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The comparison of behaviours and physiological responses of travelling by bicycle and e-Scooter in a multi-modal virtual reality setup

***Shun Su[1], Robin C. O. Palmberg[2, 3], Martyna Fidler[1], Yusak Susilo[1]**

[1] University of Natural Resources and Life Sciences (BOKU), Department of Landscape, Spatial and Infrastructure Sciences, Institute for Transport Studies, Vienna, Austria
[2] KTH Royal Institute of Technology, School of Industrial Engineering and Management, Integrated Transport Research Lab, Stockholm, Sweden
[3] CrossModal AB, Stockholm, Sweden
*shun.su@boku.ac.at

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Extended Abstract

1. Introduction

In recent years, the transportation landscape has undergone a noteworthy shift with the proliferation of new tools under the concept of micro-mobility, such as e-Bike, electric scooters (e-Scooter), e-Skateboard, and e-Monowheel (Daniel et al., 2021). These novel modes of transportation have been integrated into the existing infrastructure and have brought with them new riding activities that have had and continue to have impacts on the transportation system and other road users (Fonseca et al., 2021). Of particular intrigue is the shared utilization of city infrastructure by bikes and e-Scooters, notably in the coexistence within urban bike lanes (Lambros et al., 2023). While this shared use offers potential efficiency gains in urban mobility, it prompts a critical questions concerning urban transportation management and infrastructure planning: should these modes be segregated or treated uniformly?

In accordance with the framework proposed by Cook et al. (2022), bikes and e-Scooters both fall within the dominion of micro-mobility modes. However, a closer examination of their propulsion mechanisms reveals inherent distinctions. Specifically, e-Scooters draw power from electric assistance in tandem with user-initiated actions (Pender et al., 2020), whereas traditional bikes firmly adhere to the realm of active travel modes, relying solely on human effort (Cook et al., 2022). The dichotomous nature of these two modes raises questions about the extent of their operational differences and the criteria for assessing their adequacy and integration into the transport infrastructure. To address these inquiries necessitates a comprehensive comparative study to delve deeper into the nuanced differences characterizing these transportation modes. Presently, there are relatively few comparative studies in this field, most of efforts have predominantly focused on aspects such as their competitive coexistence in transportation operations (Moran et al., 2021; Łukasz et al., 2021), patterns of utilization (Bieliński et al., 2020; Younes et al., 2020), accident analyses (Shah et al., 2021; Haworth et al., 2021), as well as evaluations of their physical performance (Boglietti et al., 2022). Nevertheless, a conspicuous gap persists in behavioural comparisons of users, especially the quantitative exploration of decision-making processes from psychological perspectives. This knowledge, in turn, holds the potential to provide a comprehensive understanding of the overall user experience of individuals utilizing both modes of transportation, which should be the guidance of developing of management strategies and infrastructure design for those transport modes (Berrio et al., 2020).

The purpose of this research is to fill the gap by developing an advanced multi-modal virtual reality (VR) experiment data collection method that includes physiological and behavioural measurements within a sophisticated VR platform equipped with novel simulators of bike and e-Scooter, resulting in a well-structured dataset. Then, using this dataset to capture psychological effects and explore the relationship between cognition, physiological response and decision-making processes of both bike and e-Scooter users in same traffic situation, further supporting comparative studies between these modes. Meanwhile, through this study, it is expected to gain a deeper insight into the challenges associated with such data collection and processing efforts, as well as explore potential solutions that can be taken in behavioural within VR setup.

2. Method

The method comprises the experimental design and measurement design. By applying experimental studies in multi-modal virtual setup, as platform, behavioural, physiological and perception data were collected via sensors and simulators from the task sessions, then established a structured dataset.

2.1. Experimental design

The experimental setup utilizes Augmented Virtuality (AV) (Gonzalez et al., 2021) with semi-immersive configuration with two projectors. By applying the method of 3D modelling and traffic micro-simulation in VR (Erath et al., 2016), a scenario of virtual urban area in Vienna city with dynamic traffic situation was created (as show in **Figure 1**). In the scenario, a within-subject approach was adopted, where each participant was subjected to two experimental tasks of riding bike simulator as well as e-Scooter simulator on the dedicated bike lane of Schottenring street. In each task, participants need to make a round trip with a total length of 1.6 km in street, and interact with bikes, pedestrians and cars, etc. according to the traffic condition and characteristics as in real life.

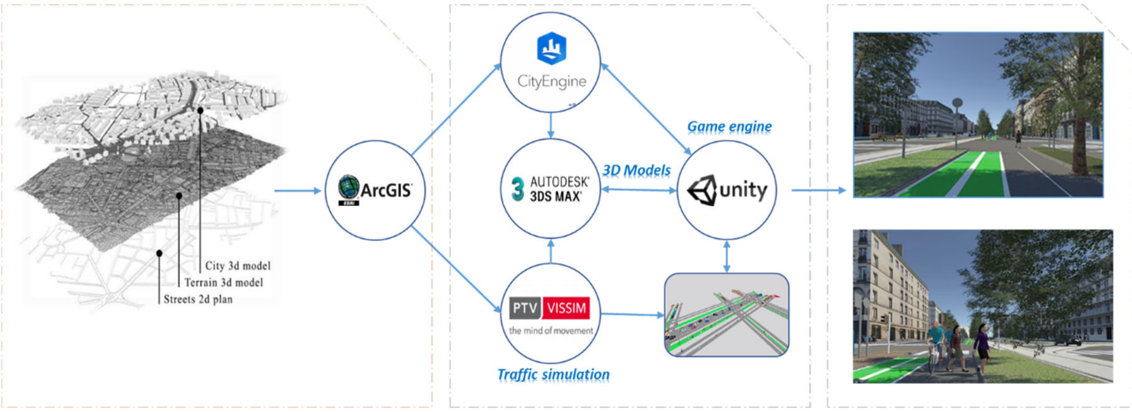

Figure 1. Virtual Reality scenario of shared bike lane in Schottenring Street with dynamic traffic in Vienna city

2.2. Measurement design

To facilitate data collection, a novel framework of a hybrid measuring system was developed, which combined the approaches of questionnaire survey, behavioural, and physiological measurements (see **Figure 2**).

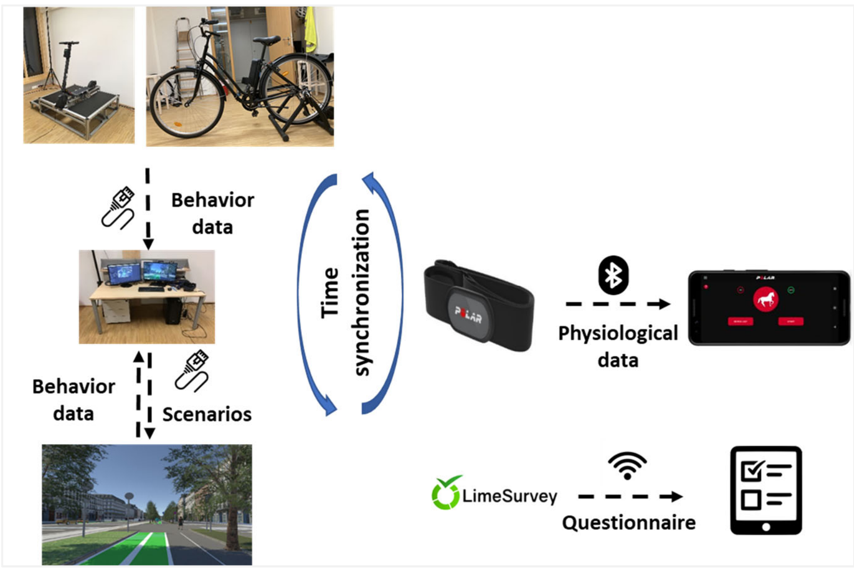

Figure 2: Framework of the measuring system in the experiment

In alignment with Schaffarczyk et al. (2022) reliability study of physiological sensors, the Polar H10 chest strap sensor was employed for precise electrocardiogram (ECG), heart rate, and R-R Interval data collection, seamlessly interfacing with a smartphone app via Bluetooth. Novel bike and e-Scooter simulators, integrated with the Unity game engine, facilitated the acquisition of behavioural data, automatically stored in an Excel file. Subjective perceptions

were measured through a standardized Paas scale (Sweller, 2018), administered via the LimeSurvey system on tablets, allowing for the collection of not only perceptual data but also socio-demographic and screening information.
Rigorous time synchronization were implemented across all devices to ensure data accuracy and temporal alignment before the start of each task. The coordinated functions of these devices are summarized in **Figure 2**.

2.3. Experiment procedure and implementation

A standard procedure that was followed by each participant before and during the experiment period, which consisted of the following steps:

- Before the experiment, each participant was required to complete the screening survey and socio-demographic survey.
- Each participant attended one testing sessions, lasting no longer than 40 minutes.
- The experimental session started with baseline task of resting in chair to collect the baseline activity of physiological responses of the participant.
- Then, the participant was given practice trials at the beginning of the experiment so that they could familiarise themselves with the equipment and ask any questions before the experiment begins.
- During the session, the participant was asked to perform two riding tasks with bike and e-Scooter simulators according to specific instructions (see in **Figure 3**).
    - Before each riding task, there are a 2-minute resting time for each participant on chair for recovery.
- Along all task sessions, according to the setup of each task, measurements and data storage were applied as in the framework of a measuring system.

Figure 3. Experimental implementation

The target group for the experiment were adults between 18 and 60 years old, they have a normal or corrected-to-normal vision and no acute or chronic physical or mental disorders.

All the participants signed a consent form after being informed about of the exact contents of the experiment, their rights and obligations.
A total of 24 individuals were recruited from students and staff of University of Natural Resources and Life Sciences and Vienna University of Technology, in addition to the general public. The data collection took place from 1st to 22nd September 2023.

2.4. Dataset establishment

During the experimental sessions, 1 GB of big data were collected via Polar H10 sensors, bike and e-scooter simulators and an online survey system. The total data comprised 5 types of variables, namely behavioural data of riding simulators, physiological signals, perceptual ratings, as well as social demographic and screening survey data (see in **Figure 4**).

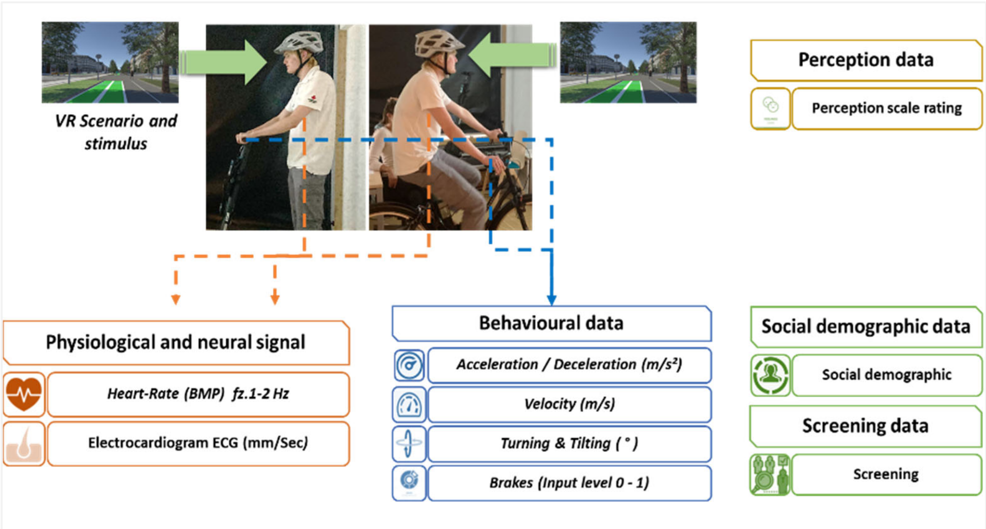

Figure 4. Dataset contents

The integration of experimental data from various sources was crucial for a comprehensive view and seamless analysis. This process aimed to achieve two key objectives: 1) support data fusion studies that explore the relationship between physiological data and behaviours, 2) facilitate the testing of cognitive and behavioural theories in dynamic scenarios. To effectively integrate several types of experimental data under various conditions and at different analytical levels, we have employed a high-temporal resolution framework featuring a 1000 Hz (1 millisecond) for saving physiological and behavioural data as well as a distinct framework for static questionnaire data on perception, socio-demographics and screening questions. The dataset structure comprised of two essential components, the dynamic data framework and static data framework, which are seamlessly connected as depicted in **Figure 5**, offering the versatility to be utilized either separately or jointly, tailored to the specific research objectives.

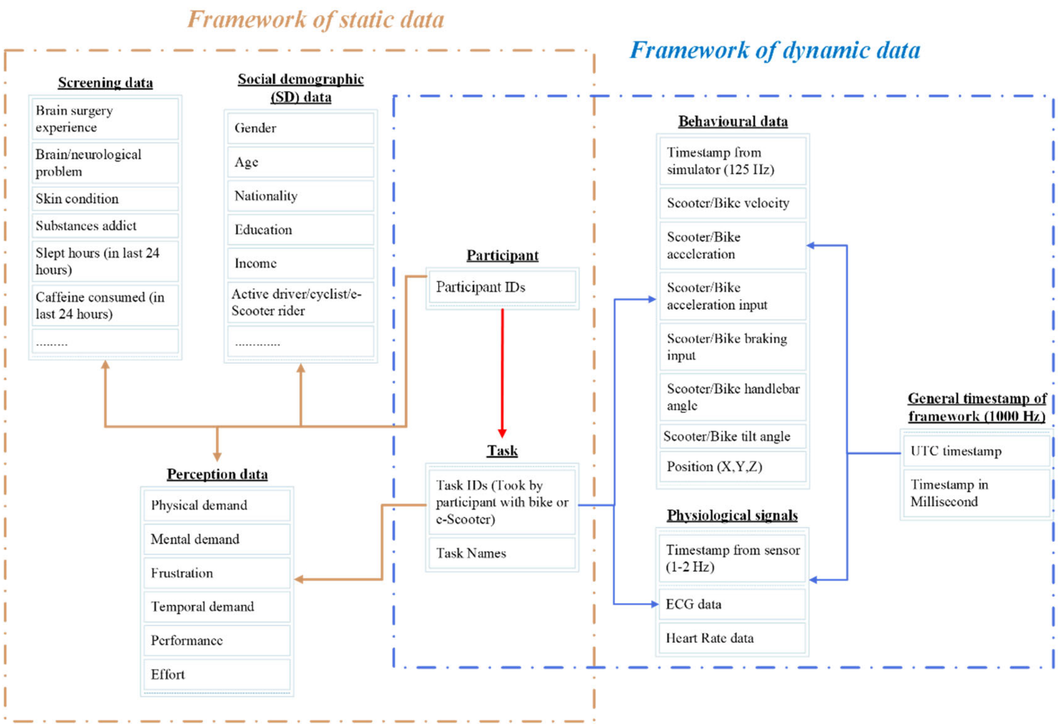

Figure 5. Dataset structure (frameworks)

3. Dataset application on a simple model development

In an effort to validate the feasibility and ability of the dataset for conducting behavioural comparison analyses, we undertook the development of a basic model. This model aimed to compare two specific riding behaviours observed in our experiments: traditional cycling and e-Scooter riding, with a particular focus on their impact on physiological responses – in this case, heart rates – of participants. Through analysis, we sought to discern and compare the distinct influences of riding behaviours of these two tasks on heart rate regulation.

3.1. Data pre-processing

According to objectives of model, pre-processing procedure was focused on raw heart rate and behavioural data due to occasional sensor system outliers. To ensure data accuracy, heart rate data were cleaned based on established adult cycling norms, setting a maximum heart rate of 192 bpm (Nakagata et al., 2019) and a minimum resting heart rate of 40 bpm (Quer et al., 2020). For behavioural data, we adhered to predefined criteria; for example, speed data from both simulators were set at 6.94 m/s (25 km/h) according to the operating policy of Vienna city (Stadt Wien, 2019). Finally, this data cleaning process resulted in a dataset of

Repeated-Measures (Kristensen et al., 2004) comprising 1,656,258 records from 24 participants.

3.2. Variables

In this model, heart rate data serves as a crucial objective indicator to represent both physical activity intensity and psychological or emotional responses, which are treated as the outcome variables. In addition, to provide information of behaviour, variable speed data in both bike and e-Scooter tasks was involved. Meanwhile, social demographic variables, such as gender, age, etc., were also considered as potential factors influencing physiological responses during tasks.

3.3. Model development

To estimate the relationship between 2 tasks (riding bike and e-Scooter) and physiological responses of participants, specifically heart rate values, we conducted repeated measurements. The repeated nature of these measurements introduced dependencies between observations that make it necessary to consider regression assumptions to accurately model the data. Specifically, we needed to account for the random heteroscestadicity resulting from differences between 24 participants (**Figure 6**), ensuring that the effects identified in the model represent the true impacts of the independent variables on the dependent variable and not unobserved variation between all participants.

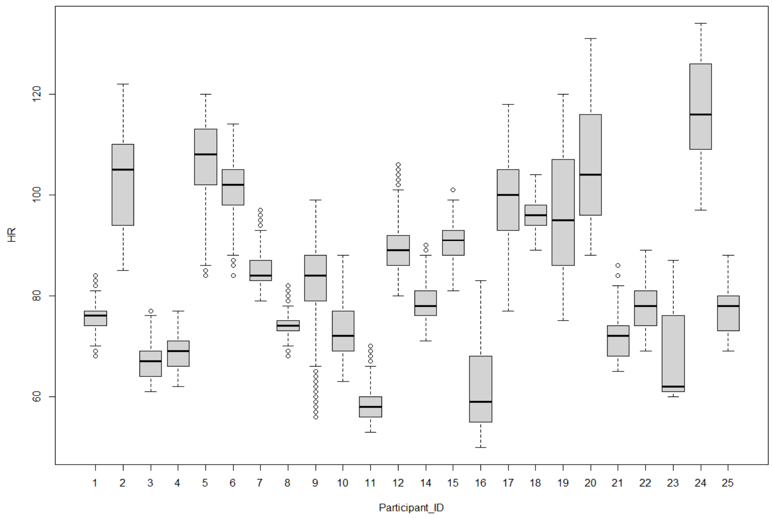

Figure 6. Heart rate value range of participant over the experiment period, n=24

To address this issue, we employed mixed-effects models incorporating both fixed and random effects that enable us to model variation between individuals and within individuals across the repeated measurements. In this case, a random intercept term was introduced to

capture the variations among participants across their multiple physiological measurements (heart rate) in all tasks, where such individual variation can be removed from the fixed effects, making fixed effects more realistic.
The linear mixed regression model is represented in **Equation 1 and 2**:

$$Y_{ij} = \beta_{0j} + \beta_1 x_{1j} + \ldots + \beta_m x_{mj} + e_{0ij} \qquad (1)$$
$$\beta_{0j} = \beta_0 + u_{0j} \qquad (2)$$

Where:

$Y_{ij} =$ $physiological\ measurement\ (heart\ rate\ value)\ i\ of$ individual j
$\beta_{0j} = intecept\ of$ individual j
$x_{mj} =$ $exposure\ variable\ m\ of$ individual j
$\beta_m = model\ coefficent\ for\ variable\ m$
$\beta_0 =$ $a\ fixed\ component$
$u_{0j} = specific\ component\ of$ individual j
$e_{0ij} = error$

From the equations 1 and 2, we assume that physiological measurement (heart rate value) 'i' of individual 'j', is influenced by their exposure to various factors denoted as x_{mj}, and these exposures have specific coefficients (β_m) that determine the strength and direction of their impact on heart rate. The equation incorporates both fixed components β_0 that are constant for all individuals and random components u_{0j} that are specific to each individual, accounting for his or her variations. Random errors (e_{0ij}) are also added.
Through the implementation of this approach, we developed a mixed linear incorporating different types of exposure variables for predicting physiological responses. The independent variables, along with their definitions and descriptive statistics, are presented in **Table 1**.
Fitting and comparisons of these four models were conducted using the coefficient of determination R-squared (R^2). All modelling procedures were carried out in R version 4.2.2 using the lme4 package.

Table 1: Selected variables and descriptive statistics (observations n = 1,656,258)

Variables	**Description**	**Mean**	**Std. Dev.**
Dependent variable			
Heart rate (HR)	Measured in beats per minute (BPM) representing physiological responses during tasks	84.85	17.01
Independent variables			

Task			
Task_Bike	Dummy variable: yes = 1, no = 0. Task of riding Bike simulator in virtual scenario.	0.45	0.50
Task_Scooter	Dummy variable: yes = 1, no = 0. Task of riding e-Scooter simulator in virtual scenario.	0.55	0.50
Behaviour			
Velocity	The speed is collected in units of meters per second (m/s) from the e-scooter and bike simulators	1.26	1.14
Social demographic			
Age_Group(<20)	Dummy variable: yes = 1, no = 0. Participant group of age lower than 20.	0.03	0.17
Age_Group(20-30)	Dummy variable: yes = 1, no = 0. Participant group of age between 20 and 30.	0.22	0.42
Age_Group(30-40)	Dummy variable: yes = 1, no = 0. Participant group of age between 30 and 40.	0.21	0.41
Age_Group(40-50)	Dummy variable: yes = 1, no = 0. Participant group of age between 40 and 50.	0.28	0.45
Age_Group(>50)	Dummy variable: yes = 1, no = 0. Participant group of age above 50.	0.25	0.44
Gender_Female	Dummy variable: yes = 1, no = 0. Gender of female	0.57	0.49
Active_cyclist	Dummy variable: yes = 1, no = 0. Active cyclist in daily life.	0.58	0.49

3.4. Preliminary results and discussion

A mixed linear model is developed to explore the relationships between different task bike and e-scooter, behaviour, social demographic factors, and physiological responses, specifically heart rate. The model diagnostics from each model are displayed in (**Table 2**).

Table 2: Mixed linear regression model results (n =1,656,258, groups: Participant_ID, 24)

Fixed effects	**Model**			**Note**
Independent variables	***Coeff.***	***t-value***		
Intercept	119.10	8.59	***	Signif. codes: 0 ‘***’, 0.001 ‘**’, 0.01 ‘*’, 0.05 ‘.’, 0.1 ‘ ’
Task				
Task_Bike	-0.37	-37.74	***	
Behaviour				
Velocity	0.34	77.41	***	
Social demographic				
Age_Group(20-30)	-9.61	-0.71		
Age_Group(30-40)	-31.84	-2.25	*	

Age_Group(40-50)	-34.12	-2.60	*	
Age_Group(>50)	-39.91	-2.98	**	
Active_cyclist	-4.98	-0.80		
Gender_Female	-7.76	-1.36		
Random effect	***Variance***	***Std.Dev.***		
Intercept	142.30	11.929		
Fit Statistics				
R2	0.89			
Model p-value	< 0.001			

The model conducted in this analysis aimed to elucidate the relationship between heart rate (HR) and several key variables, including Task_Bike, Active_cyclist, Gender, and Age_Groups (using Age_Group(<20) as the reference category). To account for the interdependence of repeated measurements within individuals, Participant_ID was included as a random effect (see in **Figure 7**). The model demonstrated a moderate level of explanatory power, with a conditional R^2 of 0.89, signifying that it could account for 89% of the variance in heart rate.

Our findings revealed several noteworthy outcomes. Task_Bike exhibited a statistically significant negative impact on HR ($\beta = -0.37$, $p < .001$) (**Figure 8A**), indicating that bike riding led to lower HR compared to e-Scooter task. Conversely, Active_cyclist and Gender_Female displayed non-significant negative effects on HR, suggesting that being an active cyclist or identifying as female did not significantly influence HR. The effects of age were particularly noteworthy. Age_Group(20-30) demonstrated a non-significant negative effect on HR (**Figure 8B**), implying that individuals in this age group did not significantly differ in HR compared to the reference group. However, as age increased, HR decreased significantly. Age_Group(30-40), Age_Group(40-50), and Age_Group(>50) all exhibited statistically significant negative effects on HR (**Figure 8C, 8D, 8E**). This pattern indicated that older age groups had lower HR compared to the reference group, highlighting the impact of age on HR during tasks.
Additionally, velocity emerged as a significant factor, exerting a positive influence on HR ($\beta = 0.34$, $p < .001$) (**Figure 8F**). This result indicates that higher velocity is associated with elevated heart rates, underlining the role of speed in affecting HR during these activities.
In summary, our analysis provides valuable insights into the relationship between HR and various factors, including task type, physical activity, gender, age, and velocity. These findings contribute to a better understanding of the physiological responses and behaviours associated with both bike and e-Scooter.

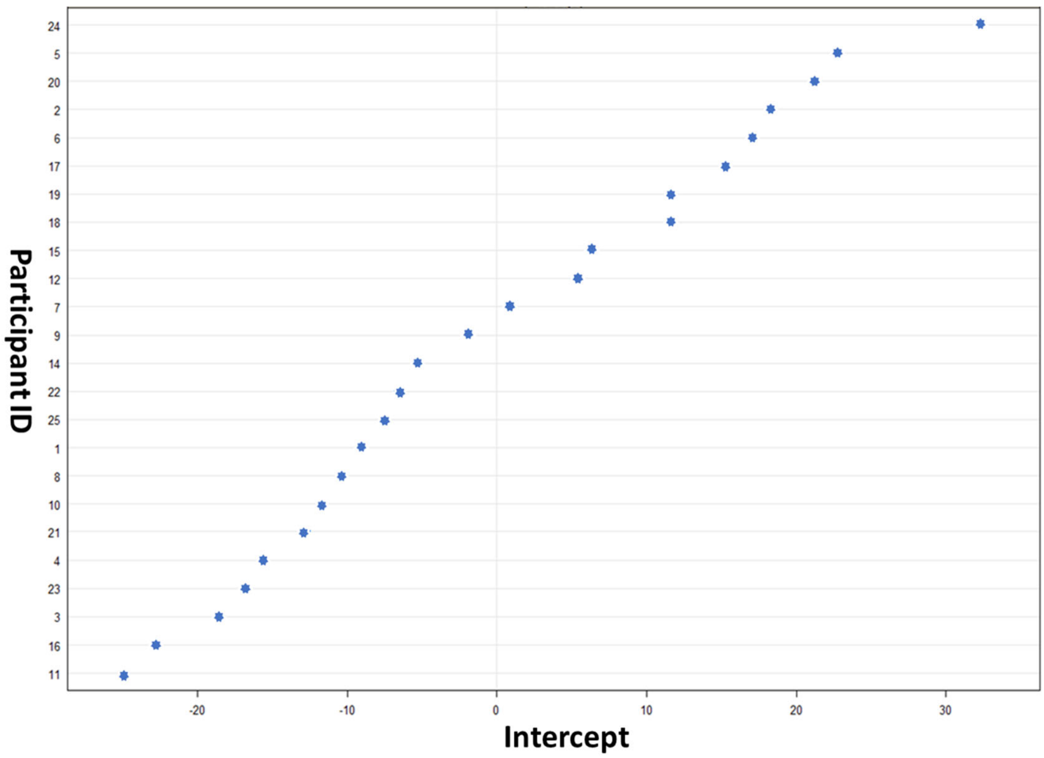

Figure 7. Random effects of individuals in mixed linear model

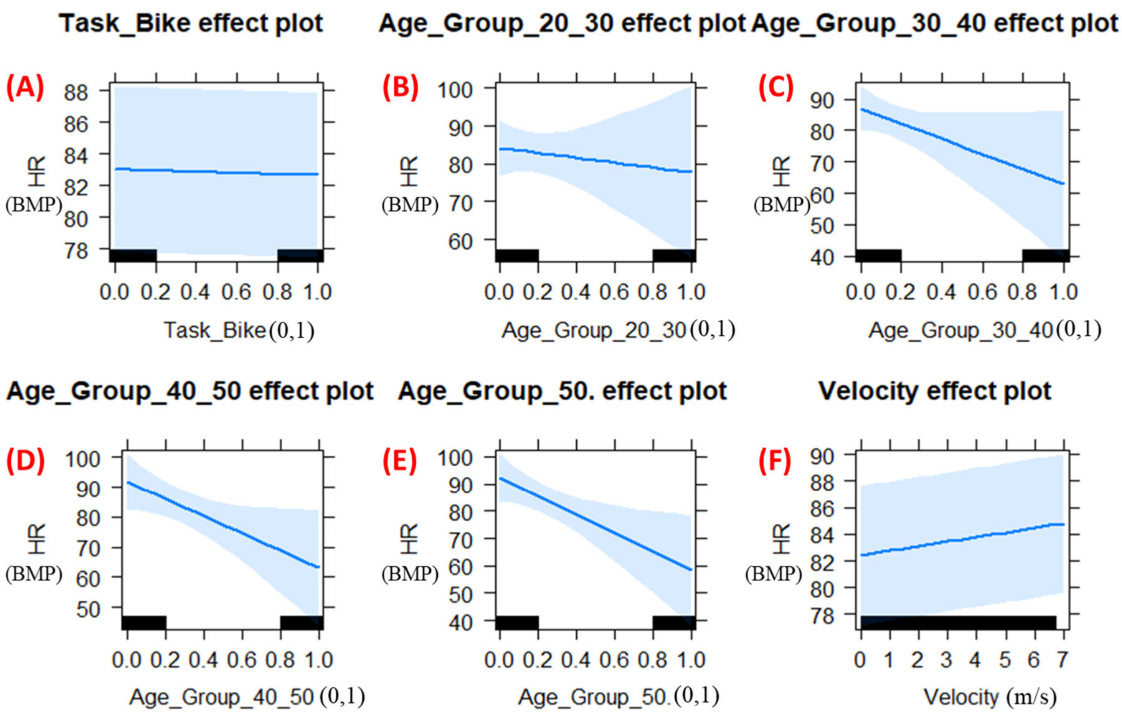

Figure 8. Fixed effects of individuals in mixed linear model

As from the primary result of the model, it proves that this dataset enabled the comparison of bike and e-Scooter riding tasks by exploring the quantitative relationship between the behaviour and physiological responses. Overall, from the exploratory data analysis on this dataset, the value and functionality of this dataset can be demonstrated.

4. Conclusion and further work

This research worked towards filling this gap of behavioural comparison study between bike and e-Scooter by using a structured dataset gathered through experiments that can explore the relationship between cognition, physiological response and decision-making processes. With these goals in mind, this paper proposed a novel data collection method that encompasses multi-modal VR experimental platforms with two novel simulators and incorporated a comprehensive framework for physiological, behavioural, and perceptual measurements. Additionally, a comprehensive dataset that integrated different types of data sources and allowed for bike and e-Scooter comparison in VR scenario has been established utilizing two frameworks comprising of static and dynamic data. Through a simple mixed effects model analysis, the dataset showed its feasibility and ability to reveal the relationship between physiological responses and behaviours among bike and e-Scooter users, and potentially enrich knowledge of the complexity of causal relationships during decision-making processes in behavioural comparison research.

As the data collection has just been completed and many of the variables are still being processed, a follow-up analysis will be comparative studies of interactive behaviours and event-related stress level detection between bike and e-Scooter using the dataset.

Ethical approval

The study was approved by the University of Natural Resources and Life Sciences Ethics Committee (Reference number: BOKU-2023/003).

Conflict of interests

The authors declare no conflict of interest.

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