Landis, B. W., Vattikuti, V. R., Ottenberg, R. M., Petritsch, T. A., Guttenplan, M., and Crider, L. B. (2003). Intersection level of service for the bicycle through movement. *Transportation research record*, 1828(1):101–106.

Lei, S. and Roetting, M. (2011). Influence of task combination on EEG spectrum modulation for driver workload estimation. *Human factors*, 53(2):168–179.

Lewis, R. S., Weekes, N. Y., and Wang, T. H. (2007). The effect of a naturalistic stressor on frontal EEG asymmetry, stress, and health. *Biological psychology*, 75(3):239–247.

Lorenzo Varela, J. M. (2018). Parameter bias in misspecified hybrid choice models: an empirical study. *Transportation Research Procedia*, 33:99–106. XIII Conference on Transport Engineering, CIT2018.

Magosso, E., De Crescenzio, F., Ricci, G., Piastra, S., and Ursino, M. (2019). EEG alpha power is modulated by attentional changes during cognitive tasks and virtual reality immersion. *Computational intelligence and neuroscience*, 2019:1–18.

Mai, K. L. (2017). *Evaluation of PC-Based Virtual Reality as a Tool to Analyze Pedestrian Behavior at Midblock Crossings.* Faculty of California Polytechnic State University, San Luis Obispo.

Makeig, S. and Jung, T.-P. (1995). Changes in alertness are a principal component of variance in the EEG spectrum. *NeuroReport-International Journal for Rapid Communications of Research in Neuroscience*, 7(1):213–216.

Mann, C. A., Sterman, M. B., and Kaiser, D. A. (1996). Suppression of EEG rhythmic frequencies during somato-motor and visuo-motor behavior. *International Journal of Psychophysiology*, 23(1-2):1–7.

Moussa, G., Radwan, E., and Hussain, K. (2012). Augmented reality vehicle system: Left-turn maneuver study. *Transportation research part C: emerging technologies*, 21(1):1–16.

Nishifuji, S., Sato, M., Maino, D., and Tanaka, S. (2010). Effect of acoustic stimuli and mental task on alpha, beta and gamma rhythms in brain wave. In *Proceedings of SICE Annual Conference 2010*, pages 1548–1554. IEEE.

Paschalidis, E., Choudhury, C. F., and Hess, S. (2019). Combining driving simulator and physiological sensor data in a latent variable model to incorporate the effect of stress in car-following behaviour. *Analytic methods in accident research*, 22:100089.

PTV-Group (2021). *PTV Vissim new.* URL: https://www.ptvgroup.com/en/solutions/products/ptv-vissim/ (Accessed: 13/01/2021).

Ram, T. and Chand, K. (2016). Effect of drivers' risk perception and perception of driving tasks on road safety attitude. *Transportation research part F: traffic psychology and behaviour*, 42:162–176.

Ray, W. J. and Cole, H. W. (1985). EEG alpha activity reflects attentional demands, and beta activity reflects emotional and cognitive processes. *Science*, 228(4700):750–752.

Riera, A., Dunne, S., Cester, I., and Ruffini, G. (2008). Starfast: A wireless wearable EEG/ECG biometric system based on the enobio sensor. In *Proceedings of the International workshop on wearable micro and nanosystems for personalised health.* Academia.

Rundmo, T. and Iversen, H. (2004). Risk perception and driving behaviour among adolescents in two Norwegian counties before and after a traffic safety campaign. *Safety science*, 42(1):1–21.

Schleinitz, K., Petzoldt, T., Franke-Bartholdt, L., Krems, J., and Gehlert, T. (2017). The German naturalistic cycling study–comparing cycling speed of riders of different e-bikes and conventional bicycles. *Safety Science*, 92:290–297.

Seo, S.-H. and Lee, J.-T. (2010). Stress and EEG. *Convergence and hybrid information technologies*, 1(1):413–424.

Shaker, M. M. (2007). EEG waves classifier using wavelet transform and Fourier transform. *International Journal of Medical, Health, Biomedical, Bioengineering and Pharmaceutical Enineering*, 1(3):1–6.

Shechtman, O., Classen, S., Awadzi, K., and Mann, W. (2009). Comparison of driving errors between on-the-road and simulated driving assessment: a validation study. *Traffic injury prevention*, 10(4):379–385.

Simon, A. J., Schachtner, J. N., and Gallen, C. L. (2019). Disentangling expectation from selective attention during perceptual decision making. *Journal of neurophysiology*, 121(6):1977–1980.

Slobounov, S., Fukada, K., Simon, R., Rearick, M., and Ray, W. (2000). Neurophysiological and behavioral indices of time pressure effects on visuomotor task performance. *Cognitive Brain Research*, 9(3):287–298.

Svensson, M. (2009). Precautionary behavior and willingness to pay for a mortality risk reduction: Searching for the expected relationship. *Journal of risk and uncertainty*, 39(1):65–85.

Teplan, M. et al. (2002). Fundamentals of EEG measurement. *Measurement science review*, 2(2):1–11.

Ulleberg, P. and Rundmo, T. (2003). Personality, attitudes and risk perception as predictors of risky driving behaviour among young drivers. *Safety science*, 41(5):427–443.

Underwood, G., Crundall, D., and Chapman, P. (2011). Driving simulator validation with hazard perception. *Transportation research part F: traffic psychology and behaviour*, 14(6):435–446.

Unity (2017). *Unity - Game Engine*. URL: https://unity3d.com (Accessed: 10/12/2019).

Vanitha, V. and Krishnan, P. (2016). Real time stress detection system based on EEG signals. *An International Journal of Medical Sciences, Biomedical Research*, Special Issue:271–275.

Vanni, S., Revonsuo, A., and Hari, R. (1997). Modulation of the parieto-occipital alpha rhythm during object detection. *Journal of Neuroscience*, 17(18):7141–7147.

Verona, E., Sadeh, N., and Curtin, J. J. (2009). Stress-induced asymmetric frontal brain activity and aggression risk. *Journal of abnormal psychology*, 118(1):131.

Vij, A. and Walker, J. L. (2016). How, when and why integrated choice and latent variable models are latently useful. *Transportation Research Part B: Methodological*, 90:192–217.

Wang, K. and Akar, G. (2018). The perceptions of bicycling intersection safety by four types of bicyclists. *Transportation Research Part F: Traffic Psychology and Behaviour*, 59:67–80.

Welch, P. (1967). The use of fast Fourier transform for the estimation of power spectra: a method based on time averaging over short, modified periodograms. *IEEE Transactions on audio and electroacoustics*, 15(2):70–73.

Chapter 5

Discussion and conclusions

1 Summary

The broad goal of this thesis was to attempt to build bridges between choice modelling and neuroscience. For this purpose, two case studies of cycling behaviour in a virtual reality setting were designed to enable the simultaneous collection of behavioural and neuroimaging data. They allowed me to explore the interplay between observed behaviour and neural measures, assess the appropriateness of virtual reality as a research tool in this context, and provide an example of preliminary efforts of cross-disciplinary research in this area. The introduction outlined several research gaps and this chapter summarises the contribution of this thesis with respect to these identified gaps and creates a link between the separate chapters.

Gap 1: Scarce interdisciplinary approach to the investigation of human behaviour on the road

In recent decades there has been enormous progress in neuroscientific research concerning understanding the underlying neural mechanisms of observable human behaviour, with the ultimate goal of departing from the concept of the brain as a "*black box*". Nevertheless, thus far, the literature has shown limited evidence of cross-disciplinary research studies in a transport context that draw on the achievements of neuroscience or employ its methodology to continuously record the neural activity of the brain while putting people in complex, dynamic situations such as driving or walking. Nonetheless, such research is crucial for providing insights into rapid changes in human perception that influence behaviour in a given dynamic situation. This has been a consequence of lacking technology that would allow, on one hand, for the gathering of neuroimaging data in a less rigorous setting, and on the other hand, would enable the recreation of dynamic situations for research purposes beyond textual description, static pictures, or short videos. More recently, the development of mobile EEG devices and virtual reality equipment made these kinds of research efforts more accessible and affordable. In order to address this gap, the initial steps in the interdisciplinary research of such nature are demonstrated, providing a prototype of the experimental setup, and attempts to build a wholesome picture of cycling behaviour to emphasise the potential of this combined research. Therefore, two case studies are conducted that gave the basis for work presented in Chapters 2, 3 and 4. Their design allowed for collecting choice (behaviour) data that could later be used to construct mathematical models, and enabled me to simultaneously collect neural data. Consequently, it was possible to make a link between the observed behavioural data and corresponding neural activations. This was an important contribution given the scarcity of existing datasets which would allow for similar analysis and modelling.

Further, a sequential approach to these case studies, where one built upon the achievements of the other, allowed me to draw conclusions in terms of the suitability of different solutions in such joint experimental efforts. In particular, both experiments used virtual scenarios and employed a mobile EEG device but they used distinct input devices. The keyboard was used to begin with because it offered more stability for participants' body movements which is crucial in the case of the collection of neural data. Hence, the first case study could be considered as a proof of concept that tested the feasibility of joint use of VR and EEG. Moreover, the successful completion of the first case study encouraged trials in a more complex setting, which, in turn, offered a higher degree of realism and gave more flexibility in terms of potential cycling behaviour that can be elicited. Consequently, it was possible to compare the joint performance of VR and EEG under different experimental settings to constitute a rich source of practical and behavioural insights. They are particularly important as currently, this is still the beginning of this research path.

Gap 2: Need for the internal validation of the studies in virtual reality

There are previous studies that used virtual reality for behaviour research in a transport context, nonetheless, little attention has been given to their internal validation. Typically, the notion of validity in the context of VR studies refers to their realism - the ability to reliably mimic the real world, the degree of immersion or experienced presence in the virtual environment (Schubert et al., 1999). Importantly, it is distinguished between internal validity which is the extent to which the observed results represent the truth in the studied population (Patino and Ferreira, 2018), and external validity which refers to generalisability of the results of a study to a different population or settings (Calder et al., 1982). This thesis focuses on an internal validity of VR due to challenges associated with data collection in similar scenarios in real life. Nonetheless, it is considered a crucial interim step towards an external validation. Therefore, it is important to test and investigate the influence of different experimental designs including audio-visual stimuli, employed equipment, or control devices on the responses elicited through these means. Gathering abundant evidence on factors that play a role in shaping the behaviour observed in VR allows for a critical assessment of its suitability in a wide range of research contexts.

The work presented in Chapter 2 aimed at diminishing this gap, where the participants were presented with two versions of the same cycling scenarios where one was presented as a 360 degree immersive simulation and the other as a non-immersive, two-dimensional video. Then, the cycling behaviour, neural processing, and stated responses are compared in these two counterparts. This approach allowed for the achievement of two goals. Firstly, it was possible to capture the influence of different presentational methods on risk elicitation in VR and discriminate between them based on the findings. Secondly, the results obtained with distinct data types could be compared and conclusions could be drawn about their suitability in a simulated cycling context. Consequently, the findings presented in Chapter 2 demonstrated that the seemingly minor change in a visual presentation led to a difference in risk perception between these two scenario types based on the analysis of cycling behaviour and neural processing. Interestingly, stated responses were not congruent with these findings, therefore no distinction in perceived risk could be made based on stated data. It suggests that this type of data may not have been a suitable approach in this context.

The developments presented thus far were further expanded through the work in Chapter 3 of this thesis, where the neural and behavioural data, elicited by keyboard and the instrumented bicycle while using the same visual stimuli, was analysed. Such a direct comparison reduced the risk of confounding effects and enabled me to attribute the observed differences to the introduced changes. The study yielded several conclusions with respect to cycling performance as well as neural processing, where it was evident that the use of the instrumented bicycle played a significant role in influencing individuals' interactions with the simulated environments. Moreover, the multi-angled approach allowed for obtaining a better understanding of its effect and could draw conclusions about the interaction between different types of responses.

Gap 3: Lack of a choice model that incorporates dynamic behavioural and neural data

In the introduction of this thesis, key constraints that hinder interdisciplinary research in this area were identified. As a result of a mismatch in data collection techniques, lacking operational model structures and established methodologies for the embodiment of neuroimaging or physiological data into a single modelling framework, there has been little progress in such cross-disciplinary research. Nevertheless, the importance of the inclusion of biometric responses in choice models in transport research has been previously recognised by attempts such as the study of Paschalidis et al. (2018) who looked at the effects of stress on driving decisions through the incorporation of heart rate measure into a discrete choice model. Therefore, in Chapter 4 of this thesis, a hybrid model was developed which not only explained the dynamic behaviour of cyclists but also incorporated neural data as an indicator for perceived risk that contributes to a better understanding of actions chosen by the cyclists. At the same time, it provided evidence of the possibility of the inclusion of biometric data in mathematical modelling.

2 Objectives and contributions

In the introduction of this thesis, three distinct objectives for bridging the gap between choice modelling and neuroscience were proposed. The following section summarises how achieving these objectives enabled me to contribute to the field of behavioural modelling.

Objective 1: To design an experiment to collect jointly behavioural and neuroimaging data

This objective was met with the developments in Chapter 2, 3 and 4, where, for the work presented in these three chapters, two experiments in virtual reality were designed. In the first experiment, participants cycled through the simulated scenarios using the keyboard while stated responses about the perceived risk, dynamic cycling behaviour data as well as the continuous EEG signal were simultaneously collected. In the second experiment, dynamic cycling data and EEG signals were collected while participants navigated the simulated scenarios on the instrumented bicycle. Therefore, this thesis contributes by proposing an experimental framework for combined research where implications are relevant for researchers interested in conducting VR studies with a neuroimaging component because it shows that HMD and EEG which are both placed on the participant's head can be effectively used at the same time. This minimises the need for time-consuming EEG equipment modifications or the involvement of alternative, often more costly, VR appliances such as immersive caves. Moreover, the findings provide guidance in terms of the suitability of different data types for the elicitation of momentarily risk perception and demonstrate the interplay between them. They emphasise the importance of the choice of appropriate measures according to the research aims, where in the dynamic context, behavioural and neural data were shown to be more appropriate in capturing changes in perceived risk, while stated data was less relevant. This gives some indication of the relative advantages of different data types. Behavioural as well as neural data could have been recorded which much higher frequency than stated data where it would be impossible to ask participants to report their perceived risk four times per second (which is the recording resolution of behavioural data in the experiments). Additionally, the reliance on observed behaviour and neural measures rather than stated responses addresses the issue of misreported or biased responses with regard to perceived risk.

Overall, this practical work demonstrated the feasibility of combined research in a transport context, providing a benchmark for future studies and increased the awareness concerning the challenges associated with this integrated research.

Objective 2: To evaluate the impact of different experimental designs on behaviour in virtual reality

This objective was met with the developments in Chapter 2 and 3. In particular, in Chapter 2, multinomial logit model (MNL) was estimated to obtain insights into differences in cycling behaviour between immersive and non-immersive presentation methods in VR. Moreover, an ordered logit model was used to investigate how these two presentation methods influence stated risk and finally their effect on neural processing was tested with the paired t-test. Furthermore, in Chapter 3, the differences in behaviour and neural processing, elicited by two experiments where one used a keyboard and the other employed the instrumented bicycle to navigate through the simulated environment, were statistically tested. The work from both chapters showed significant differences as a result of the applied modification in the experimental design, highlighting its importance for the validity and generalisability of the findings.

Firstly, the results emphasise the importance of the experimental design concerning the impact of visual stimuli on behaviour. It is important because in the VR domain, there are frequently studies that aim at investigating the perceptions of thus far non-existent products such as fully autonomous vehicles or novel contexts, for example, a new public transport route. The research of such exploratory nature, presented in this thesis, is valuable since all the considerations concerning equipment and/or graphic design of the VR study ought to be weighed against their costs. Consequently, this thesis contributes by increasing researchers' awareness of the impact of different designs on the results which only then allows for drawing valid conclusions.

Secondly, it was found that the type of data chosen for the study can lead to distinct conclusions. Therefore, it should be selected carefully depending on the design of the study and its purpose to minimise its impact on participants' choices. For instance, surveys and stated responses are a popular and useful tool in social and psychological research where respondents can rely on their past experience or have sufficient general knowledge about the context to reliably compare the situation in question to a number of other scenarios, quantitatively assess and report it. Naturally, these do not guarantee that what people report conforms with their behaviour, however, it at least gives the researchers some degree of confidence in the results. This, however, may not be the case for dynamic contexts where a person's momentary perceptions fluctuate with changing situations, henceforth, the measurement approach has to be adjusted accordingly. Alternatively, it is possible to combine two distinct methods (eg. static and dynamic) to increase the certainty in the observed findings. Therefore, the crucial contributions of this thesis show the trade-off between different technological solutions and the participants' behaviour and provide insights into the suitability of distinct research methods in dynamic experimental designs.

Objective 3: To apply a joint model structure for behavioural and neural data

This objective was met with the developments in Chapter 4, where a hybrid choice model that incorporated both behavioural cycling data and α wave amplitudes was presented to provide an example of a single mathematical structure that encompasses two different data types. The proposed modelling allowed me to explain the dynamic behaviour of the cyclists with respect to the changing circumstances in the simulation i.e., the presence of cars and distance to the junctions and enabled me to use α amplitudes as an indicator of unobserved perceived risk to then relate it to observed actions. This work provides evidence that neuroscientific inputs can be used in mathematical models where they contribute to a better understanding of human behaviour and improve the efficiency of the model. Therefore, the main contribution is the proposed hybrid structure for the simultaneous use of behavioural and neural data. It allows for future developments in this direction where other hypotheses linking the behaviour and different neural and biometric data can be tested. For example, the developed framework can be applied in other contexts to explore the relationship between choices and different brainwaves. Furthermore, the existing framework could be expanded by combining neural data and traditional data within a latent construct to not only explore their relative performance in explaining individuals' choices but also provide the basis for their cross-validation.

3 Limitations

This section discusses the main limitations of this thesis that emerged due to the study design, equipment availability or lack of previous studies that could serve as a blueprint for experimental approach and data analysis.

The work presented in this thesis is to a high degree interdisciplinary, henceforth, it not only required the expertise of different disciplines and collaboration between departments but also involved a variety of equipment and resources including virtual reality headsets, instrumented bicycle, mobile EEG devices as well as appropriate simulated scenarios. Consequently, to minimise the costs while ensuring that the research objectives are met, the physical equipment available at the department and the existing virtual reality scenarios were used. As a result, the two experiments presented in Chapter 3 used different HMDs, where the first study employed an Oculus Rift and the second one HTC Vive. Therefore, a limitation emerged, that was associated with the fact that different headsets have different fields of view (FOV), defined as the area that each of the user's eyes is expected to see (Arvilab.com, 2018; Yoo, 2017). Both headsets have the same diagonal FOV of 110° (Lange et al., 2020; Soffel et al., 2016; Yoo, 2017). However, the horizontal FOV differs between them, where Oculus is said to have about 90° while HTC Vive 100° FOV (Hunt, 2016). Consequently, these differences could have had an impact on the extent of horizontal head movement required to compensate for smaller FOV in the case of the Oculus Rift headset and the results presented in section 5.2 in Chapter 3. Importantly, though, these values are an approximation because HMD's field of view is a subjective measure that depends on different factors such as face geometry, the distance between eyes and lenses or distance between pupils, which lead to different space perceptions among individuals. For example, Borrego et al. (2018) reported values of 94° and 100° horizontal FOV for Oculus Rift and HTC Vive, respectively. Beyond, FOV is only one of many HMD features, together with display resolution, refresh rate and types of lenses, that influence the overall experience of the simulated environment (Bezmalinovic, 2020). In the case of currently used devices, all these parameters are the same, with a resolution of 2169 x 1200 pixels per eye OLED, Fresnel lenses and 90 Hz refresh rate (Borrego et al., 2018).

Altogether, given the individual subjectivity of FOV and similarity of other parameters between these two devices, it is assumed that the effect of different headsets on the overall results, although cannot be ruled out, is expected to be negligible.

Furthermore, the study presented in Chapter 2 used a newly purchased mobile EEG device that has not been previously tested within the department, hence the specific guidelines for experimental design have not been developed yet. Moreover, the experiment itself allowed for more flexibility and movement than typical EEG studies. For these reasons, as well as limited existing literature that would use the specific device, the case study in Chapter 2 faced an issue of low-quality EEG data, which consequently led to an exclusion of data for 16 participants. The resulting sample size made it impossible to construct the choice model. A pilot study and preliminary tests of the equipment conducted before the main data collection helped to reduce the extent of the data loss caused by the misplacement of electrodes or interference of VR googles. However, some factors such as participants movement (as discussed in section 3) could have been minimised if more precise instructions were given. This has been later rectified in the second experiment, where the participant's instructions were improved (see section 1 in appendix B).

Next, the study presented in Chapter 3 uses a between-subject design, while the study in Chapter 2 adopts the within-subject approach. Therefore, the implications of the use of both methods are discussed. Firstly, in the between-subject design, each participant is exposed to only one experimental treatment and the cause-and-effect is concluded based on the comparison of respondents in different conditions (Charness et al., 2012; Hampton, 2018). In contrast, the within-subject design exposes the respondent to all experimental treatments and the comparison is made within the same person across different treatments to establish a causal relationship (Charness et al., 2012; Hellier, 2018). The 'within' approach is more prone to different confounds resulting from one participant being repetitively subjected to experimental conditions such as sequence or order effects, where the possibility arises that the order of the treatments may matter and the next treatment will be affected by the preceding treatment (Glen, 2014). Further, practice and fatigue effects may respectively lead to an improvement or deterioration in performance due to task repetition (Süss and Schmiedek, 2000). Finally, carryover or context effect can give rise to the situation where being tested in one treatment changes how participant perceives the stimuli in the following treatments (Chong and Ahmed, 2017).

In the current study, in Chapter 2, there has been a particular potential for the emergence of context effect when participants' responses regarding their perceived risk and willingness to cycle could have been influenced by the comparison to the stimulus observed in the previous treatment. Nonetheless, this and other potential biases due to within-subject design were minimised by counterbalancing (through orthogonal design and randomisation) in which the participants received all combinations of treatments in different orders (Hellier, 2018). On the other hand, the within-subject design offers internal validity that is not dependent on random assignment, as is the case in the between-subject approach. It frequently reaches higher statistical power and is more aligned with theoretical foundations that are more likely to apply to a single person being affected by a change, for example, in observed risk level rather than two individuals being affected by different levels of risk in two different situations (Charness et al., 2012).

With respect to between-subject design, its validity is based on a random assignment of individuals to two separate groups to ensure that the baseline characteristics are comparable across them (Charness et al., 2012). This gives rise to the limitation of the study presented in Chapter 3, where there are considerable differences in socio-demographic characteristics between the samples. The comparison of the mean level of several variables using an unpaired t-test showed that some of the values are significantly different. In particular, the sample in the first study is significantly older (t-ratio = 2.68) and has more car drivers (t-ratio = 5.74) as compared to the sample in the second study. Furthermore, on average individuals in the first study perceived cycling as significantly more risky (t-ratio = 5.66). Moreover, gender differences between the two samples were marginally significant (t-ratio = 1.91). At the same time, the statistical analysis found that the education level (t-ratio = 0.88) and cycling frequency between November and February (t-ratio = 0.84) and March to October (t-ratio = 0.70) as well as the involvement in the accident on the bicycle (t-ratio = 1.06) do not significantly differ between the two samples.

Even though these differences exist, they are expected to have a limited impact on the results presented in Chapter 3, for two reasons. Firstly, the sample sizes in both studies are relatively small, therefore, they are expected to have little influence on the results. In particular, a similar situation was observed in the models' outputs presented in Chapter 2 where socio-demographic characteristics were mostly insignificant, suggesting that they do not have considerable importance for the modelled behaviour. Secondly, the conducted analysis refers to the operational level of behaviour as discussed in Chapter 1, hence the individual-specific characteristics are expected to have minimal impact as compared to time-dependent scenario attributes such as current level of observed risk, cycling speed or distance to other agents. This is further supported by the previous literature where the impact of socio-demographic characteristics was mainly explored in the context of cycling behaviour on a strategical level such as frequency of bicycle use (Wang and Lindsey, 2019), travel activity patterns (Mitra and Nash, 2019) or active travel choices (Freeman et al., 2013) but less so in a dynamic cycling behaviour on the road (Auer et al., 2021).

The final limitation emerged due to the fact that in the existing virtual reality scenarios the cyclists could only move straight ahead, without the possibility of steering. This constrained the scope of the study where steering can be considered an alternative action, beyond accelerating and decelerating, that is used to avoid collision with other roads users (Gavriilidou et al., 2019). Consequently, the choice modelling assumption about the choice set being collectively exhaustive (encompassing all possible alternatives), as discussed at the beginning of Chapter 1, is relaxed. Instead, a restricted choice set is used to represent the actual spectrum of alternatives faced by the individual in the scenario (Thill, 1992). Restricted choice set (in the literature also called constrained choice set) is often observed in the transport context, for example, with respect to route (Prato and Bekhor, 2007) or mode choice (Ton et al., 2018). For instance, Gehrke and Clifton (2014) excluded public transport as an alternative for individuals who lived further than a certain distance from the nearest bus stop or train station to ensure that only available modes are present in the choice set. Beyond, constrained choice sets have been previously used in studies concerning residential choices (Timmermans et al., 1996; Zolfaghari et al., 2012), shopping destinations (Ma et al., 2017; Scott and He, 2012) or locations of discretionary activities (Mariante et al., 2018). Nonetheless, in the current study this limited the range of cycling behaviour that could have been explored, henceforth, the future work should consider the inclusion of steering to provide more comprehensive analysis, as discussed in the next section.

4 Future work

This thesis presented several contributions that demonstrated the attempts to advance the interaction between choice modelling and neuroscience with respect to the following:

- The design of primary data collection;

- The internal validation of the novel research tools;
- The evidence of the complementarity of data from these two fields;
- The methodological developments for the use of behavioural and neural data in a single model structure.

The work presented in this thesis is to a large extent exploratory, but can nonetheless be considered a vital first step that paves the way for future investigations. Therefore, in this section, future directions of this work are discussed with respect to identified research gaps.

Firstly, two experiments that provided a foundation of this thesis and used a combined approach by incorporating the EEG signal, dynamic VR simulation and stated data demonstrate that current technological advancement makes this kind of research efforts possible. Nonetheless, the scope of current work was limited to cycling. Therefore, it is advisable to gather more evidence in different contexts to be able to generalise the findings to a larger extent and assess the joint performance of VR and neuroimaging tools. Interesting examples include risky driving, evacuation behaviour or interaction between autonomous vehicles and traditional human-operated ones, where the investigation of neural correlates could shed some light on people's behaviour in these extraordinary or new circumstances.

Secondly, the complexity of the data collection constrained the sample size used in the studies in this thesis and did not allow to fully capture the role of demographics. Therefore, future research with larger and more diverse samples could enable the exploration of different aspects of the observed behaviour, for example, gender or cultural effects in these contexts. Furthermore, as discussed in section 3, the limitation emerged due to the differences in sample composition while employing between-subject design. Hence, the analysis of cycling behaviour elicited with different input devices with a more homogenous sample would further reinforce current findings.

Thirdly, the studies conducted in this thesis remained within the virtual reality sphere. Consequently, they did not allow for comparing virtual reality and real-life behaviour, making an external validation impossible. Therefore, future studies that would compare the cycling behaviour between real-life and simulated scenarios are advisable to contribute to the literature on the external validity of VR studies in the cycling context. More sophisticated and robust EEG devices may make it feasible to collect at least some field data. Therefore, it would also be beneficial to test and compare the applicability of different neuroimaging devices available on the market in a single experiment as well as in a real-life setting to be able to compare their performance and determine relative advantages in these frameworks. This is important because neuroimaging equipment offers a variety of features, for example, EEG equipment has a significant advantage in terms of its temporal resolution, while fMRI or portable fNIRS are superior in terms of spatial precision (Wallois et al., 2012).

Further, given the limitation of current choice set identified in the previous section, future work should aim at accounting for the whole spectrum of possible behaviours including steering (Gavriilidou et al., 2019). The inclusion of steering manoeuvres as a collision evasive action is an important extension to current work because it would allow for gaining a more complete perspective on the trade-offs between different actions as a result of the current situation on the road and perceived level of risk (Lin et al., 2014). In particular, it would allow for assessing the extent of compensatory behaviour in cases, such as the current one, when not all the actions are available. For example, it would indicate the degree to which deceleration/braking is chosen more often to compensate for the lack of steering possibility to bypass the potential collision. This would, then, expand current understanding of cycling behaviour and contribute to a better design of cycling studies in VR.

Moreover, the differences in behaviour and neural processing that are a result of different presentation methods or input devices, as demonstrated in this thesis, can identify the congruence (or lack thereof) between different data types. Consequently, it calls for gathering more evidence of the impact of different experimental designs in VR using this integrated approach, possibly in a more varied context. It would then increase our confidence in this novel data collection method and facilitate its popularisation in a variety of disciplines. Further, it is necessary to conduct studies that combine the established and novel data types and allow for their cross-validation and assessment of the relative performance which will put us in a better position to determine their suitability in specific research contexts.

Finally, a wider application of biometric data in choice models would accelerate the diffusion of new modelling techniques and structures. It is important because at the moment, there is little evidence in the literature on appropriate methods for the inclusion of biometric data in mathematical models and what aspects of data collection are crucial in this respect. Moreover, methodological questions arise while using jointly behavioural and biometric data. For example, in psychology, biometric data is typically collected with very high resolution such as 128 Hz or 256 Hz. On the other hand, the behavioural or stated data collected for the purpose of choice modelling are less temporally rich, where dynamic driving simulator studies usually record one observation per second (1 Hz). Therefore, there is a significant difference in the format/resolution of the biometric and behavioural data, which poses difficulties in how they can be used jointly without losing their richness. The literature proposes transformations such as averaging, majority voting or a maximum/minimum value within a certain time frame, however, it is still unknown which is the most appropriate for choice models or how these methods would affect the results. Similarly, the relative advantages of temporal and spatial features of the data could be compared in mathematical models. Therefore, it can be seen that studies of this nature are needed, and could contribute to the more varied application of these data. For instance, in the provision of neural foundations of the models or new decision rules, reductions in the random model components or providing the new basis for discrimination between models.

The future research proposed in this section would extend the findings of current work and gather more evidence in a broader range of contexts to facilitate more informed and efficient research efforts with respect to the use of VR as a research tool, use of biometrics data in mathematical models, or the design of studies using an integrative approach.

References

Arvilab.com (2018). *What do we need to know about HMD?* URL: https://vr.arvilab.com/blog/hmd-visual-features (Accessed: 09/07/2021).

Auer, K., Badarinath, P. V., Kakhki, F. D., and Chierichetti, M. (2021). Statistical analysis of adult cyclists' socio-demographic factors and helmet-wearing behavior. In *International Conference on Applied Human Factors and Ergonomics*, pages 101–106. Springer.

Bezmalinovic, T. (2020). *Diese VR-Brillen haben das größte Sichtfeld*. URL: https://mixed.de/diese-vr-brillen-haben-das-groesste-fov/ (Accessed: 20/06/2021).

Borrego, A., Latorre, J., Alcaniz, M., and Llorens, R. (2018). Comparison of Oculus Rift and HTC Vive: feasibility for virtual reality-based exploration, navigation, exergaming, and rehabilitation. *Games for health journal*, 7(3):151–156.

Calder, B. J., Phillips, L. W., and Tybout, A. M. (1982). The concept of external validity. *Journal of consumer research*, 9(3):240–244.

Charness, G., Gneezy, U., and Kuhn, M. A. (2012). Experimental methods: Between-subject and within-subject design. *Journal of economic behavior & organization*, 81(1):1–8.

Chong, Y. S. and Ahmed, P. K. (2017). On happiness, sadness or indifference: Investigating the carryover effect of outcome valence in service perceptions. *Journal of Service Theory and Practice*, 27:69–86.

Freeman, L., Neckerman, K., Schwartz-Soicher, O., Quinn, J., Richards, C., Bader, M. D., Lovasi, G., Jack, D., Weiss, C., Konty, K., et al. (2013). Neighborhood walkability and active travel (walking and cycling) in New York City. *Journal of Urban Health*, 90(4):575–585.

Gavriilidou, A., Daamen, W., Yuan, Y., and Hoogendoorn, S. (2019). Modelling cyclist queue formation using a two-layer framework for operational cycling behaviour. *Transportation research part C: emerging technologies*, 105:468–484.

Gehrke, S. R. and Clifton, K. J. (2014). Operationalizing land use diversity at varying geographic scales and its connection to mode choice: Evidence from Portland, Oregon. *Transportation Research Record*, 2453(1):128–136.

Glen, S. (2014). *Counterbalancing in Research*. URL: https://www.statisticshowto.com/counterbalancing-2/ (Accessed: 11/07/2021).

Hampton, J. (2018). The between-subjects experiment. In *Laboratory Psychology*, pages 15–37. Psychology Press, London.

Hellier, E. J. (2018). Within-subject designs. In *Laboratory Psychology*, pages 39–58. Psychology Press, London.

Hunt, C. (2016). *Field of view face-off: Rift vs Vive vs Gear VR vs PSVR*. URL: https://www.vrheads.com/field-view-faceoff-rift-vs-vive-vs-gear-vr-vs-psvr (Accessed: 09/07/2021).

Lange, D., Stratmann, T. C., Gruenefeld, U., and Boll, S. (2020). Hivefive: Immersion preserving attention guidance in virtual reality. In *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems*, pages 1–13.

Lin, C.-F., Juang, J.-C., and Li, K.-R. (2014). Active collision avoidance system for steering control of autonomous vehicles. *IET Intelligent Transport Systems*, 8(6):550–557.

Ma, T.-y., Mariante, G., and Van Acker, V. (2017). Location choice modeling based on mixed logit model and sampling of alternatives. In *BIVEC-GIBET Transport Research Days 2017: Towards an autonomous and interconnected transport future*. BIVEC-GIBET.

Mariante, G. L., Ma, T.-Y., and Van Acker, V. (2018). Modeling discretionary activity location choice using detour factors and sampling of alternatives for mixed logit models. *Journal of Transport Geography*, 72:151–165.

Mitra, R. and Nash, S. (2019). Can the built environment explain gender gap in cycling? An exploration of university students' travel behavior in Toronto, Canada. *International journal of sustainable transportation*, 13(2):138–147.

Paschalidis, E., Choudhury, C. F., and Hess, S. (2018). Modelling the effects of stress on gap-acceptance decisions combining data from driving simulator and physiological sensors. *Transportation research part F: traffic psychology and behaviour*, 59:418–435.

Patino, C. M. and Ferreira, J. C. (2018). Internal and external validity: can you apply research study results to your patients? *Jornal brasileiro de pneumologia*, 44(3):183–183.

Prato, C. G. and Bekhor, S. (2007). Modeling route choice behavior: How relevant is the composition of choice set? *Transportation Research Record*, 2003(1):64–73.

Schubert, T., Friedmann, F., and Regenbrecht, H. (1999). Embodied presence in virtual environments. In *Visual representations and interpretations*, pages 269–278. Springer.

Scott, D. M. and He, S. Y. (2012). Modeling constrained destination choice for shopping: a GIS-based, time-geographic approach. *Journal of Transport Geography*, 23:60–71.

Soffel, F., Zank, M., and Kunz, A. (2016). Postural stability analysis in virtual reality using the htc vive. In *Proceedings of the 22nd ACM Conference on Virtual Reality Software and Technology*, pages 351–352.

Süss, H. and Schmiedek, F. (2000). Fatigue and practice effects during cognitive tasks lasting several hours. *Zeitschrift fur experimentelle Psychologie: Organ der Deutschen Gesellschaft fur Psychologie*, 47(3):162–179.

Thill, J.-C. (1992). Choice set formation for destination choice modelling. *Progress in human geography*, 16(3):361–382.

Timmermans, H., Van Noortwijk, L., Oppewal, H., and van der Waerden, P. (1996). Modeling constrained choice behaviour in regulated housing markets by means of discrete choice experiments and universal logit models: an application to the residential choice behaviour of divorcees. *Environment and Planning A*, 28(6):1095–1112.

Ton, D., Duives, D., Cats, O., Hoogendoorn-Lanser, S., and Hoogendoorn, S. (2018). Determinants of the consideration mode choice set. In *hEART 2018: 7th Symposium of the European Association for Research in Transportation, 5-7 September, Athens, Greece*.

Wallois, F., Mahmoudzadeh, M., Patil, A., and Grebe, R. (2012). Usefulness of simultaneous EEG–NIRS recording in language studies. *Brain and language*, 121(2):110–123.

Wang, J. and Lindsey, G. (2019). Neighborhood socio-demographic characteristics and bike share member patterns of use. *Journal of transport geography*, 79:102475.

Yoo, K.-H. (2017). *HMD based VR service framework*. URL: https://www.web3d.org/sites/default/files/page/Korea%20Chapter%20Meeting%20SIGGRAPH%202017/4_hmd-vr-service-framework_20170731.pdf (Accessed: 03/07/2021).

Zolfaghari, A., Sivakumar, A., and Polak, J. W. (2012). Choice set pruning in residential location choice modelling: a comparison of sampling and choice set generation approaches in Greater London. *Transportation Planning and Technology*, 35(1):87–106.

Appendix A

Appendix to Chapter 2

1 Participant task instructions

You will be presented with 24, 2D and 3D road simulations in virtual reality environment (in Oculus Rift Headset) from the perspective of a cyclist. Your task is to take an active role as a cyclist by manipulating your speed using keyboard. On my sign, you can start cycling through the scenario. You can perform two actions: accelerate and brake. To accelerate press arrow up on the keyboards and to brake press arrow down on the keyboard. You are free to move your head around while interacting with the virtual reality but please remain seated back on the chair. At the end of each simulation you will hear a number of questions regarding the riskiness of the scenario that you have just observed and you will be asked to state your answer verbally. In particular you will be asked to rate different aspects of the scenario on the scale 1-7 where (1 is minimum value, 7 is maximum value).In particular, the questions will ask: *On a scale 1-7 (where 1-no risk, 7-maximum risk) rate how risky did you find the observed scenario?* You are asked to say a number corresponding to level of riskiness perceived between 1-7. Then, *On a scale 1-7 rate how willing are you to cycle in the conditions observed in the scenario?* You are asked to say a number corresponding to level of willingness to cycle between 1-7. Whilst performing the task you will be wearing an electroencephalogram (EEG) scanner that will record your brain activity and e4 wristband to measure your heart rate.

2 Socio-demographic questionnaire used in the experiment

1. Please state your age group:

- ☐ 18-24
- ☐ 25-29
- ☐ 30-39
- ☐ 40-49
- ☐ 50-59
- ☐ 60-65
- ☐ 66-75
- ☐ 76 or above

2. Please state your gender:

- ☐ Male
- ☐ Female

3. What is your country of origin?

4. What is the highest level of education you have obtained? (If currently enrolled, highest degree received.)

- ☐ O level/Secondary Education/General Certificate of Education
- ☐ A-Level/Baccalaureate/Pre-University Education
- ☐ Vocational qualification
- ☐ Undergraduate degree
- ☐ Masters
- ☐ Ph.D

5. Please state your marital status:

- ☐ Single
- ☐ Married
- ☐ Cohabiting
- ☐ Divorced
- ☐ Widowed

6. How many children in the following age categories, do you have? *(Please tick the box that applies to you)*

- 0-3 years: 0 ☐ 1 ☐ 2+ ☐
- 4-7 years: 0 ☐ 1 ☐ 2+ ☐
- 8-11 years: 0 ☐ 1 ☐ 2+ ☐
- 12-15 years: 0 ☐ 1 ☐ 2+ ☐
- 15+ years: 0 ☐ 1 ☐ 2+ ☐

7. Please state your personal annual income (before tax):

☐ Below £10,000

☐ £10,000 - £20,000

☐ £30,000 - £40,000

☐ £40,000 - £50,000

☐ £50,000 - £75,000

☐ £75,000 - £100,000

☐ £100,000 - £125,000

☐ £125,000 - £150,000

☐ Above £150,000

☐ Do not know

☐ Prefer not to say

8. Please state your household annual income (before tax):

☐ Below £10,000

☐ £10,000 - £20,000

☐ £30,000 - £40,000

☐ £40,000 - £50,000

☐ £50,000 - £75,000

☐ £75,000 - £100,000

- ☐ £100,000 - £125,000
- ☐ £125,000 - £150,000
- ☐ Above £150,000
- ☐ Do not know
- ☐ Prefer not to say

9. Are you an active car driver?
   - ☐ Yes
   - ☐ No
10. How often do you use a bike between March and October?
   - ☐ Everyday
   - ☐ Multiple times a week
   - ☐ On weekends only
   - ☐ A few times a month
   - ☐ Rarely
   - ☐ Never
11. How often do you use a bike between November and February?
   - ☐ Everyday
   - ☐ Multiple times a week
   - ☐ On weekends only
   - ☐ A few times a month
   - ☐ Rarely
   - ☐ Never
12. What was the most serious accident you had as a cyclist?
   - ☐ No accident
   - ☐ Only material damage
   - ☐ Injuries to me/others

☐ Fatal injuries to others

13. On a scale 1-10, how risky do you consider cycling as an activity?

Not risky	1	2	3	4	5	6	7	8	9	10	Very risky

14. How frequently do you engage in these activities?

Using your mobile while cycling	Always	Often	Sometimes	Rarely	Never
Listening to music while cycling	Always	Often	Sometimes	Rarely	Never
Cycling after drinking alcohol	Always	Often	Sometimes	Rarely	Never
Cycling after taking drugs	Always	Often	Sometimes	Rarely	Never
Wearing a helmet and high visibility elements	Always	Often	Sometimes	Rarely	Never
Turning rear lights on while cycling at night	Always	Often	Sometimes	Rarely	Never
Turning front lights on while cycling at night	Always	Often	Sometimes	Rarely	Never
Watching speed limits while cycling	Always	Often	Sometimes	Rarely	Never
Ignoring red light	Always	Often	Sometimes	Rarely	Never

3 Additional sample characteristics

1. Origin:

- Europe: 62%
- Asia: 23%
- South America: 10%
- Others (Inc. North America, Australia and Africa): 5%

2. Education:

- A-level: 25%
- Undergraduate: 30%
- Masters: 35%
- PhD: 10%

3. Marital status:

- Single: 62%
- Married/Cohabiting: 37%
- Divorced: 1%

4. Proportion of cyclists in the sample (defined as those who cycle more than few times a month): 45%
5. Proportion of drivers in the sample: 44%
6. Most serious accident while cycling:

- No accident: 46%
- Injuries to me or others: 35%
- Only material damage: 19%

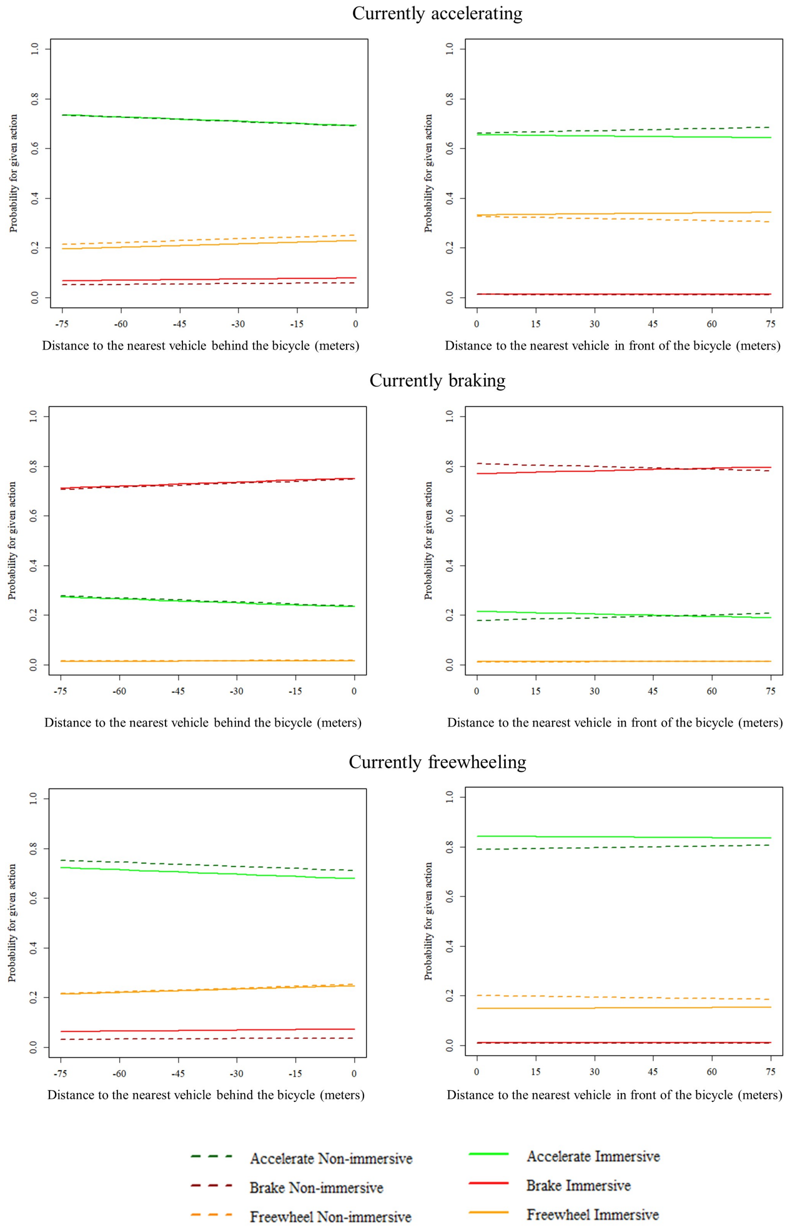
7. Mean score of cycling riskiness (answer to question 13 in the survey): 6.18

4 Graph illustrating impact of distance to cars

As described in section 5 of Chapter 2, we present the additional graphs illustrating the impact of distance to cars on the choice of the next action.

4. Graph illustrating impact of distance to cars

Fig. A.1: The impact of distance to cars on the choice of the next action.



Appendix B

Appendix to Chapter 3

1 Participant task instructions

You will be presented with immersive road simulations in virtual reality environment (in HTC Vive headset) while being seated on the stationary bicycle. Your task is to cycle through the scenarios on the bike until reaching a finish line. You should strictly avoid collisions with other road users. If you crush, you will have to start again. On my sign, you can start cycling through scenario. You can perform two actions: accelerate and brake. To accelerate start pedalling and to brake press hand break on the bike. You are free to move your head around while interacting with the virtual reality but please remain seated on the bicycle. Whilst performing the task you will be wearing an electroencephalogram (EEG) scanner that will record your brain activity and a wristband to measure your heart rate. Within the duration of the experiment, please refrain yourself from touching your head, face or the equipment that you are wearing.

2 Socio-demographic questionnaire used in the experiment with instrumented bicycle.

1. Please state your age group:

   ☐ 18-24

   ☐ 25-29

   ☐ 30-39

   ☐ 40-49

   ☐ 50-59

☐ 60-65

☐ 66-75

☐ 76 or above

2. Please state your gender:

☐ Male

☐ Female

3. What is your country of origin?

4. What is the highest level of education you have obtained? (If currently enrolled, highest degree received.)

☐ O level/Secondary Education/General Certificate of Education

☐ A-Level/Baccalaureate/Pre-University Education

☐ Vocational qualification

☐ Undergraduate degree

☐ Masters

☐ Ph.D

5. Please state your marital status:

☐ Single

☐ Married

☐ Cohabiting

☐ Divorced

☐ Widowed

6. How many children in the following age categories, do you have? *(Please tick the box that applies to you)*

- 0-3 years: 0 ☐ 1 ☐ 2+ ☐
- 4-7 years: 0 ☐ 1 ☐ 2+ ☐
- 8-11 years: 0 ☐ 1 ☐ 2+ ☐
- 12-15 years: 0 ☐ 1 ☐ 2+ ☐

- 15+ years: 0 ☐ 1 ☐ 2+ ☐

7. Please state your personal annual income (before tax):

☐ Below S$10,000

☐ S$10,000 - S$20,000

☐ S$30,000 - S$40,000

☐ S$40,000 - S$50,000

☐ S$50,000 - S$75,000

☐ S$75,000 - S$100,000

☐ S$100,000 - S$125,000

☐ S$125,000 - S$150,000

☐ Above S$150,000

☐ Do not know

☐ Prefer not to say

8. Please state your household annual income (before tax):

☐ Below S$10,000

☐ S$10,000 - S$20,000

☐ S$30,000 - S$40,000

☐ S$40,000 - S$50,000

☐ S$50,000 - S$75,000

☐ S$75,000 - S$100,000

☐ S$100,000 - S$125,000

☐ S$125,000 - S$150,000

☐ Above $150,000

☐ Do not know

☐ Prefer not to say

9. Are you an active car driver?

☐ Yes

☐ No

10. How often do you use a bike between March and October?

☐ Everyday

☐ Multiple times a week

☐ On weekends only

☐ A few times a month

☐ Rarely

☐ Never

11. How often do you use a bike between November and February?

☐ Everyday

☐ Multiple times a week

☐ On weekends only

☐ A few times a month

☐ Rarely

☐ Never

12. What was the most serious accident you had as a cyclist?

☐ No accident

☐ Only material damage

☐ Injuries to me/others

☐ Fatal injuries to others

13. On a scale 1-10, how risky do you consider cycling as an activity?

Not risky	1	2	3	4	5	6	7	8	9	10	Very risky

14. How frequently do you engage in these activities?

Using your mobile while cycling	Always	Often	Sometimes	Rarely	Never
Listening to music while cycling	Always	Often	Sometimes	Rarely	Never
Cycling after drinking alcohol	Always	Often	Sometimes	Rarely	Never
Cycling after taking drugs	Always	Often	Sometimes	Rarely	Never
Wearing a helmet and high visibility elements	Always	Often	Sometimes	Rarely	Never
Turning rear lights on while cycling at night	Always	Often	Sometimes	Rarely	Never
Turning front lights on while cycling at night	Always	Often	Sometimes	Rarely	Never
Watching speed limits while cycling	Always	Often	Sometimes	Rarely	Never
Ignoring red light	Always	Often	Sometimes	Rarely	Never

3 Additional sample characteristics

1. Origin:

- Asia: 92%
- Europe: 6%
- South America: 2%

2. Education:

- A-level: 22%
- Undergraduate: 38%
- Masters: 30%
- PhD: 10%

3. Marital status:

- Single: 90%
- Married: 10%

4. Proportion of cyclists in the sample (defined as those who cycle more than few times a month): 41%
5. Proportion of drivers in the sample: 8%
6. Most serious accident while cycling:

- No accident: 54%
- Only material damage: 26%
- Injuries to me or others: 20%

7. Mean score of cycling riskiness (answer to question 13 in the survey): 3.85

Appendix C

Appendix to Chapter 4

1 Full output of the reduced discrete-continuous model

In this appendix, we present the full output of the reduced discrete-continuous model, as described in section 6.4 of Chapter 4.

Table C.1: A reduced discrete-continuous model (robust standard errors and t-ratios in brackets).

LL(start): -76846.10
LL(final, whole model): -74840.15
AIC: 149762.3
BIC: 150126.2
LL(final, choice component): -45088.89
LL(final, acceleration when static): 464.95
LL(final, acceleration when moving): -14384.50
LL(final, deceleration): -7492.83
LL(final, braking deceleration): -8338.87

		Action	**Estimate (rob. std.err.; rob.t-ratios)**
ASC (δ)		Maintain	-0.2479 (0.0734; -3.38)
		Brake	-2.1230 (0.0988; -21.49)
		Decelerate	-2.8950 (0.1129; -25.65)
		Wait	4.1069 (0.1869; 21.98)
		Accelerate	0
Individual's heterogeneity (σ)		Maintain	0.2650 (0.0301; 8.80)
		Decelerate	0.1763 (0.0274; 6.42)
Collision ($\beta_{collision}$)		Maintain	0.2007 (0.0389; 5.16)
		Brake	0.7376 (0.1529; 4.82)
		Decelerate	0.4067 (0.1249; 3.26)
		Wait	0.6291 (0.1758; 3.58)
Time to collision ($\lambda_{time-collision}$)		Brake	-0.5257 (0.0916; -5.74)
		Decelerate	-0.2144 (0.1459; -1.47)
Distance to junction ($\beta_{dist-to-junction}$)	1^{st} order	Maintain	0.0458 (0.0624; -4.70)
	2^{nd} order	Maintain	-0.0835 (0.0079; 2.73)
	1^{st} order	Brake	0.1410 (0.0184; 7.66)
	2^{nd} order	Brake	-0.2661 (0.0683; -3.90)
	3^{rd} order	Brake	0.0187 (0.0089; 2.10)
	1^{st} order	Decelerate	0.0967 (0.0124; 7.82)
	2^{nd} order	Decelerate	-0.2931 (0.0624; -4.70)
	3^{rd} order	Decelerate	0.0216 (0.0079; 2.73)
Speed (β_{Speed})	1^{st} order	Maintain	0.0606 (0.0062; 9.71)
	2^{nd} order	Maintain	-0.0025 (0.0005; -5.61)
	1^{st} order	Brake	0.0481 (0.0137; 3.51)
	2^{nd} order	Brake	0.0013 (0.0006; 2.22)
	1^{st} order	Decelerate	0.1265 (0.0151; 8.40)
	2^{nd} order	Decelerate	-0.0031 (0.0044; -0.70)
	3^{rd} order	Decelerate	0.0028 (0.0050; 0.56)
Continuous acceleration when stopped		μ	-3.0631 (0.1386; -22.10)
		σ	2.2931 (0.0795; 28.84)
Continuous acceleration when in motion		μ	-0.3722 (0.0336; -11.09)
		σ	1.0912 (0.0144; 75.58)
		Speed	0.0518 (0.0022; 23.90)
Continuous deceleration		μ	-0.2864 (0.0435; -6.59)
		σ	1.1047 (0.0196; 56.38)
		Speed	0.0394 (0.0026; 15.15)
Continuous braking deceleration		μ	-0.4394 (0.0639; -6.87)
		σ	1.1958 (0.0253; 47.32)
		Speed	0.0602 (0.0038; 15.97)
Latent risk (θ)		Brake ($\beta_{risk_{Br}}$)	0.1159 (0.0176; 6.58)
		Distance to the junction ($\gamma_{dist-to-junction}$)	-0.0524 (0.0305; -1.72)
		Presence of the car at the junction ($\gamma_{car-present}$)	0.0047 (0.0021; 2.27)
		ζ_{α}	-