



Deposited via The University of Leeds.

White Rose Research Online URL for this paper:

<https://eprints.whiterose.ac.uk/id/eprint/159231/>

Version: Accepted Version

Article:

Bogacz, M, Hess, S, Calastri, C et al. (2020) Comparison of Cycling Behavior between Keyboard-Controlled and Instrumented Bicycle Experiments in Virtual Reality.

Transportation Research Record: Journal of the Transportation Research Board. ISSN: 0361-1981

<https://doi.org/10.1177/0361198120921850>

© National Academy of Sciences: Transportation Research Board 2020. This is an author produced version of an article published in Transportation Research Record: Journal of the Transportation Research Board. Uploaded in accordance with the publisher's self-archiving policy.

Reuse

Items deposited in White Rose Research Online are protected by copyright, with all rights reserved unless indicated otherwise. They may be downloaded and/or printed for private study, or other acts as permitted by national copyright laws. The publisher or other rights holders may allow further reproduction and re-use of the full text version. This is indicated by the licence information on the White Rose Research Online record for the item.

Takedown

If you consider content in White Rose Research Online to be in breach of UK law, please notify us by emailing eprints@whiterose.ac.uk including the URL of the record and the reason for the withdrawal request.

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

3

4 **Martyna Bogacz**

5 Institute for Transport Studies & Choice Modelling Centre

6 University of Leeds

7 34-40 University Road, Leeds LS2 9JT

8 Email: tsmb@leeds.ac.uk

9

10 **Stephane Hess**

11 Institute for Transport Studies & Choice Modelling Centre

12 University of Leeds

13 34-40 University Road, Leeds LS2 9JT

14 Email: s.hess@leeds.ac.uk

15

16 **Chiara Calastri**

17 Institute for Transport Studies & Choice Modelling Centre

18 University of Leeds

19 34-40 University Road, Leeds LS2 9JT

20 Email: c.calastri@leeds.ac.uk

21

22 **Charisma Choudhury**

23 Institute for Transport Studies and & Choice Modelling Centre

24 University of Leeds

25 34-40 University Road, Leeds LS2 9JT

26 Email: c.f.choudhury@leeds.ac.uk

27

28 **Alex Erath**

29 Singapore-ETH Centre

30 1 Create Way, CREATE Tower, #06-01, Singapore 138602

31 Email: erath@erveco.ch

32

33 **Michael van Eggermond**

34 The University of Applied Sciences and Arts of Western Switzerland

35 Hofackerstrasse 30, 4132 Muttenz, Switzerland

36 Email: michael.vaneggermond@fhnw.ch

37

38 **Faisal Mushtaq**

39 Institute of Psychological Sciences

40 University of Leeds

41 4 Lifton Pl, Leeds LS2 9JZ

42 Email: f.mushtaq@leeds.ac.uk

43

44 **Mohsen Nazemi**

45 Singapore-ETH Centre

46 1 Create Way, CREATE Tower, #06-01, Singapore 138602

47 Email: nazemi@ivt.baug.ethz.ch

48

49 **Muhammad Awais**

50 Energy and Environmental Institute

Bogacz, M., Hess, S., Calastri, C., Choudhury, C. F., Erath, A., van Eggermond, M. A., Mushtaq, F., Nazemi, M. & Awais, M.

1 University of Hull

2 Hull, HU6 7RX

3 Email: mawais102@gmail.com

4

5 Word Count: 8083 words + 2 table (250 words per table) = 8583 words

6 *Submitted [26/03/2020]*

7

1 **ABSTRACT**

2 The use of virtual reality (VR) in transport research offers the opportunity to collect behavioural data in a
3 controlled dynamic setting. VR settings are useful in the context of hypothetical situations where real-
4 world data does not exist and/or in situations which involve risk and safety issues making real-world data
5 collection infeasible. Nevertheless, VR studies can contribute to transport-related research only if the
6 behaviour elicited in a virtual environment closely resembles real-world behaviour. Importantly, as VR is
7 a relatively new research tool, the best-practice in terms of the experimental design is still to be
8 established. In this paper, we contribute to a better understanding of the implications of the choice of the
9 experimental setup by comparing cycling behaviour in VR between two groups of participants in similar
10 immersive scenarios – the first group controlling the manoeuvres using a keyboard and the other group
11 riding an instrumented bicycle. We critically compare the speed, acceleration, braking and head
12 movements of the participants in the two experiments. We also collect electroencephalography (EEG)
13 data to compare the alpha wave amplitudes and assess the engagement levels of participants in the two
14 settings. The results demonstrate the ability of VR to elicit behavioural patterns in line with those
15 observed in the real-world and indicate the importance of the experimental design in a VR environment
16 beyond the choice of audio-visual stimuli. The findings will be useful for researchers in designing the
17 experimental setup of the VR for behavioural data collection.

18
19 **Keywords:** virtual reality, instrumented bicycle, keyboard, EEG

1 INTRODUCTION

2 Virtual reality (VR) has become an increasingly popular tool for travel behaviour research. This
3 is because in the transport domain, it is often inherently difficult to collect real-life data in hazardous road
4 circumstances. VR provides a high degree of experimental control, safety and ease of data collection,
5 while at the same time allowing to collect data in a dynamic setting. Further, as in other domains, VR
6 makes it possible to collect data in hypothetical future scenarios allowing to pre-test behavioural
7 responses in the context of new modes and novel urban design. Consequently, it has been widely used in
8 previous studies in a transport context. For example, Mai (1) evaluated VR as a tool to analyse pedestrian
9 behaviour at midblock crossings and Frankenhuis et al. (2) explored male risk-taking behaviour while
10 crossing a bridge in an immersive environment. Finally, Moussa et al. (3) tried to apply the Augmented
11 Reality Vehicle system to left-turn manoeuvres at two-way stop-controlled intersections.

12 Nevertheless, the potential disadvantages of VR include motion sickness, high costs and most
13 importantly, the risk of an unrealistic representation of reality. The ecological validity of VR experiments
14 is one of its main issues, as it is widely known that experimental designs which have a different degree of
15 immersion or employ different equipment can elicit distinct behavioural responses. For example, Farooq
16 et al. (4) elicited preferences over Connected and Autonomous Vehicles comparing three methods: an
17 immersive reality technology, a conventional visual presentation and text-only descriptions. The findings
18 showed that preference for autonomous vehicles increased from 40% in text-only case, through 50% in a
19 visual presentation to 70% if VR was used. It was concluded that preferences elicited with immersive
20 equipment were more consistent with real world preferences and the understanding of scenarios
21 improved. Furthermore, Bogacz et al. (5), which looked at the differences in risk processing between 2D
22 and 3D cycling scenarios in VR, showed that the behavioural patterns from the experiments were similar
23 to the actual behaviour of cyclists on the roads. Moreover, the study found that the propensity to brake
24 was higher in the 3D presentations compared to the 2D scenarios. Patterson et al. (6) conducted two
25 experiments to investigate the influence of the presentation method on neighbourhood choice. The first
26 one was based on the textual description of the living area, while the second used VR simulations of the
27 neighbourhood. The results showed that preferences elicited with text-only surveys reflected participants'
28 subjective, imagined illustration of the described place, whereas, in the case of the visualizations, the
29 preferences were based on the observed material. It suggests that VR technology allows for constructing
30 experimental scenarios that give the researcher more control over factors that affect the respondents'
31 choices, but at the same time these studies clearly exhibit the fact that preferences are highly dependent
32 on the presentation format. This effect is expected to be even stronger within immersive technology
33 experiments, as they engage individuals to a larger extent than traditional survey methods. However, as
34 VR is still an innovative and relatively new research tool, the best practices are yet to be established
35 especially in the light of mixed evidence in the existing literature.

36 In contrast, the domain of driving simulators represents an exception, as there has been extensive
37 research on the factors that affect the behavioural congruence in simulated driving. For instance,
38 Underwood et al. (7), who assessed the comparability of driving on a road and in a simulator, concluded
39 that driving simulators can demonstrate similar patterns of differences across drivers as observed on
40 actual roads. However, this was only relative, in the sense that they were unable to create the same
41 hazardous situations on a road as can be designed in a simulator. Furthermore, Godley (8) examined the
42 validity of driving simulators by comparing driving behaviour in an instrumented car vs a simulator. They
43 showed similar deceleration activity under both conditions. Yet, on the other hand, individuals tended to
44 drive faster in the instrumented car relative to the simulator. To the best of our knowledge, there has not
45 been any similar in-depth investigation on the factors that affect the behavioural congruence in the
46 context of different variants of immersive cycling environments.

47 In this paper, we address this research gap and contribute to a better understanding of the
48 implications of the choice of the experimental setup by comparing the cycling behaviour in VR between
49 two groups of participants in similar immersive scenarios – the first group controlling the manoeuvres
50 using a keyboard and the other group riding an instrumented bicycle.

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

7 This is also likely to be reflected in their neural activity, which can be used as an indicator of the
8 level of engagement.

9 There are several studies in cognitive psychology which have looked at the effects of the use of
10 different input devices on the neural processing and the elicited behaviours. For example, key presses can
11 be considered discrete decisions and while they have been widely used in PC-based experiments before
12 (9), many studies have shown a continuous flow of information between the brain systems involved in
13 motor processes as opposed to previous assumptions about sequential stages in motor outputs (10-11).
14 These findings suggest that devices which allow for continuous rather than discrete input in terms of
15 motor decisions better mimic the neural processing of such decisions. Moreover, a study by Rupp et al.
16 (12) demonstrated that the use of a joystick, as opposed to a keyboard, resulted in lower mental workload
17 in a difficult task, which could suggest that keyboards are unsuitable input devices in complex control
18 tasks. Finally, a study by Chung et al. (13) investigated online shopping experience and purchase patterns
19 using both mouse-controlled and touch interface settings. They found that shoppers who used a touch
20 interface to browse products (vs. mouse) have a significantly higher engagement with their shopping
21 experience. The studies mentioned above show that there are possible differences in behaviour resulting
22 from the type of input device adopted, making the search for and testing of alternative solutions in
23 dynamic experiments a research priority.

24 In addition to comparing cycling behaviour in VR when using different devices to elicit
25 preferences, we also set out to explore the latter's impact on participants' neural activity as a proxy
26 measure of engagement. For this reason, we employed electroencephalography (EEG), a scalp-recorded
27 measure of the electrical activity generated by the brain. Typically, in the transport literature, the use of
28 EEG has largely focused on the investigation of driver fatigue and drowsiness (14-17), level of
29 alertness/attention or cognitive performance (18). However, little has been done to evaluate the
30 engagement of participants in the immersive environment from a neural perspective. In particular, the use
31 of neuroimaging devices in applied experimental research has been heavily constrained by the signal-to-
32 noise ratio of EEG, where artefacts in the data can stem from physiological (e.g. ocular, facial and body
33 muscle movements) and non-physiological sources (e.g. electric signals generated by nearby equipment,
34 as shown by Puce et al. (19)). Therefore, VR experiments which allow a great degree of flexibility in
35 participants' head and body movements are more prone to producing artefactual data. However, recent
36 wireless systems such as Emotiv EPOC+ (20) and Enobio (21) are designed for dynamic experimental
37 setups and attempt to mitigate the impact of movement artefacts on the scalp-recorded EEG.

38 In this paper, we compare a particular pattern of oscillatory brain activity known as occipital
39 alpha (α) to infer participant's engagement in the task. Occipital α , which is quantified through frequency
40 analysis of the signal ranging from 8 to 14 Hz, is one of the most commonly observed signatures of brain
41 activity, with numerous studies demonstrating a relationship between oscillations in this frequency band
42 and attentional processing (22-25). As such, the signal presents an ideal candidate to investigate the
43 impact of presentation format on participants' degree of task-relevant engagement.

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

48
49
50
51

1 **HYPOTHESES**

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

6 **Cycling speed**

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

9
10 Hypothesis 1B: There is more variance in speed in the instrumented bicycle experiment than in the
11 keyboard experiment.

12
13 It is hypothesized that the average speed will be higher in the keyboard-controlled experiment as it
14 requires less physical effort to accelerate compared to an instrumented bicycle. Moreover, the
15 acceleration is more instantaneous when using the keyboard. For the same reason, we expect that there
16 will be more variation in the speed observed in the instrumented bicycle experiment, as more physical
17 effort is needed to move through the scenarios, making it more difficult to maintain constant speed levels.

18
19 **Head movement**

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

22
23 We expect that the use of the instrumented bicycle will induce participants to inspect the environment,
24 resulting in more head movement (26-27). This would be due to the higher level of immersion in the
25 environment, due to the improved design compared to the keyboard, and due to the fact that braking in
26 case of any hazardous circumstances on the road will take longer on the instrumented bike compared to
27 instantaneous reaction while pressing the arrows on the keyboard.

28
29 **Acceleration & Braking**

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

32
33 Hypothesis 4: There is more variance in the braking behaviour in the instrumented bicycle experiment
34 than in the keyboard experiment.

35
36 Hypotheses 3 and 4 stem from the fact that the use of the instrumented bicycle provides more scope to
37 control behaviour, as participants intertwine acceleration and deceleration more often compared to a
38 keyboard. Cycling on the bike requires more physical effort and time to switch between subsequent
39 actions or respond to changing conditions on the road, whereas acceleration and braking are more
40 instantaneous with the keyboard.

41
42 **Neural processing**

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

45
46 Hypothesis 5 is based on the evidence from a large body of work showing the α wave to be a well-
47 established correlate of attentional processing with an increase in amplitude found as participants'
48 attention drifts away from the task (17, 28). On the other hand, current understanding in neuroscience
49 holds that a low α wave implies increased excitability, and thus an increased response to external stimuli

(29-30). 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.

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.

Keyboard-controlled experimental setup

The experimental session started with the participant being seated on a chair and having an Emotiv EPOC+ EEG headset (31) and an Oculus Rift VR (32) 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.



Figure 1: The immersive scenarios used in the experiment.

The experiment used 6 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 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 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

1 with their distance to the cyclist so that the sound of an approaching car increased as it got closer to the
2 cyclist.

3 The experiment comprised the same 6 scenarios. The repetition was used because we also
4 collected neural data which requires a higher number of trials in order to obtain more stability in the EEG
5 signal. The task for the participant was to cycle through the scenario at the desired pace until the finish
6 line at the end of each scenario. In order to navigate through the scenario, participants used the keyboard
7 to adjust their speed but had no ability to turn left or right. They pressed the up arrow to accelerate and the
8 down arrow to brake. The keyboard was placed on the table in front of them, and before the experiment
9 began, they were guided by the experimenter to find the appropriate keys on the keyboard. The
10 experimental setup of a keyboard-controlled experiment can be seen on right-hand side of **Figure 2**.

11 The visual stimuli in the experiment come from VR road simulations developed by Future Cities
12 Laboratory (33) using Unity 3D Game Engine (34). These stimuli involve pre-programmed environments
13 where the cars and pedestrian movements do not respond to the actions of the cyclist. That is to say, other
14 road users do not accelerate or decelerate in reaction to the chosen action of the cyclist (participant),
15 therefore collisions between the cyclist and cars/pedestrians were possible. Collisions were detected if a
16 cyclist overlapped visually with any other agent. Even though participants were specifically instructed to
17 avoid any collisions, there were 19 instances (3.2% of all scenarios by all participants) of collisions with
18 other road users. When this happened, the experiment was interrupted, and the participant was asked to
19 start again from the beginning of that scenario.

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

24 **Instrumented bike experimental setup**

25 The experimental design for the instrumented bicycle data collection was similar to the keyboard
26 counterpart in terms of the audio and visual stimuli used and number and types of cycling scenarios. The
27 experimental session commenced by familiarizing the participant with the instrumented bicycle, including
28 demonstrating how to use a hand brake (all the participants could ride a bike in reality). Subsequently, the
29 participant mounted the bike and the HTC Vive head mounted display (HMD) (35) and Enobio (36)
30 devices were placed on their head. The Enobio headset uses 8 electrodes (at FP1, FP2, Fz, C3, Cz, C4, P3
31 and P4) sampling across the scalp. The system allowed joint use with HTC Vive HMD. As a first step, the
32 baseline brain activity was recorded with the sampling rate of 128 Hz, while participants had their eyes
33 open and focused their gaze on one point on the screen for 1 minute. The same procedure was then
34 repeated with eyes closed. Before the main part of the experiment started, participants could familiarise
35 themselves with the use of the bicycle and the environment in a trial session.

36 The experiment consisted of 6 immersive presentations of traffic scenarios from the perspective
37 of the cyclists, shown in random order. The visual stimuli proceeded from the same source as before.
38 Similarly, the participant was asked to cycle through the scenario at the desired pace until the finish line
39 at the end of each scenario. In order to navigate through the scenario, the participant used the pedals of
40 the bicycle and had no ability to turn left or right. To brake, the participant used a hand brake positioned
41 on the right side of the handlebar. The instrumented bike can be observed on the left-hand side of **Figure**
42 **2**. The instrumented bike belongs to Future Cities Laboratories in Singapore.
43
44



Figure 2: Instrumented bicycle (FCL Singapore) and keyboard-controlled experiments (University of Leeds)

The scenarios used in these experiments 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 2 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.

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 (37- 38, 3) as the experiment duration is much longer and the associated cost much higher compared to typical stated preference (SP) studies.

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 (39) 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 (40) 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 1**:

$$a = \frac{\Delta v}{\Delta t} \quad (1)$$

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

1 *Braking*

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

7
 8 *Speed*

9 The speed is expressed in kilometres per hour (km/h). In the keyboard-controlled experiment, the
 10 maximum speed was capped at 25 km/h. This level was chosen based on the previous literature which
 11 showed that the average speed of cycling in the real world is between 13.5-16 km/h with standard
 12 deviation ranging from 3.2 - 8.4 km/h (41-43). Differently, in the instrumented bicycle experiment, there
 13 was no limit on the maximum speed. The restriction on the keyboard-controlled experiment was imposed
 14 in order to avoid unreasonable speeds, which could have been easily achieved with the constant pressing
 15 of the key, and to minimize the risk of motion sickness.

16
 17
 18 *Head movement*

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

23
 24 *EEG*

25 For the EEG analyses, we examined differences in mean α amplitude in keyboard-controlled and
 26 instrumented bicycle experiments. As the EEG signal collected through the scalp are inherently noisy, we
 27 undertook a number of steps to eliminate artefacts and improve the signal-to-noise ratio. Specifically, we
 28 first applied a 1-20 Hz bandpass filtering (BPF), a linear transformation that retains the components of the
 29 data within this specific band of frequencies (44) and removes frequencies outside of this range that may
 30 stem from physiological sources such as galvanic skin responses or external environmental sources such
 31 as electronic equipment (45). Next, we cleaned the data to remove noise stemming from eyeblinks
 32 (movement artefacts were corrected using a multiple source analysis method (46-47)). Finally, we
 33 computed the power spectrum of the EEG data using Welch’s method (48) which estimates the power
 34 spectra based on the Fast Fourier Transform (FFT) (49). Because of our interest in occipital α , we
 35 performed a region-of-interest analysis and took an average of the activity from electrodes O1, O2, P7,
 36 P8, T7 and T8 in the keyboard-experiment and electrodes P7, P8, C3, C4 in the instrumented bicycle to
 37 increase the stability of the signal (50).

38
 39 **RESULTS**

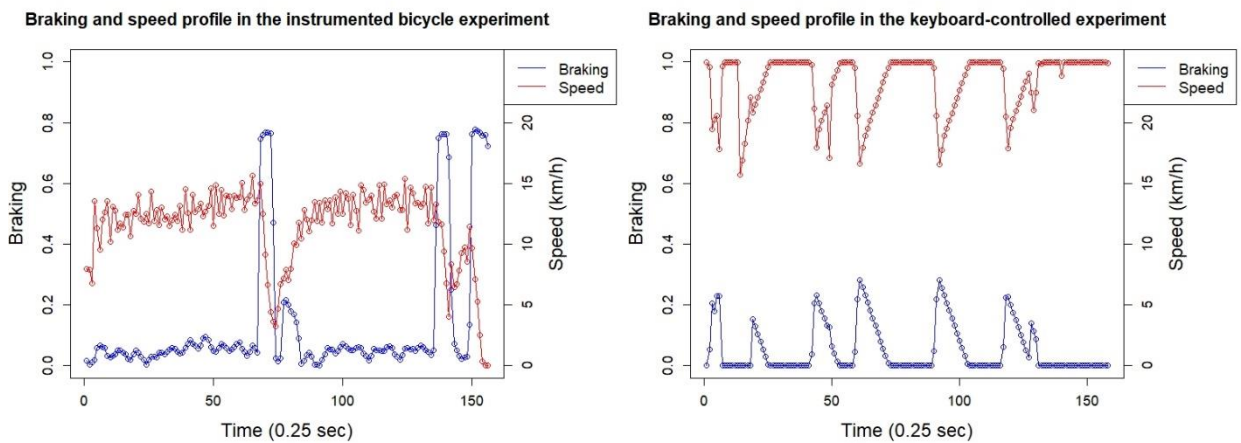
40 In this section, we present visual profiles of *Speed* and *Braking* for the two experiments and an
 41 overview of the descriptive statistics in **Table 1**. The table highlights clear differences between the mean
 42 values of the variables of interest in the two samples. Next, these differences are tested more rigorously
 43 using t-test and F-test, and the results are reported for each variable.

44
 45 **Table 1: Summary statistics of the variables of interest**

Variable	Units of measurement	Mean values in the keyboard-	Standard deviation values in the keyboard-	Mean values in instrumented	Standard deviation values in instrumented
----------	----------------------	------------------------------	--	-----------------------------	---

		controlled experiment	controlled experiment	bicycle experiment	bicycle experiment
<i>Speed</i>	km/h	22.90	4.93	14.32	7.03
<i>Head Yaw</i>	degrees	1.76	8.52	4.93	27.71
<i>Break</i>	degrees	0.03	0.10	0.23	0.25
<i>Acceleration</i>	m/s ²	0.11	1.29	0.02	2.68

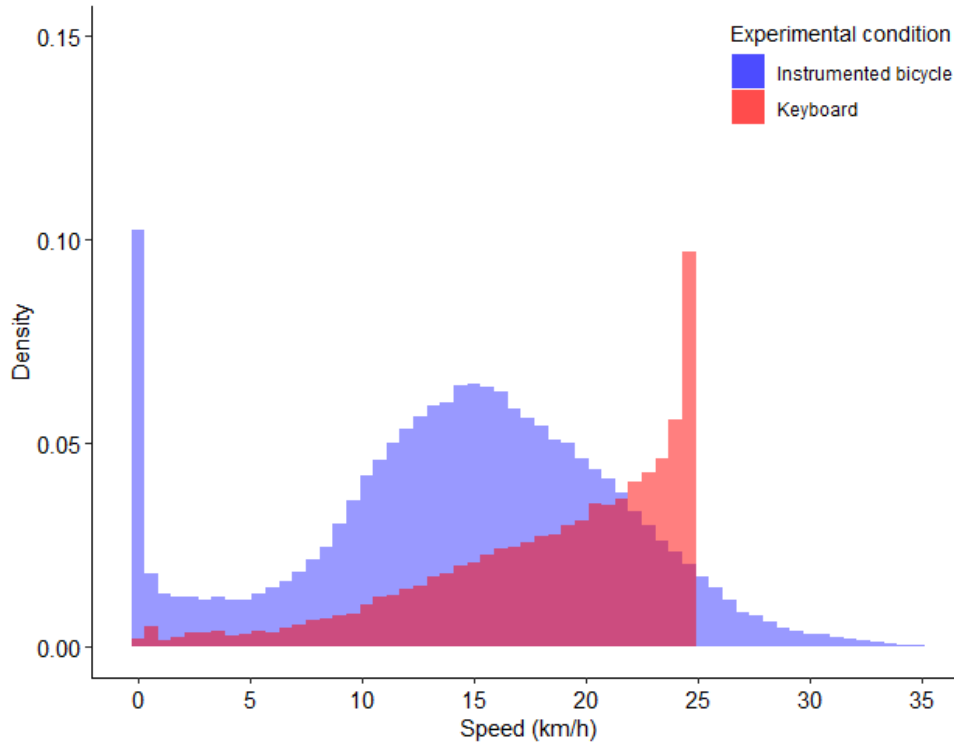
1
2 In **Figure 3**, we plot the profiles of the variables *Speed* and *Braking* for two randomly chosen participants
3 cycling in similar immersive scenarios but in the two different experimental settings. The graphs highlight
4 that both experiments captured participants' behaviour correctly, as higher values of *Braking* are
5 associated with lower *Speed*. At the same time, it is clear that the employment of the instrumented bike
6 resulted in a considerably higher amount of variation in *Speed* and *Braking* compared to the keyboard
7 experiment, where the profiles are smoother and less dynamic.
8



9
10 **Figure 3: Profiles of Braking and Speed in the two experiments for two randomly chosen participants.**

11 **Speed**

12 The one-sided Welch's t-test performed on the mean values of *Speed* at the individual level showed that
13 the mean *Speed* is significantly higher in the keyboard-controlled experiment ($t = -16.163$, $df = 70.134$, p -
14 value ~ 0). This result is in line with our Hypothesis 1A, where we expected that the lack of physical
15 effort and consequently relative easiness in developing higher speed would result in higher average speed
16 in the keyboard-controlled experiment. Moreover, when we compared the variances in mean *Speed*, we
17 found that the variance in the instrumented bicycle experiment was significantly higher compared to the
18 keyboard-controlled counterpart ($F(47,45) = 3.9252$, p -value = 0.000004777). Again, this result
19 conforms to our Hypothesis 1B. We show that the use of the bicycle induces people to adjust their speed
20 more often. It is also interesting to look at the density histogram of *Speed* in these two experiments
21 (**Figure 4**). We can see the near bell-shaped distribution of *Speed* in the experiment using the bicycle,
22 where the values are centred around the mean and there is more variation observed in contrast with the
23 keyboard-controlled experiments. A peak near zero can be observed in the instrumented-bicycle setting:
24 this relates to small movements when participants slowed down to stop (while waiting to cross the street
25 or give priority to pedestrians who crossed their bike lane). In contrast, in the keyboard experiment, we
26 observe a skewed distribution of *Speed* where the majority of observations correspond with the maximum
27 possible level, equal to 25 km/h. This suggests that the removal of physical effort and the use of a
28 keyboard contributes to the choice of maximum speed regardless of the scenario conditions.



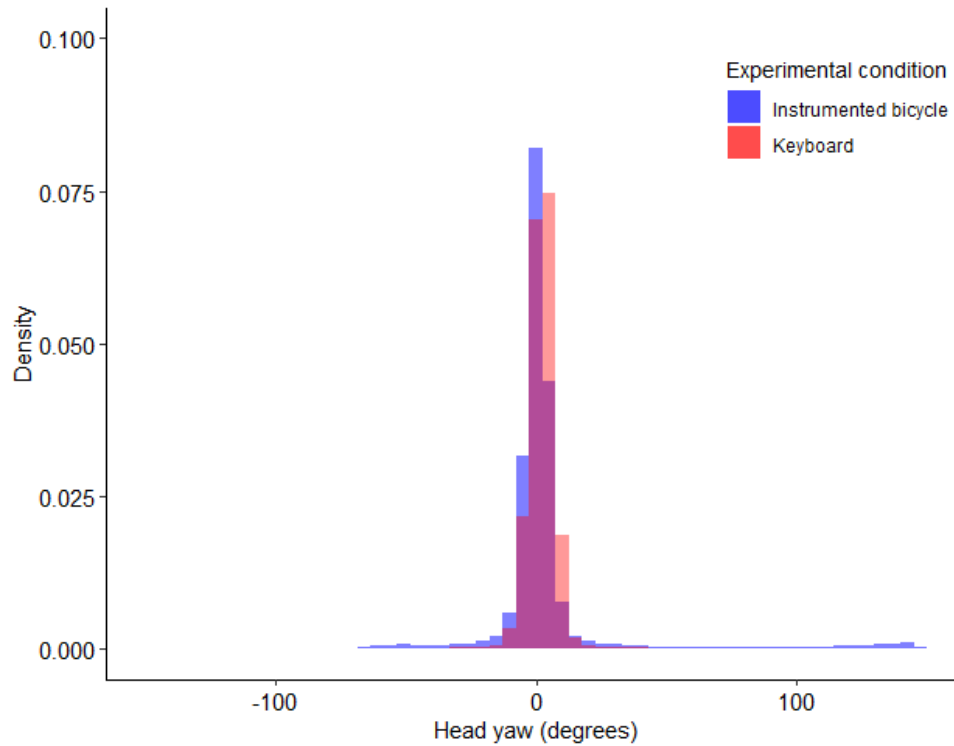
1

2 **Figure 4: Histograms of Speed in the two experimental settings.**

3

4 **Head movement**

5 Head movement is an indication that the participant is making an effort to gather information beyond the
6 peripheral vision. The one-sided Welch's *t*-test of *Head Yaw* demonstrated that the average head
7 movement is significantly higher in the instrumented bicycle experiment as opposed to the keyboard-
8 controlled setting ($t = 2.3944$, $df = 89.987$, $p\text{-value} = 0.009362$). This is in line with our Hypothesis 2,
9 where we expected more head movement to the sides in the instrumented bicycle experiment due to more
10 complex mechanism of control over the bicycle compared to keyboard, which in turn required
11 participants to explore the environment to a larger extent in order to be able to react more quickly. The
12 density histogram of the *Head Yaw* values (**Figure 5**) shows this trend, as it includes a wider range of
13 values for instrumented bicycle compared to the keyboard experiment. It suggests that the use of the
14 instrumented bicycle induces participants to inspect the environment more than a keyboard due to the
15 higher level of immersion in the environment and due to the fact that braking in case of any hazardous
16 circumstances on the road will take longer on the instrumented bike compared to instantaneous reaction
17 while pressing the arrow on the keyboard.



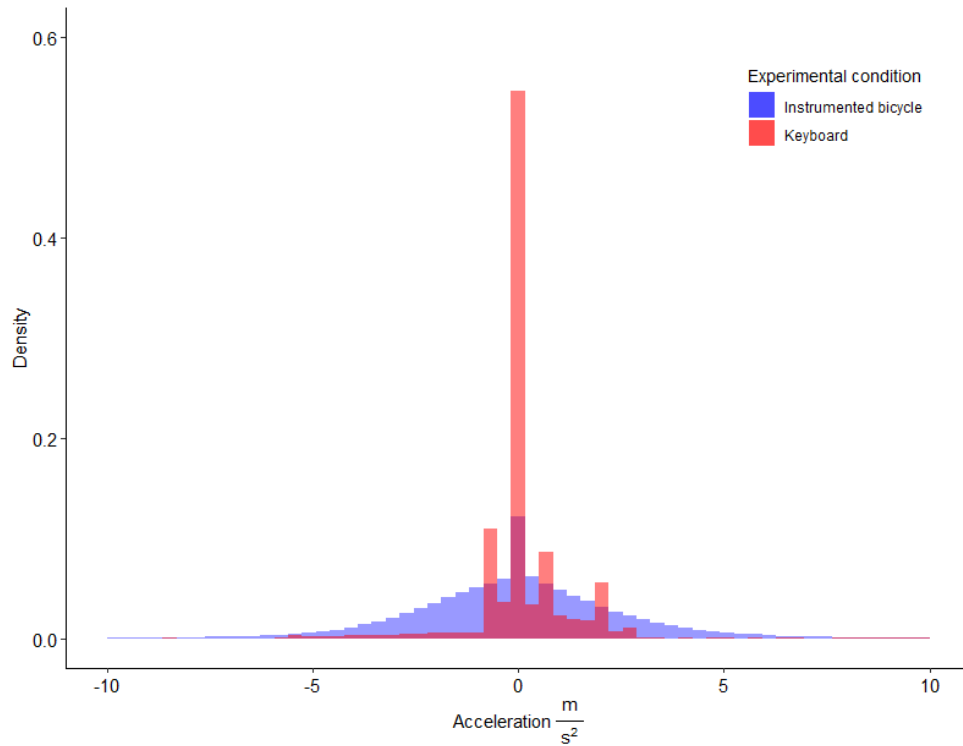
1

2 **Figure 5: Histograms of Head Yaw in the two experimental settings.**

3

4 **Acceleration**

5 The results of the one-sided F-test showed that the variance of *Acceleration* is significantly larger in the
6 instrumented-bike experiment ($F(47,45) = 3.1474$, $p\text{-value} = 0.00008789$). This is in line with our
7 Hypothesis 3: we expected higher variation in acceleration due to the presence of physical effort and
8 higher difficulty in maintaining constant speed. The density histogram for *Acceleration* presented in
9 **Figure 6** reflects the results of the test, as we observe that the *Acceleration* values are accumulated near
10 the mean with little variation in the keyboard-controlled experiment and have a near bell-shape
11 distribution in the other experiment.

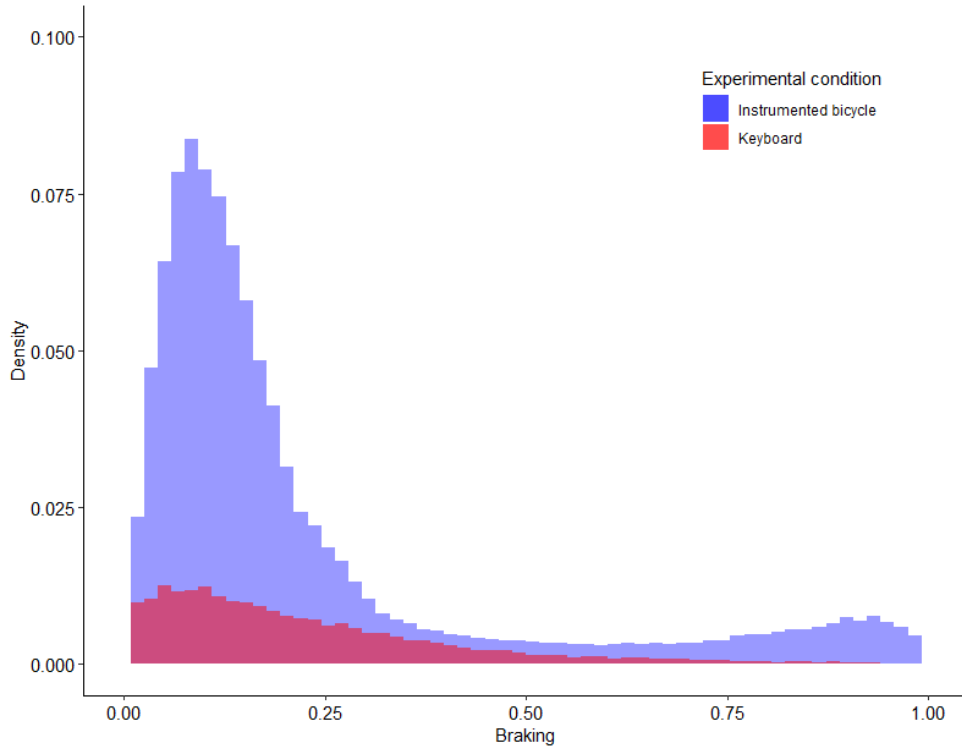


1

2 **Figure 6: Histograms of Acceleration in the two experimental settings.**

3 **Braking**

4 The result of one-sided F-test showed that the variance of *Braking* is significantly larger in the
5 instrumented-bike experiment ($F(47,45) = 3.8141$, $p\text{-value} = 0.000007114$). This result conforms to our
6 Hypothesis 4 that more variance is present in the instrumented-bicycle experiment. Again, the density
7 histogram of *Braking* in **Figure 7** visually reflects the results of the test, as there is more variation in an
8 experiment that used an instrumented bicycle.



1
2 **Figure 7: Histograms of Braking in the two experimental settings.**

3
4 **Amplitude of α wave**
5 The one-sided Welch’s t-test demonstrated that the mean α amplitude is lower in the instrumented bicycle
6 experiment as opposed to the keyboard-controlled at the 90% confidence level ($t = 1.35$, $df = 40.79$, p -
7 $value = 0.09$), which is in line with our Hypothesis 5, where we expected a lower α amplitude in
8 instrumented bicycle experiment due to the more immersive setting and higher cognitive engagement
9 compared to the keyboard.

10
11
12 **DISCUSSION**

13 VR experiments can effectively contribute to transport research only if the behaviour elicited in a
14 virtual environment closely resembles real-world behaviour. Hence, it is important to be able to
15 discriminate between different experimental designs that employ immersive technologies. The objective
16 of the present paper was to compare the cycling behaviour elicited in two separate experiments which
17 used the same visual stimuli but different devices to control the navigation through the simulated
18 scenarios. The first one employed a keyboard and the second one an instrumented bicycle. In order to
19 draw conclusions about the behaviour, we analysed participants’ speed, acceleration, braking and head
20 movements, along with data about their neural activity. The results are summarized in **Table 2**, where we
21 also show examples from the existing literature which reached similar results in different experimental
22 contexts. This highlights not only that our findings are in line with the literature, but that we confirm
23 these results for the context of cycling and for the joint use of immersive technology and EEG.

24 **Table 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 (51) with driving simulator
1B	There is more variance in speed in the instrumented bicycle experiment than in the keyboard experiment.	True	Godley et al. (8) with driving simulator
2	The average head movement is higher in the instrumented bicycle experiment than in the keyboard experiment.	True	Sitzmann et al. (26) focusing on head movement in VR; Underwood et al. (7) 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. (52) with driving simulator
4	There is more variance in the braking behaviour in the instrumented bicycle experiment than in the keyboard experiment.	True	Godley et al. (8) 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. (53) in the context of brainwave entertainment in VR

1
2 Overall, the results show significant differences in behaviour. A more active and varied behaviour
3 is observed in the instrumented bicycle experiment as compared to the keyboard-controlled study. For
4 instance, the average speed is lower and more heterogeneous in the instrumented bicycle experiment,
5 suggesting that participants dedicate more time to explore the environment. Moreover, the average speed
6 in the instrumented bicycle experiment of 14.32 km/h is closer to the average speed of cycling in reality,
7 which ranges between 13.5-16 km/h, in contrast to the keyboard counterpart where average speed was
8 considerably higher in spite of the cap of 25km/h. It suggests that the use of the instrumented bicycle
9 instead of the keyboard allows for better approximation of the real cycling kinematics.

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

15 Our work provides evidence that the instrumented bicycle is more effective than the keyboard
16 controls in eliciting behavioural patterns demonstrated by previous naturalistic studies of cycling
17 behaviour. We use these studies as a benchmark due to the lack of evidence in the previous literature with
18 regard to typical, real-life cycling behaviour in absolute terms. Moreover, our results are consistent with
19 previous studies conducted in other contexts that investigated the effects of the use of various input
20 devices on behaviour, as presented in the introduction and in **Table 2**. The use of a keyboard, or in fact
21 any other input device such as a joystick or touchpad, makes the cycling experience clearly less realistic
22 as the user does not need to exert physical effort, a crucial component associated with cycling. It then
23 follows that changes in action could be seen as less consequential as they do not impact on physical
24 fatigue. This relates both to the actual action (e.g. accelerate) as well as the degree thereof. On the other
25 hand, the advantages of the use of a keyboard or other simple devices cannot be ignored. Their use as an
26 input device is cheaper and less time consuming than the employment of the stationary bicycle. They are
27 also more portable which makes it easier to collect data in different locations. Moreover, if VR is used
28 jointly with neuroimaging devices, then a simpler input device offers a more static approach, reducing the
29 extent of potential noise in the neural data stemming from body movements. The choice of the input
30 device for VR experiments is thus not an arbitrary decision and should be aligned with the objectives of
31 the study to not constrain the spectrum of behaviour which can be captured and minimise the potential

1 biases resulting from the mere choice of the controller. The decision of an appropriate input tool also has
2 to be weighed against technical capabilities such the budget, duration of the experiment and comfort of
3 the participants as well as a possibility of joint use with other equipment employed in the study. In this
4 paper, we compare only two devices. However, it is important to take into consideration other available
5 appliances such as a 3D mouse, joystick, steering wheel, gamepad or hybrid controller which may offer
6 different benefits depending on the design of the study.

7 The results thus emphasize the importance of the experimental setup in a VR experiment beyond the
8 choice of appropriate visual stimulus. The findings extend understanding of the effects of the use of
9 distinct input devices within the VR domain by demonstrating that the use of an instrumented bicycle
10 increases the realism of the cycling simulations by influencing the manoeuvring decisions. These results
11 were further reinforced by the analysis of neural data. Further research needs to be conducted to
12 generalize these findings. In particular, we recommend testing different cycling scenarios as well as
13 experiments focusing on different aspects of travel behaviour to compare participants' actions in the
14 experimental setting with real-world decisions. The findings shed light on the level of behavioural
15 congruence of the state-of-the-art VR studies which will be valuable in the interpretation and the level of
16 confidence in the results of different VR studies. It is also expected to be a valuable resource to
17 researchers and practitioners planning to administer VR-based data collection and help them to better
18 design the experimental setup as there has been a significant interest in using VR for modelling cycling
19 behaviour (54-55). By comparing and contrasting the behaviour of cyclists in the two VR environments,
20 the paper is expected to provide guidance to researchers investigating cycling behaviour in dynamic
21 setting and hence improve the modelling of speed and acceleration of cyclists which can feed into safety
22 research or capacity analyses for instance. The findings are also expected to be useful for planners who
23 are interested in deploying VR to more realistically test the impact of different urban designs on the
24 propensity to cycle, indicating, for example, the road and pavements features which contribute to the
25 higher perception of safety among cyclists. The research findings can hence help transport and urban
26 planners in making more informed choices regarding urban infrastructure. Finally, VR tools are
27 increasingly being used in designing vehicles of the future – the interaction between connected and
28 automated vehicles (CAVs) and other road users. The findings can help researchers modelling the
29 interaction between cyclists and CAVs in designing their experiments and better interpreting the results
30 by giving an idea about the comparative realism of the collected data.

31 32 33 **ACKNOWLEDGMENTS**

34 Martyna Bogacz, Stephane Hess, Charisma Choudhury and Chiara Calastri acknowledge the support of
35 the European Research Council through the consolidator grant 615596-DECISIONS.

36 37 **AUTHOR CONTRIBUTIONS**

38 The authors confirm contribution to the paper as follows: study conception and design: M. Bogacz, S.
39 Hess, C. Choudhury, C. Calastri, A. Erath, M. Van Eggermond ; data collection: M. Bogacz, M. Nazemi;
40 analysis and interpretation of results: M. Bogacz, S. Hess, C. Choudhury, C. Calastri, F. Mushtaq; draft
41 manuscript preparation: M. Bogacz, S. Hess, C. Choudhury, C. Calastri. All authors reviewed the results
42 and approved the final version of the manuscript.

43 44 **DECLARATION OF CONFLICTING INTERESTS**

45 The authors declared no potential conflicts of interest with respect to the research, authorship, and/or
46 publication of this article.

REFERENCES

1. Mai, K. L. (2017). *Evaluation of PC-Based Virtual Reality as a Tool to Analyze Pedestrian Behavior at Midblock Crossings*. (Master's thesis, California Polytechnic State University).
2. Frankenhuys, W. E., Dotsch, R., Karremans, J. C., & Wigboldus, D. H. (2010). Male physical risk taking in a virtual environment. *Journal of Evolutionary Psychology*, 8(1), 75-86.
3. Moussa, G., Radwan, E., & Hussain, K. (2012). Augmented reality vehicle system: Left-turn manoeuvre study. *Transportation research part C: emerging technologies*, 21(1), 1-16.
4. Farooq, B. Cherchi, E., & Sobhani, A. (2018). Virtual immersive reality for travel behaviour analysis: A case study of autonomous vehicles on urban roads. forthcoming *Journal of the Transportation Research Board*.
5. Bogacz, M., Calastri, C., Choudhury, C. F., Hess, S., Erath, A., van Eggermond, M. A., & Mushtag, F. (2018, August). *Processing cycling risk under different elicitation methods: comparing 2D and 3D in virtual reality choice environments*. Presented at 99th Annual Meeting of the Transportation Research Board, Washington, D.C., 2019.
6. Patterson, Z., Mostofi-Darbani, J., Rezaei, A. & Zacharias, J. (2017) Comparing Text-only and Virtual Reality Discrete Choice Experiments of Neighborhood Choice. *Landscape and Urban Planning*, 157, 63-74.
7. Underwood, G., Crundall, D., & Chapman, P. (2011). Driving simulator validation with hazard perception. *Transportation research part F: traffic psychology and behaviour*, 14(6), 435-446.
8. Godley, S. T., Triggs, T. J., & Fildes, B. N. (2002). Driving simulator validation for speed research. *Accident analysis & prevention*, 34(5), 589-600.
9. Szul, M. J., Bompas, A., Sumner, P., & Zhang, J. (2019). The validity and consistency of continuous joystick response in perceptual decision-making. *bioRxiv*, 501536.
10. Cisek, P., & 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, 801–814.
11. Spivey, M. J., Grosjean, M., & Knoblich, G. (2005). Continuous attraction toward phonological competitors. *Proceedings of the National Academy of Sciences*, 102, 10393–10398.
12. Rupp, M. A., Oppold, P., & McConnell, D. S. (2015). Evaluating input device usability as a function of task difficulty in a tracking task. *Ergonomics*, 58(5), 722-735.
13. Chung, S., Kramer, T., & 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.

Bogacz, M., Hess, S., Calastri, C., Choudhury, C. F., Erath, A., van Eggermond, M. A., Mushtaq, F., Nazemi, M. & Awais, M.

14. Awais, M., Badruddin, N., & Driberg, M. (2017). A hybrid approach to detect driver drowsiness utilizing physiological signals to improve system performance and wearability. *Sensors*, 17(9), 1991.
15. Lal, S. K., & Craig, A. (2001). A critical review of the psychophysiology of driver fatigue. *Biological psychology*, 55(3), 173-194.
16. Eoh, H. J., Chung, M. K., & Kim, S. H. (2005). Electroencephalographic study of drowsiness in simulated driving with sleep deprivation. *International Journal of Industrial Ergonomics*, 35(4), 307-320.
17. Craig, A., Tran, Y., Wijesuriya, N., & Nguyen, H. (2012). Regional brain wave activity changes associated with fatigue. *Psychophysiology*, 49(4), 574-582.
18. 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.
19. Puce, A., & Hämäläinen, M. (2017). A review of issues related to data acquisition and analysis in EEG/MEG studies. *Brain sciences*, 7(6), 58.
20. Duvinage, M., Castermans, T., Dutoit, T., Petieau, M., Hoellinger, T., De Saedeleer, C., ... & Cheron, G. (2012). A P300-based quantitative comparison between the Emotiv Epoc headset and a medical EEG device. *Biomedical Engineering*, 765(1), 2012-2764.
21. Ratti, E., Waninger, S., Berka, C., Ruffini, G., & Verma, A. (2017). Comparison of medical and consumer wireless EEG systems for use in clinical trials. *Frontiers in human neuroscience*, 11, 398.
22. Klimesch, W., Doppelmayr, M., Russegger, H., Pachinger, T., & Schwaiger, J. (1998). Induced alpha band power changes in the human EEG and attention. *Neuroscience letters*, 244(2), 73-76.
23. Sauseng, P., Klimesch, W., Stadler, W., Schabus, M., Doppelmayr, M., Hanslmayr, S., ... & 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.
24. Thut, G., Nietzel, A., Brandt, S. A., & 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.
25. Klimesch, W. (2012). Alpha-band oscillations, attention, and controlled access to stored information. *Trends in cognitive sciences*, 16(12), 606-617.
26. Sitzmann, V., Serrano, A., Pavel, A., Agrawala, M., Gutierrez, D., Masia, B., & Wetzstein, G. (2016). How do people explore virtual environments?. *arXiv preprint arXiv:1612.04335*.
27. Hu, B., Johnson-Bey, I., Sharma, M., & Niebur, E. (2017, March). Head movements during visual exploration of natural images in virtual reality. In *2017 51st Annual Conference on Information Sciences and Systems (CISS)* (pp. 1-6). IEEE.

Bogacz, M., Hess, S., Calastri, C., Choudhury, C. F., Erath, A., van Eggermond, M. A., Mushtaq, F., Nazemi, M. & Awais, M.

28. Hawkins, G. E., Mittner, M., Boekel, W., Heathcote, A., & Forstmann, B. U. (2015). Toward a model-based cognitive neuroscience of mind wandering. *Neuroscience*, 310, 290-305.
29. Jensen, O., & Mazaheri, A. (2010). Shaping functional architecture by oscillatory alpha activity: gating by inhibition. *Frontiers in human neuroscience*, 4, 186.
30. Klimesch, W., Sauseng, P., & Hanslmayr, S. (2007). EEG alpha oscillations: the inhibition-timing hypothesis. *Brain research reviews*, 53(1), 63-88.
31. EMOTIV EPOC+ - 14 Channel Wireless EEG Headset. (2018). Available at: <https://www.emotiv.com/epoc/>. [Accessed: 17.12.2018]
32. Oculus. (2018). Available at: <https://www.oculus.com>. [Accessed: 17.12.2018]
33. Schramka, F., Arisona, S., Joos, M., & Erath, A. (2017). Development of Virtual Reality Cycling Simulator, in 3rd *International Conference on Virtual Reality*, paper presented at 3rd International Conference on Virtual Reality, Hong Kong.
34. Unity. (2017). *Unity - Game Engine*. [online] Available at: <https://unity3d.com> [Accessed 10.11.2018].
35. Vive.com. (2019). *VIVE™ | Discover Virtual Reality Beyond Imagination*. [online] Available at: <https://www.vive.com/uk/> [Accessed 2.08.2019].
36. Neuroelectronics. (2019). *Products / ENOBIO / ENOBIO 8 5G*. [online] Available at: <https://www.neuroelectronics.com/products/enobio/enobio-8-5g/> [Accessed 2.08.2019].
37. Di Stasi, L. L., Renner, R., Catena, A., Cañas, J. J., Velichkovsky, B. M., & 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.
38. Katsis, C. D., Goletsis, Y., Rigas, G., & Fotiadis, D. I. (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.
39. Welch, B. L. (1947). The generalization of student's' problem when several different population variances are involved. *Biometrika*, 34(1/2), 28-35.
40. Johnston, J. (1972). *Econometric Methods* (Second ed.). New York: McGraw-Hill.
41. Dozza, M., & 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.
42. Schleinitz, K., Petzoldt, T., Franke-Bartholdt, L., Krems, J., & 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.

43. Huertas-Leyva, P., Dozza, M., & 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.
44. Christiano, L. J., & Fitzgerald, T. J. (2003). The band pass filter. *international economic review*, 44(2), 435-465.
45. Repovs, G. (2010). Dealing with noise in EEG recording and data analysis. In *Informatica Medica Slovenica*, 15(1), 18-25.
46. Berg, P., & Scherg, M. (1994). A multiple source approach to the correction of eye artifacts. *Electroencephalography and clinical neurophysiology*, 90(3), 229-241.
47. Ille, N., Berg, P., & 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.
48. 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.
49. Shaker, M. M. (2006). EEG waves classifier using wavelet transform and Fourier transform. *brain*, 2, 3.
50. Oken, B. S., & Chiappa, K. H. (1986). Statistical issues concerning computerized analysis of brainwave topography. *Annals of Neurology: Official Journal of the American Neurological Association and the Child Neurology Society*, 19(5), 493-494.
51. Bella, F. (2008). Driving simulator for speed research on two-lane rural roads. *Accident Analysis & Prevention*, 40(3), 1078-1087.
52. Reymond, G., Kemeny, A., Droulez, J., & 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.
53. Argento, E., Papagiannakis, G., Baka, E., Maniadakis, M., Trahanias, P., Sfakianakis, M., & 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.
54. Nazemi, M., van Eggermond, M. A., Erath, A., & Axhausen, K. W. (2018). Studying cyclists' behavior in a non-naturalistic experiment utilizing cycling simulator with immersive virtual reality. *Arbeitsberichte Verkehrs-und Raumplanung*, 1383.
55. Nazemi, M., van Eggermond, M. A., Erath, A., Schaffner, D., Joos, M., & Axhausen, K. W. (2019). Studying bicyclists' perceived level of safety using a cycling simulator combined with immersive virtual reality. In *8th International Cycling Safety Conference (ICSC 2019)*.