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Cycling in virtual reality: modelling behaviour in an immersive environment

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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 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. We then develop 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 focussed 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 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.

Keywords: *road user behaviour, risk, cycling, virtual reality, EEG*

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., 2017; Melson et al., 2014); and the study of how travel mode choices affect traffic congestion (Madhuwanthi et al., 2016; Chen et al., 2018) 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 & Hartley, 1999) are believed to be related to the low incidence of cycling as a commuting mode (Department of Transport, 2013).

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 & 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 (Li et al., 2018; Harrison, 2006; Hensher, 2010 & 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., 2018). Virtual reality is typically defined as the computer-generation of three-dimensional interactive environments (Wann & 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 Lin et al. (2017) and Powell et al. (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 focussed 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), cf. 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 & 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 focussed on the investigation of driver fatigue and drowsiness (Awais et al., 2017; Lal & Craig, 2001; Eoh et al., 2005; Craig et al., 2012), 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 focussed 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, focussing on signal power in the 8-14 Hz range. Occipital alpha 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 & 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 (WTC) 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 (see Rovira et al., 2009; Slater et al., 2006; Farooq et al., 2018; Frankenhuis et al., 2010; Underwood et al., 2011; Erath et al., 2017; Patterson et al., 2017), 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:

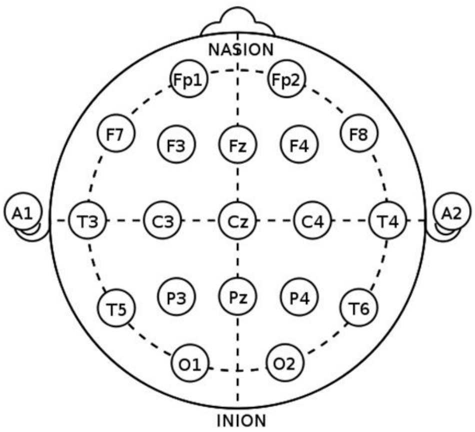
- Hypothesis 3: the peak amplitude of the α waves in trials with non-immersive presentations format are higher than in the immersive presentation conditions, reflecting differences in task-relevant attentional processing.

3. Data collection & 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. After the introduction, the participant was seated and had an Emotiv Epoc+ EEG headset (EMOTIV EPOC+, 2018) and an Oculus Rift VR (Oculus, 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 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 focussed their gaze on one point on the screen for 15 seconds. The same procedure was then repeated with eyes closed.

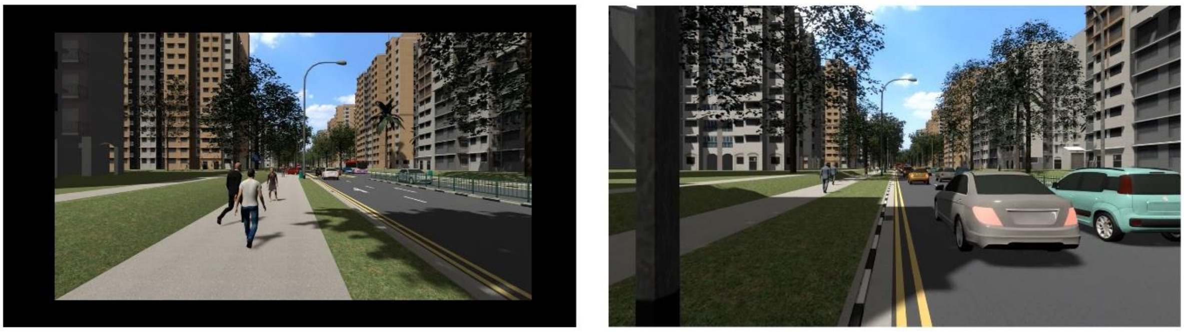
Figure 1: Electrodes position on the scalp (Khazi et al., 2012)



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 (Hawkins et al., 2015; Ergenoglu et al., 2004; Van Dijk et al., 2008; Mathewson et al., 2009).

The experiment encompassed two distinct treatments, where we used a within-subject design. Both treatments consisted in 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). In contrast, the immersive condition was a 360-degree view of the road which surrounded the participant and responded to their head movements (the right pane in Figure 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.

Figure 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 3, namely, cycling on the pavement (on the left) and cycling on the side of the road (on the right). 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 3.

Figure 3: A high-risk condition in the pavement and road scenarios

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 1.

Table 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

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. It is important to note that the use of 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. 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. Importantly, for the EEG data analysis, an additional 16 participants were dropped due to low quality of the EEG data. 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. 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 (see 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 models in a linear, quadratic and cubic fashion to determine any nonlinearity in the relationship between the speed and the dependent 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:

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

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

$$V_{FW} = 0 \tag{3}$$

In Equation (1) and (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:

$$\delta_{Acc_{n,t,s}} = \left(\delta_{Acc-current-Acc} + \Delta_{\delta,Acc-current-Acc_I} \cdot x_{I_{n,s}} + \Delta_{\delta,Acc-current-Acc_{road}} \cdot x_{road_{n,s}} + \Delta_{\delta,Acc-current-Acc_{road_I}} \cdot x_{road_{n,s}} \cdot x_{I_{n,s}}\right) \cdot x_{Acc_{t-1}} + \left(\delta_{Acc-current-Br} + \Delta_{\delta,Acc-current-Br_I} \cdot x_{I_{n,s}} + \Delta_{\delta,Acc-current-Br_{road}} \cdot x_{road_{n,s}} + \Delta_{\delta,Acc-current-Br_{road_I}} \cdot x_{road_{n,s}} \cdot x_{I_{n,s}}\right) \cdot x_{Br_{t-1}} + \left(\delta_{Acc-current-FW} + \Delta_{\delta,Acc-current-FW_I} \cdot x_{I_{n,s}} + \Delta_{\delta,Acc-current-FW_{road}} \cdot x_{road_{n,s}} + \Delta_{\delta,Acc-current-FW_{road_I}} \cdot x_{road_{n,s}} \cdot x_{I_{n,s}}\right) \cdot x_{FW_{t-1}} \tag{4}$$

$$\delta_{Br_{n,t,s}} = \left(\delta_{Br-current-Acc} + \Delta_{\delta,Br-current-Acc_I} \cdot x_{I_{n,s}} + \Delta_{\delta,Br-current-Acc_{road}} \cdot x_{road_{n,s}} + \Delta_{\delta,Br-current-Acc_{road_I}} \cdot x_{road_{n,s}} \cdot x_{I_{n,s}}\right) \cdot x_{Acc_{t-1}} + \left(\delta_{Br-current-Br} + \Delta_{\delta,Br-current-Br_I} \cdot x_{I_{n,s}} + \Delta_{\delta,Br-current-Br_{road}} \cdot x_{road_{n,s}} + \Delta_{\delta,Br-current-Br_{road_I}} \cdot x_{road_{n,s}} \cdot x_{I_{n,s}}\right) \cdot x_{Br_{t-1}} + \left(\delta_{Br-current-FW} + \Delta_{\delta,Br-current-FW_I} \cdot x_{I_{n,s}} + \Delta_{\delta,Br-current-FW_{road}} \cdot x_{road_{n,s}} + \Delta_{\delta,Br-current-FW_{road_I}} \cdot x_{road_{n,s}} \cdot x_{I_{n,s}}\right) \cdot x_{FW_{t-1}} \tag{5}$$

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:

- $\delta_{Acc-current-Acc}$, $\delta_{Acc-current-Brake}$ 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, $\Delta_{\delta,Acc-current-Acc_{\mathrm{I}}}$, $\Delta_{\delta,Acc-current-Brake_{\mathrm{I}}}$ and $\Delta_{\delta,Acc-current-FW_{\mathrm{I}}}$ are the interaction terms that capture the shift in the values of the baseline parameters $\delta_{Acc-current-Acc}$, $\delta_{Acc-current-Brake}$ 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:

$$P_{ints}(\beta) = \frac{e^{V_{i,n,t,s}}}{\sum_{i=1}^{3} e^{V_{i,n,t,s}}}, \tag{6}$$

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 1-3.

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 (WTC) in non-immersive and immersive scenarios. We use an ordered logit model (cf. Greene & Hensher, 2010) as the dependent variables were measured on a 7-point Likert scale, where we do this separately for risk and the WTC. Consequently, Y_{ns} is an observed value of perceived risk/WTC 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:

$$P_{Y_{ns=m}} = \frac{e^{\tau_m - V_{n,s}}}{1 + e^{\tau_m - V_{n,s}}} - \frac{e^{\tau_{m-1} - V_{n,s}}}{1 + e^{\tau_{m-1} - V_{n,s}}} \tag{7}$$

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 WTC can be seen below:

$$\begin{aligned}V_{stated\,risk_{n,s}} = {} & \Delta_{SR,I} \cdot x_{I_{n,s}} + \Delta_{SR,road} \cdot x_{road_{n,s}} + \Delta_{SR,male} \cdot x_{male_n} + \Delta_{SR,high\,traffic} \\ & \cdot \left(x_{pavement,high\,traffic_{n,s}} + x_{road,high\,traffic_{n,s}}\right) + \Delta_{SR,high\,traffic,road} \\ & \cdot x_{road,high\,traffic_{n,s}} + \Delta_{SR,high\,traffic,I} \cdot (x_{pavement,high\,traffic_{n,s}} \\ & + x_{road,high\,traffic_{n,s}}) \cdot x_{I_{n,s}} + \Delta_{SR,high\,traffic,road,I} \\ & \cdot x_{road,high\,traffic_{,ns}} \cdot x_{I_{n,s}}\end{aligned} \tag{8}$$

$$\begin{aligned}V_{WTC_{n,s}} = {} & \Delta_{WTC,I} \cdot x_{I_{n,s}} + \Delta_{WTC,road} \cdot x_{road_{n,s}} + \Delta_{WTC,male} \cdot x_{male_n} + \Delta_{WTC,high\,traffic} \\ & \cdot \left(x_{pavement,high\,traffic_{n,s}} + x_{road,high\,traffic_{n,s}}\right) \\ & + \Delta_{WTC,high\,traffic,road} \cdot x_{road,high\,traffic_{n,s}} + \Delta_{WTC,high\,traffic,I} \\ & \cdot (x_{pavement,high\,traffic_{n,s}} + x_{road,high\,traffic_{n,s}}) \cdot x_{I_{n,s}} \\ & + \Delta_{WTC,high\,traffic,road,I} \cdot x_{road,high\,traffic_{,ns}} \cdot x_{I_{n,s}}\end{aligned} \tag{9}$$

In an ordered logit model, the probabilities are driven by comparisons between the utility and the thresholds. When all attributes (x) in Equation (8) and (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 $x_{road,high\,traffic_{n,s}}$ and $x_{pavement,high\,traffic_{n,s}}$ 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.

[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.

We estimate parameters that explain the shifts in utility for different types of scenarios. For example, and for ease of notation not showing the subscripts SR (for stated risk) and WTC (for 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 & 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, 2006). 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 & Palma, 2019) where robust t-ratios have been used to account for the repeated choices of the individuals (cf. Daly & 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 and Table 4, 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 and the associated Figure 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.

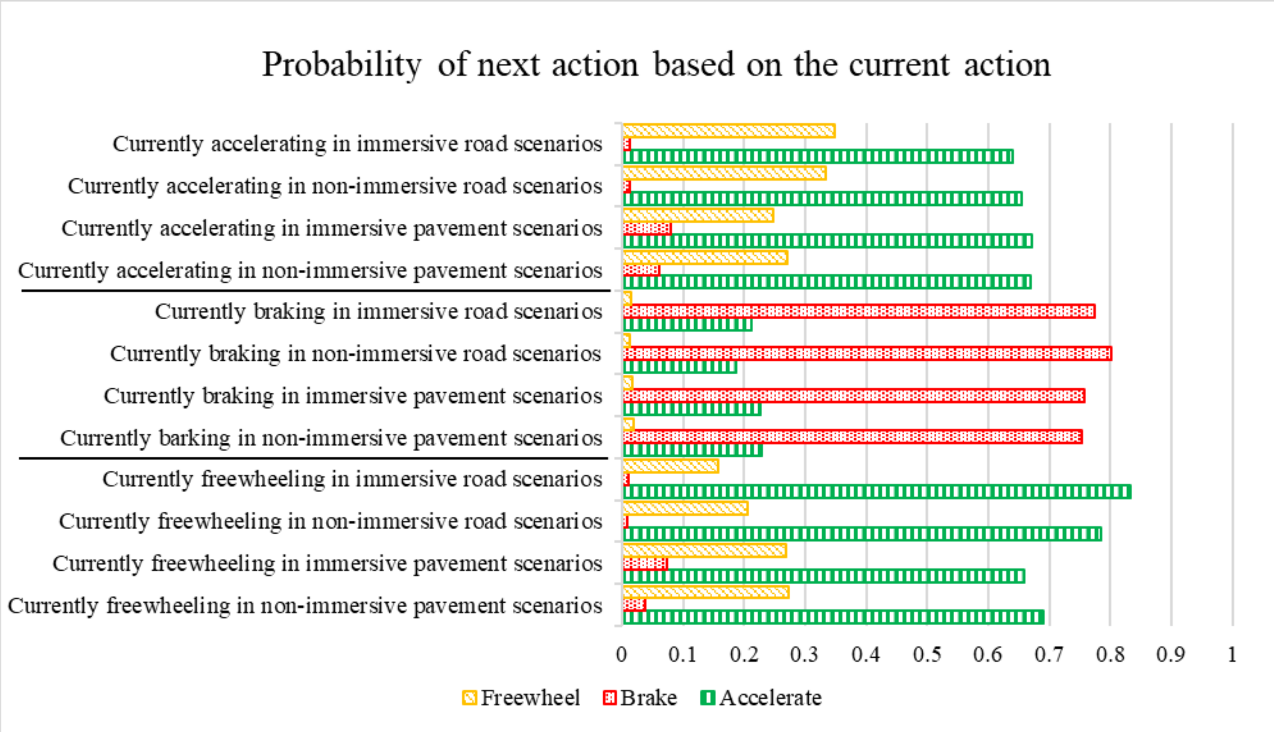
Table 2: A joint MNL model – action switch (robust t-ratios in brackets).

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 (Δ_δ)	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 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 behavioural differences can clearly be observed in the bottom panel of Figure 4.

Figure 4: Visual representation of probabilities of next actions conditional on the current action.



Altogether, the results in Table 2 highlight differences in cycling behaviour 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.

Table 3: A joint MNL model – lagged speed (robust t-ratios in brackets).

Impact on utility for	1st order lagged speed	2nd order lagged speed	3rd 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)	-

In Table 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 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.

Figure 5: Impact of speed on the probability of accelerating, braking and freewheeling at different current actions.

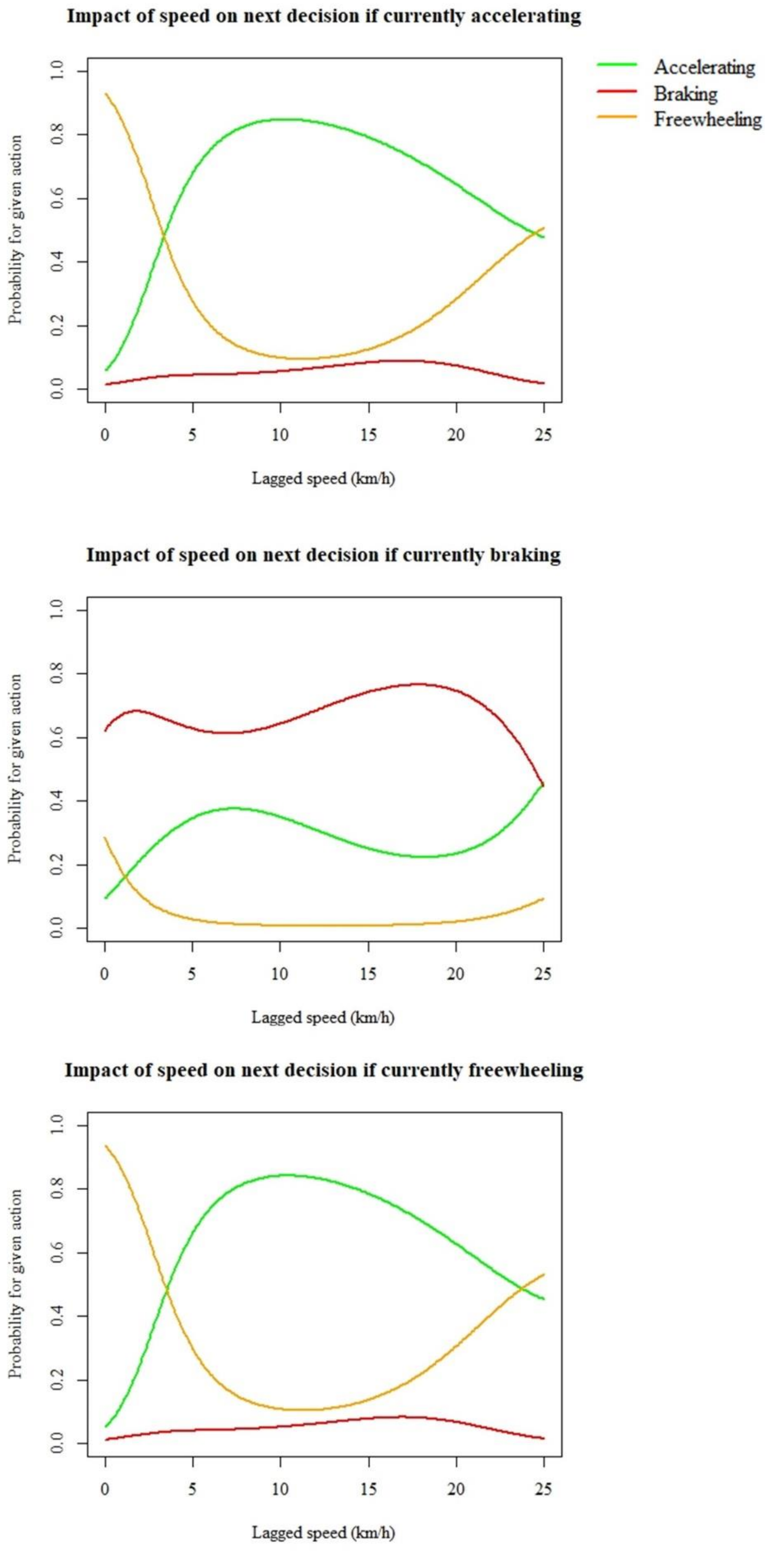


Table 4 shows the effects of the distance to the nearest passing vehicle or pedestrian on behaviour. Here, it is crucial to note that a negative sign of the estimate means that the further away a vehicle or pedestrian is, the more the utility for that action is reduced and hence the less likely it is 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.

Table 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)	-

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 distance 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 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 6, where we look only at the pavement scenarios[2]. 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 shows 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 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.

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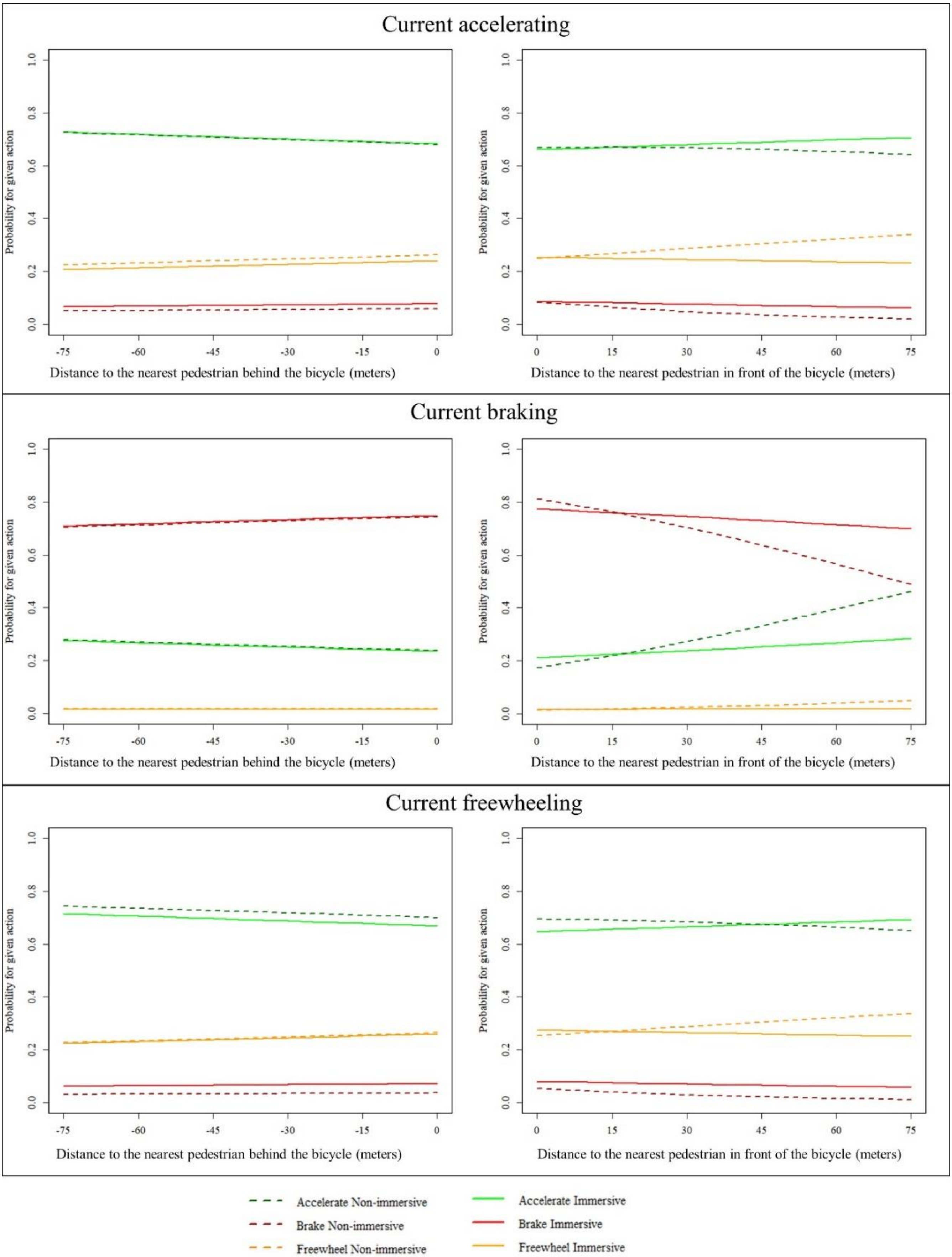
[2]Similar figures for the road scenarios are available in the supplementary file at: www.stephanehess.me.uk/papers/Bogacz_et_al_2020_online_appendix.pdf

Figure 6: Example of the impact of distance to pedestrians on the choice of the next action.



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 tendency 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 WTC 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 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. However, no differences are observed between the non-immersive and immersive scenarios, nor is the difference between low and high risk different 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 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 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 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 variables 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.

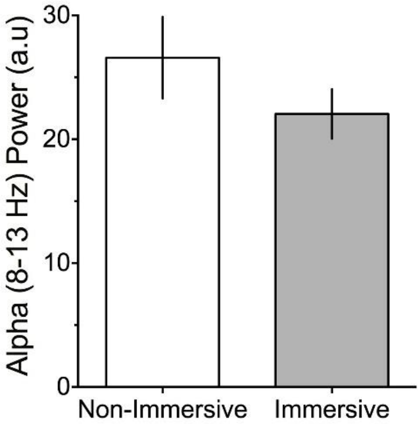
Table 6: An ordered logit model for stated willingness to cycle with interactions (classical and robust t-ratios in brackets)

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)
WTC 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 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).

Figure 7: Differences in α as a function of condition. Error bars represent standard errors of the mean (SEM).



The results presented here are in line with previous literature showing a robust relationship between increases in α power and relaxed states (Lagopoulos et al., 2009; Eoh et al., 2005) and decreases in α power and increased cognitive workload (Osaka, 1984; Glass & Kwiatkowski, 1970). 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 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 WTC 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 WTC 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 & 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 (De Hartog et al., 2010). 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. 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.

Disclosure statement

The authors declare no conflict of interest.

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