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Modelling the effect of travel experiences in modal choice using virtual reality and physiological sensor data

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ABSTRACT

The effect of experiences on travel mode choices is well established in the literature. Additionally, there is evidence that psychophysiological signals, such as skin conductance, can capture travel experiences without relying on self-reported measures, given their strong correlation with psychological states. However, using physiological data to estimate the effect of experiences on choices remains unexplored due to challenges in data collection. The advent of virtual reality (VR) presents a unique opportunity to gather such data under controlled laboratory conditions and explore how travel experiences shape future demand. This paper uses data collected from a set of VR experiments where participants repeatedly chose between different travel modes, including current (car, bus, ride-hailing) and futuristic options (autonomous vehicle, air-taxi, hyperloop). After making their choice, they experienced the mode in the VR environment, and indicated whether they would have preferred another option. This is the first experiment to analyse psychological states and modal choice within a VR environment, and the first to use physiological data to assess how experienced psychological states affect future choices. We estimate a dynamic hybrid model that accounts for the effects of inertia and lagged latent stress, meassured through Galvanic Skin Conductance. Our findings show that driving in VR was the most stress-inducing option, reducing the likelihood of repeating that choice. Additional results, methodological implications, and the potential of VR for other travel behaviour studies are discussed.

1. Introduction

The transportation literature has widely acknowledged the effect of experience on travel choices (De Vos et al., 2021; Abou-Zeid et al., 2012), as well as the backward effect of modal choices on travel satisfaction (Gärling et al., 2019; Abou-Zeid and Ben-Akiva, 2010; De Vos, 2019; Guan et al., 2024; Susilo and Cats, 2014; Le and Carrel, 2021), by analysing ex-post questionnaires. On the other hand, studies that account for the relationship between past and present behaviour use inertia variables (Ramadurai and Srinivasan, 2006; Cantillo et al., 2007; Cherchi and Manca, 2011; Gao et al., 2020, 2022). However, ex-post questionnaires are subjected to different types of bias and may not capture the true underlying latent travel satisfaction (Rholes et al., 1987; Abou-Zeid et al., 2012), and inertia variables do not recognise the fact that what influences choices is the outcome of past choices not only the

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choices themselves (Webb et al., 2024). Hence, both approaches may fail to properly capture the behavioural consequences of travel satisfaction.

Thus, travel behaviour analysis can benefit from enriched discrete choice models that integrate unbiased (not derived from individuals' subjective responses) measures of travel satisfaction. However, the measurement of travel experience in a discrete choice framework is challenging since the explanatory variables in real-world trips are not controllable and hard to measure, and the dependent variables (non-observable psychological states) are often only accessible through post-experience questionnaires. Recently, psychophysiological indicators (PPI) have been proposed to be used to capture complex latent psychological states, which are otherwise hard to capture (Castro et al., 2020; Hancock and Choudhury, 2023). This is possible since psychological stimuli affect the autonomous nervous system, triggering both changes in psychological states and variations in PPI (Cacioppo et al., 2007; Ganglbauer et al., 2011). PPI can change the way travel satisfaction is measured, increase the granularity and depth of the analysis and also be used for travel behaviour analysis. With data from a real-life experiment in Santiago, Chile, Barría et al. (2023) showed that skin temperature was significantly correlated with the valence of the stated emotions in a public transport trip and Henriquez-Jara et al. (2025) used skin temperature, electrodermal activity, heart rate, and heart rate variation to estimate the latent satisfaction of travellers. PPIs have also been used in laboratory studies under controlled conditions, leveraging the advent of VR and augmented reality as a tool for travel experiments with high ecological validity (Farooq et al., 2018; Sadeghi et al., 2023b; Farooq and Cherchi, 2024; Bogacz et al., 2021; Mudassar et al., 2021; Paschalidis et al., 2019). However, none of these studies analysed modal choice or the impact of travel satisfaction on future choices.

Although the current state of the art recognises an effect of the travel experience on mode choice and the use of PPI to measure the experience, it has not yet been shown how physiological measures can help estimate the effect of latent psychological states perceived in travel experiences on the choice of travel mode. In this paper, we address this gap in the literature by testing this effect under controlled laboratory conditions as part of the 'Future Modes Study' (FMS, Choudhury et al., 2025). The FMS study included 3 waves of VR experiments . Each wave had different consideration sets: car, bus and ride-hailing; car, autonomous vehicle (AV), and shared autonomous vehicle (SAV); and hyperloop, air-taxi and train. Each participant chose a mode (pre-experience choice), experienced it, and then stated whether they would like to change their initially chosen mode (post-experience choice). Our main research questions are: (1) Does the latent stress associated with experiencing an alternative result in subjects avoiding reselecting the same alternative? In addition, we also address the following two questions: (2) Do the preferences of subjects change after experiencing an alternative, or do attributes that are hard to perceive in SP become more relevant after the VR experiences? and (3) Does the inertia effect get mediated by the effect of previous latent stress? To answer these questions, we employ a dynamic Integrated Choice and Latent Variable model (ICLV) (Ben-Akiva et al., 2002). This modelling approach allows us to test the influence of the VR experience on latent stress, measured with the galvanic skin response (GSR) of the participants, on subsequent decisions. GSR is related to the amount of sweat on the skin and is therefore often used as a stress indicator when other factors that may increase sweating are controlled (Ganglbauer et al., 2011; Bitkina et al., 2019; Scheirer et al., 2002). It is one of the most popular aspects of the autonomic nervous system used to study human cognition and emotions (Carter and Tranel, 2012).

The potential of VR has mainly been discussed in terms of its use for travel satisfaction analysis (e.g. Sadeghi et al., 2023a). We contribute by analysing its potential for the estimation of the effects of travel satisfaction on demand, which is necessary to capture to move towards the evaluation of projects aimed at maximising Subjective Wellbeing (Henriquez-Jara and Guevara, 2025). Also, we discuss the validity of VR transport-related stimuli in inducing changes in emotion and the extent to which these can be generalised to the real world. The remainder of this article is organised as follows. The second section shows the summary of the experimental design. The third section presents the modelling framework. Section four details the data and sample characteristics. The fifth section shows the results, and lastly we discuss the main conclusions and further research lines.

2. Experimental design

The data used in this research was collected as part of the 'Future Modes Study'(FMS). In this section, we briefly present the experimental set up. The full details are available at Choudhury et al. (2025).

The experiments were conducted as part of the 'Next Generation Travel Behaviour Models' project using the Virtuocity facilities at the University of Leeds (https://uolds.leeds.ac.uk/facility/virtuocity/). It consisted of three waves, each with different consideration sets. In the first wave, participants chose between car, bus and ride-hailing. The second wave included car, AV and SAV. In the third wave, participants chose among air-taxi, hyperloop and train. Participants did four choice tasks per consideration set. The FMS data collection setting consisted of a VR headset connected with a static driving simulator, a Shimmer sensor (to record GSR), and an EEG sensor[1]. The Shimmer sensor measures GSR at a rate of 120 Hz. For the first and second waves, the setting included a steering wheel and brake and acceleration pedals for actively controlling the car in the virtual environment. Fig. 1 shows an example of the first wave experimental setting.

The attributes presented in each wave and how they were incorporated in VR are shown in Table A.2, Table A.3 and Table A.4 (Appendix). Each participant completed four choice tasks. Each choice task included three main parts (Fig. 2):

1. **Pre-experience choice:** Participants chose among three travel modes based on attribute values shown in a table as in traditional SP surveys. An example of the SP survey is presented in Fig. 3.

[1] The data from the EEG was not used in this study, mainly because of measurement errors.

Fig. 1. Example of experiment setting of the first wave.

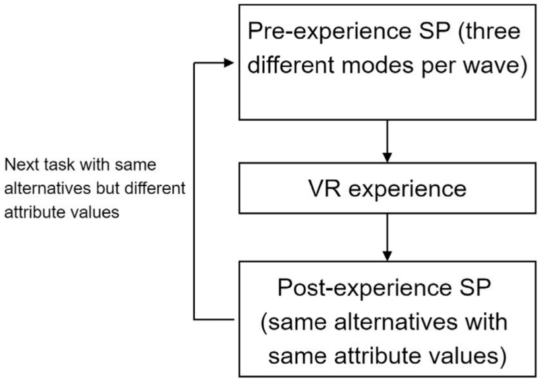


Fig. 2. Schematic representation of the structure of the experiment. The scheme represents one task, and was repeated 4 times per participant for each wave.

2. **VR experience:** The chosen alternative was experienced in a VR environment. Travel attributes experienced in the VR environment were mapped as a function of the attributes displayed in the pre-experience choice. For instance, 1 min of travel time in the SP corresponded to 10 s of travel time in the simulation. Additionally, if the comfort level in the SP was 'low', this translated to aggressive driving in the simulation, and 'bad weather' implied a night trip with foggy weather conditions (reduced visibility within the VR environment).
3. **Post-experience choice:** After the experience, the same SP choice task was shown to the participants, so that they could modify or confirm their initial choice. The choice of a different alternative implies that the participant regretted their pre-experience choice, potentially due to an unpleasant or unexpected experience. This part of the task also aimed to test if some travel attributes gained importance after being experienced in the VR.

Finally, at the end of the session, participants responded to the Simulator Sickness Questionnaire (SSQ) (Walter et al., 2019) and stated the level of satisfaction perceived on each of the four experiences in a Likert scale. 71 participants took part in the first wave of the experiment, of which 50 participated in the second wave and 45 in the third wave (Table A.1 in Appendix shows the sample composition). Fig. 4 shows the VR environment from the point of view of the participant while inside the modes of each wave. Also, to illustrate the differences between scenarios, Fig. 5 shows the view when driving at night in foggy weather.

Fig. 6 shows the VR environment from the perspective of the participants while they were waiting for the different travel modes. Car and AV are not included as these modes did not involve waiting.

3. Modelling framework

This section presents the structure of the model and the mathematical specification of it. We compare four models, but we describe the most complex of them (referred to as LS-Full) as the other three are constrained versions of it. First, we describe the structure and the dynamic effects. Then, we detail the specification of LS-Full.

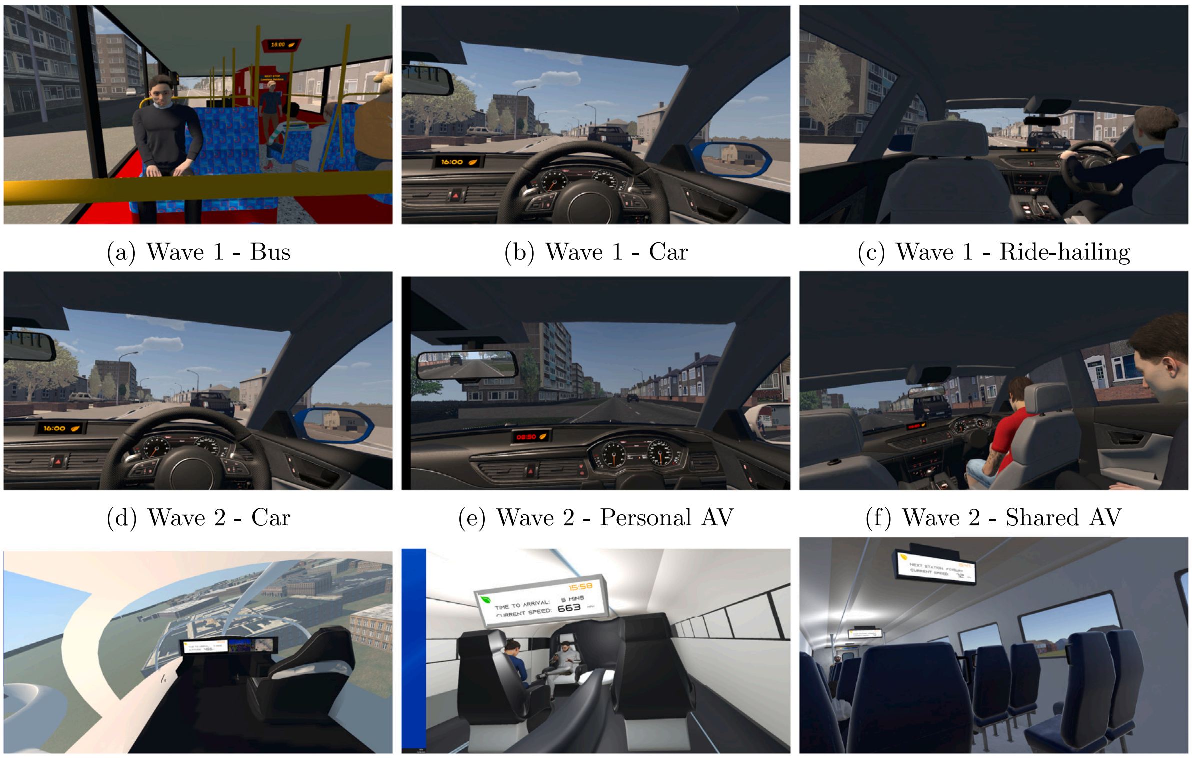
	Private Car	Ride-hail	Bus
Trip type	Work		
Traffic/weather conditions	Bad		
Time	20 mins (in-vehicle) 10 mins (parking and walk from parking)	20 mins (in-vehicle) 2 mins (pickup)	30 mins (in-vehicle) 10 mins (pickup)
Cost	£2.5 (petrol) £2.5 (parking)	£10 (hire)	£5 (fare)
Passengers	on your own	on your own	50% full
Carbon	50 g/km	245 g/km	105 g/pkm
Comfort	★★★	★★★	★
You prefer:	○	○	○

How certain are you with this choice?

Not at all certain | Neutral | Extremely certain

0 1 2 3 4 5 6 7 8 9 10

Fig. 3. Example of SP survey.



(a) Wave 1 - Bus (b) Wave 1 - Car (c) Wave 1 - Ride-hailing
(d) Wave 2 - Car (e) Wave 2 - Personal AV (f) Wave 2 - Shared AV
(g) Wave 3 - Air-Taxi (h) Wave 3 - Hyperloop (i) Wave 3 - Train

Fig. 4. VR environment from the participant's point of view inside each wave's different travel modes.

Fig. 5. VR environment from the participant's point of view while travelling by car in bad weather.

(a) Wave 1 - Bus waiting (b) Wave 1 - Ride-hailing waiting (c) Wave 2 - Shared AV waiting

(d) Wave 3 - Air-Taxi waiting (e) Wave 3 - Hyperloop waiting (f) Wave 3 - Train waiting

Fig. 6. VR environment from the participant's point of view while waiting for the chosen travel mode. Car and AV are not included as these modes did not involve waiting.

The dynamic nature of the framework is explained in Fig. 7. In the figures of this section, ovals represent latent variables, rectangles are observed variables, solid lines are structural equations, and dashed lines are measurement equations. In this framework, in the **pre-experience stage** of the initial task, individuals compute a utility associated with each alternative (pre-experience utility), based on the provided descriptive information. After making a pre-experience choice, the individual experiences some level of stress during the trip in the VR environment which is not observed (latent) by the analyst, but cause observable variation in GSR. Then, the participant is asked if, given the experience, they would like to have chosen another alternative (i.e. to regret the pre-experience choice). We refer to this stage as the **post-experience stage** of the task. For that, the participant is presented with the same SP table keeping the same descriptive information of the alternatives. The subject re-evaluates their pre-experience choice, computing the post-experience utility, i.e. the utility after the VR experience phase of the experiment. We assume that this utility is explained by a combination of the pre-experience choice itself, the pre-experience utility, and the perceived latent stress. In the subsequent task, utility is additionally influenced by three intertemporal effects, labelled D_1–D_3[2] in Fig. 7 and defined below:

D_1: **Inertia:** This effect assumes that the likelihood of repeating a choice increases with the difference between the utility of the chosen and not chosen alternatives. The most attractive the chosen alternative is in comparison to the not chosen alternatives, it is more likely to be chosen again. That is, there is a lagged effect caused by both the utility of the previously chosen alternative and the not chosen alternatives. This captures not only the tendency to repeat past behaviour, but also the fact that repeating a choice is more likely when the utility of that choice is higher. It captures the serial correlation of choices, as proposed by Cantillo et al. (2007).

[2] A Markov assumption is made to ensure that the model is tractable. This assumption can be relaxed in future research. Note, however, that it is not necessary to model the accumulation of stress or inertia to evaluate whether travel stress causes individuals to shift modes.

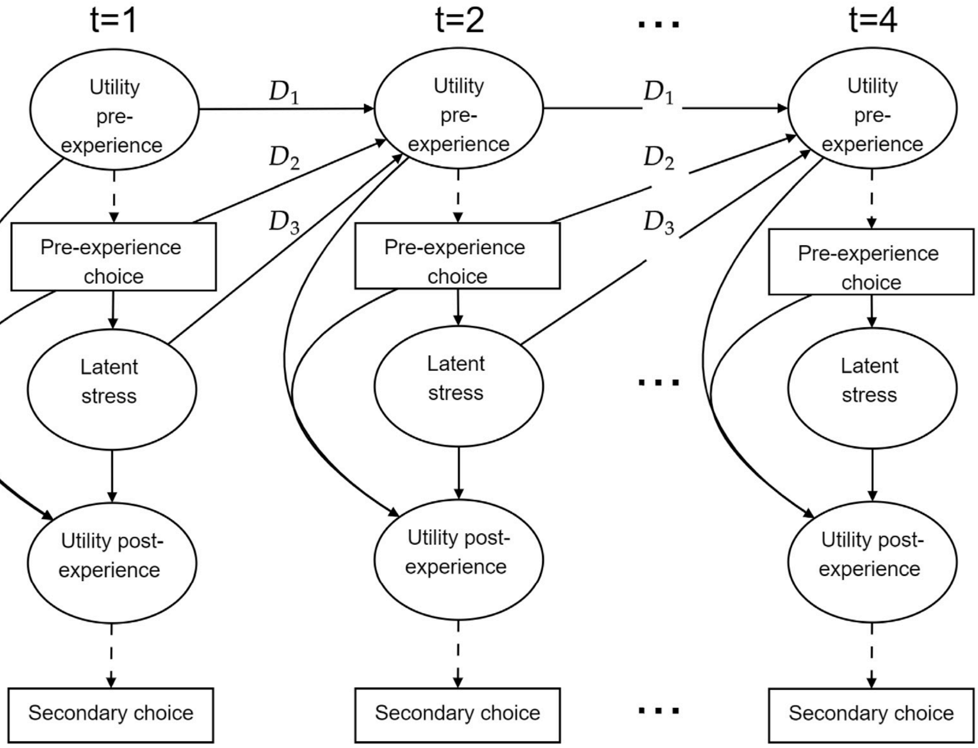


Fig. 7. Dynamic representation of the model LS-Full. D_1 represents the inertia effect (Cantillo et al., 2007), D_2 is the dummy inertia or carrying-over effect (Heckman, 1981), and D_3 is the latent stress effect.

D_2: **Carrying-over effect:** This effect also captures a serial correlation of choices, but assumes that an alternative is more likely to be chosen simply because it has been chosen in the past, regardless of how convenient (utility level) it was. That is, it simply captures the tendency to repeat past behaviour. It is modelled as the effect of the choice of task t on the task $t+1$. This is known as carrying-over effect (Heckman, 1981), or dummy inertia (Cherchi and Manca, 2011).

D_3: **Lagged latent stress:** Finally, the lagged latent stress captures the effect of experiences on future choices. The latent stress is explained by attributes of the experience and is measured by features of the GSR observed during the experience.

From these effects, only the first two have been tested in previous research. The measurement of the effect of stress on future choices (D_3) represents the main research questions of this article. The inclusion of the first two aims to test the influence of previous preferences in future choices, while the third aims to test the effect of the experienced stress in future choices.

This model is compared with three other constrained models. The first baseline model (MNL1) is a simple multinomial logit which considers only two inter-temporal effects: the carrying-over and inertia effects, and does not model the post-experience choice. The second (MNL2) includes the post-experience choice and both inertia effects. The third baseline (LS1) considers the post-experience choice, but only with latent stress as a dynamic effect. The complete model is referred to as LS-Full. Fig. 8 summarises the four models to be analysed in this article.

3.1. Specification

This section provides the details of the main model, i.e. LS-Full (Fig. 8(d)). First, we detail the structural equations, then the measurement equations, and finally the likelihood functions.

Throughout this section, the indicator function y_{nti} will denote the choice in task t ($y_{nti} = 1$ if subject n chooses i in task t and 0 otherwise). In addition, we denote N as the total number of individuals, T_n the number of tasks faced by subject n, and J the number of alternatives in the consideration set C (equal across subjects).

Structural equations

The specification of the utility that individual n has for alternative i in choice task t (U_{nti}) at the pre-experience choice stage can be expressed in general terms as a function of the systematic utility (V_{nti}) and the three dynamic effects: the carrying-over effect (I^d_{nti}), the inertia caused by previous utilities (I^v_{nti}), and the lagged latent stress ($S_{n,t-1,i}$):

$$U_{nti} = V_{nti} + \lambda^d I^d_{nti} + \lambda^v I^v_{nti} + \omega_i S_{n,t-1,i} + \eta_{nti} \tag{1}$$

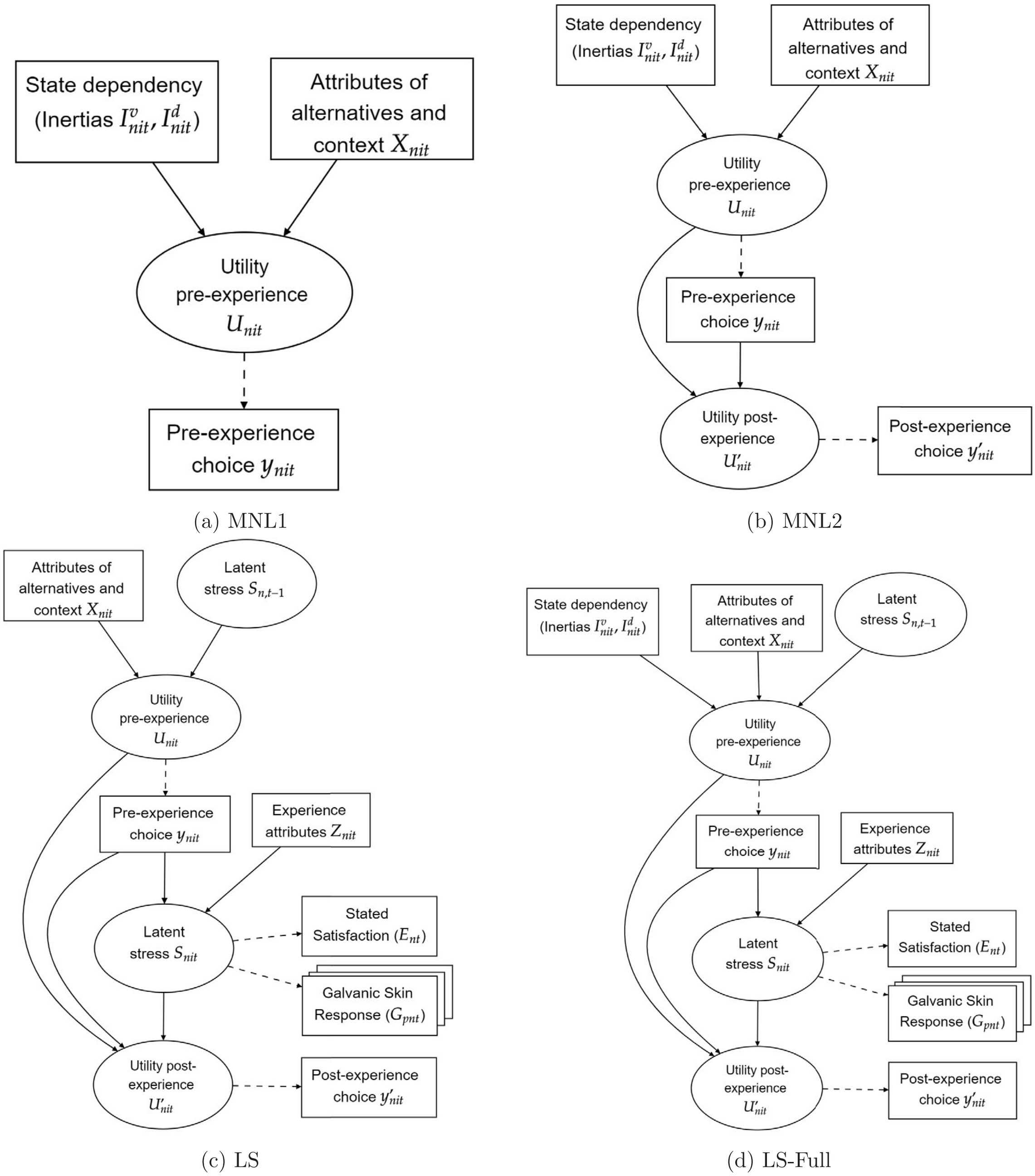


Fig. 8. Four models summary (error terms are omitted). Ovals represent latent variables and boxes observed variables. The boxes behind the GSR represent the different features used to estimate the latent stress.

where the error term η_{nti} is assumed to have an Extreme Value (EVI) distribution with scale 1. We denote $\tilde{V}_{nti}$ to the sum of the components of utility without the error term, i.e. $\widetilde{V}_{nti} = V_{nti} + \lambda^d I^d_{nti} + \lambda^v I^v_{nti} + \omega_i S_{n,t-1,i}$. Next, we detail the four explanatory elements of the utility. Eq. (2) shows the systematic utility (V_{nti}):

$$V_{nti} = \beta_{0,i} + \sum_{k=1}^{K} \beta_k x_{ntik} \tag{2}$$

where x_{ntik} represents the value of each k attribute for alternative i, subject n and task t; K is the total number of attributes; β_k is the respective parameter; and $\beta_{0,i}$ represents the alternative specific constant of alternative i.

Then, the inertia effects can be specified as follows, where I^d_{nti} is the dummy inertia and I^v_{nti} is the inertia caused by previous systematic utilities (Cantillo et al., 2007):

$$I^d_{nti} = 1[y_{n,t-1,i} = 1] \tag{3a}$$

$$I^v_{nti} = V_{n,t-1,i} - V_{n,t-1,r}, \text{ with } y_{n,t-1,r} = 1 \text{ and } r \in C \tag{3b}$$

where $V_{n,t-1,r}$ represents the systematic utility of the alternative chosen in the choice task $t-1$. Note that, I^v_{nti} takes positive values if the chosen alternative (r) in $t-1$ has lower systematic utility that the non-chosen alternative i. It is negative when the chosen alternative is better than the non-chosen. Then, if the parameter λ_v is positive (Eq. (1)), it means that in task t the utility of the previously non-chosen alternative decreases if in the past it was a dominated alternative in terms of expected outcome. If the parameter is negative, it is interpreted as a exploratory behaviour, as the utility of non-chosen alternatives increase even when in the past they were dominated by another alternative.

On the other hand, latent stress S_{nti} (Eq. (4)) is specified as a function of the Q experience attributes and individual characteristics (z_{ntq}) of subject n in task t. Recall that these attributes were scaled from the attributes presented in the SP survey. The experienced attributes included: travel time, comfort (aggressive driving or normal), weather (foggy or normal), an environmental cue (indicating if the mode was sustainable), crowding (in case of shared modes) and parking space (in the case of car).

$$S_{nti} = \begin{cases} \gamma_0 + \sum_{q=1}^{Q} \gamma_v z_{ntq} + \eta^S_{nt}, & \text{if } y_{nti} = 1 \\ 0, & \text{otherwise} \end{cases} \tag{4}$$

Then, at the post-experience choice stage, the utility U'_{nti} of each alternative is also represented by a systematic part and an EVI error term with unitary scale (η'_{nti}). The systematic utility of the alternatives in the post-experience choice is a function of the previous utility (V_{nti}) scaled by μ, the stress recently experienced S_{nti} and the pre-experience choice y_{nti}. The stress S_{nti}, as defined in Eq. (4), takes value only for the chosen and experienced alternative. The parameter ω' represents the variation in utility caused by the latent stress, and δ_i is a stickiness parameter, that is, the tendency to stick to the pre-experience choice. For example, $\mu = 0$ and $\delta_i > 0$ would represent participants sticking with the chosen alternative and not evaluating the possible alternatives again when given the opportunity. The parameter $\alpha_{0,i}$ is an alternative-specific constant.

$$U'_{nti} = \alpha_{0,i} + \mu V_{nti} + \delta_i y_{nti} + \omega'_i S_{nti} + \eta'_{nti} \tag{5}$$

Measurement equations

The latent stress is measured by a set $\mathcal{G}$ of features extracted from the GSR. The value of each feature of the set is denoted G_{pnt}, with $p \in \mathcal{G}$. Each feature is an aggregation of all the signal observed during the VR experience of task t of subject n (Eq. (6)).

$$G_{pnt} = \theta_p S_{nt} + \theta_A A_n + \theta_{ET} ET_{nt} + \varepsilon^{exp}_{pnt}, \tag{6}$$

where θ_p is the relation between the latent stress and the feature p of the GSR. In order to control for other exogenous factors that could cause changes in GSR, we controlled for the reported use of substances by individuals prior to the experiment. However, none of these turned out to be significant except the level of alcohol consumption (A_n) for participants of the second wave (as shown in Section 5). Also, we controlled for the elapsed time in the experiment (ET_{nt}). The error term ε^{exp}_{pnt} is assumed to have distribution $N(0, \sigma_p)$.

In addition, we use the stated satisfaction with the VR experience. Participants indicated a level of satisfaction on a scale of 1–5. Then, we estimate the probability of stating a specific level of satisfaction using an ordered logit model. The estimated satisfaction with the experience of choice task t (E_{nt}) is given by equation Eq. (7), where θ_E is the slope parameter and ε^E_{nt} is an EVI error term.

$$E_{nt} = \theta_E S_{nt} + \varepsilon^E_{nt} \tag{7}$$

Likelihood functions

The probability P_{nti} of subject n choosing an alternative i in task t is then given by:

$$\begin{aligned} P_{nti} &= \mathbb{P}(y_{nti} = 1 | V_{nt}, I^d_{nt}, I^v_{nt}, S_{nt-1}, \gamma, \omega) \\ &= \frac{exp(V_{nti} + \lambda^d I^d_{nti} + \lambda^v I^v_{nti} + \omega S_{n,t-1,i})}{\sum_{j\in C} exp(V_{ntj} + \lambda^d I^d_{ntj} + \lambda^v I^v_{ntj} + \omega S_{n,t-1,j})} \end{aligned} \tag{8}$$

The probability of observing the vector G_{nt} of PPI indicators, is given by:

$$P^{PPI}_{nt} = \mathbb{P}(G_{nt} | \theta, S_{nt}) = \prod_{p\in\mathcal{G}} \frac{1}{\sigma_p} \phi\left(\frac{G_{pnt} - \theta_p S_{nt}}{\sigma_p}\right) \tag{9}$$

where ϕ is the standard normal distribution function, and σ_p is the standard deviation of the error of the measurement equation of the indicator $p \in \mathcal{G}$.

For the measurement equation of the stated satisfaction, we denote e_{nlt} an indicator function which takes the value of 1 if the subject n ranks the experience t with level l, and 0 in other case. In this case, a 1–5 Likert scale was used. Then, the probability of stating a satisfaction level l is given by:

$$\begin{aligned} P_{nlt} &= \mathbb{P}(e_{nlt} = 1 | \theta_E, S_{nt}) = \mathbb{P}(\tau_{l-1} < E_{nt} < \tau_l | \theta_E, S_{nt}) \\ &= \frac{exp(\tau_l - \theta_E S_{nt})}{1 + exp(\tau_l - \theta_E S_{nt})} - \frac{exp(\tau_{l-1} - \theta_E S_{nt})}{1 + exp(\tau_{l-1} - \theta_E S_{nt})}, \end{aligned} \tag{10}$$

where $\tau_1, \ldots, \tau_4$ are estimated cut-off points of the ordered logit model. Note that $\tau_0 = -\infty$ and $\tau_5 = \infty$. The probability P'_{nti} of choosing the alternative i as post-experience choice can be calculated as:

$$P'_{nti} = \mathbb{P}(y'_{nti} = 1|\omega', \delta, \mu, \widetilde{V}_{nti}, S_{nt}, y_{nti}) = \frac{exp(\alpha_{0,i} + \mu\widetilde{V}_{nti} + \delta_i y_{nti} + \omega' S_{nt})}{\sum_{j\in C} exp(\alpha_{0,j} + \mu\widetilde{V}_{ntj} + \delta_j y_{ntj} + \omega' S_{ntj})} \tag{11}$$

Finally, the likelihood Lik of the model is calculated as:

$$Lik = \prod_{n=1}^{N}\left(\prod_{t=1}^{T_n}\int_{\eta_{S_{nt}}}\left(\left[\prod_{i=1}^{J}(P_{nti})^{y_{nti}}(P'_{nti})^{y'_{nti}}\right]P_{nt}^{PPI}\prod_{l=1}^{L}(P_{nlt}^{E})^{e_{nlt}}\right)d\eta_{S_{nt}}\right) \tag{12}$$

The model was estimated with the maximum simulated likelihood method, using *Apollo* (Hess and Palma, 2019) in *R4.2.0* (R Core Team, 2023).

4. Data

71 participants took part in the first wave, 50 of whom completed the second wave and 45 of whom also completed the third. The choices in all waves are shown in Fig. 9. The reason for attrition between waves is not known with certainty. However, a plausible reason is that some participants felt uncomfortable with the VR environment. This can be analysed by looking at the total scores on the motion sickness questionnaire (SSQ). The difference between the mean SSQ score of participants who dropped out of the experiment in the second or third wave (6.43) and those who participated in all waves (2.96) is significant (t-test = −3.98, p-value < 0.001). This suggests that participants who dropped out were less comfortable with VR than those who participated in all waves.

In the first wave, the participants preferred the bus over the car and ride-hailing. The participants changed their pre-experience choice in 22% of the tasks. In the second wave, the car was the preferred option, with 46.3% of the pre-experience choices. AV alone was the less preferred option (10.4%). In this case, the participants changed their pre-experience chosen option in 25% of the tasks. Finally, in the third wave, hyperloop was preferred (46.11%), followed by air-taxi (33.89%) and train (20.0%). In this case, the participants changed their pre-experience choice in only 10% of the choice tasks.

Fig. 10 shows an example of the GSR measures (vertical axis) of a single participant during the experiment. Red areas indicate the subject was riding a bus in the VR environment, the blue area highlights the use of ride-hailing and the green area is the use of car. Red vertical lines mark when the participant makes a pre-experience choice and blue vertical lines mark when the participant makes a post-experience choice. Grey areas show the time window where the participant was deliberating. The first part of the plot (to the left of the filled areas) corresponds to the test trials. As can be seen, the subject experienced higher skin conductance peaks during the deliberation process, which tended to increase with time and was higher when the participant was driving in VR.

Physiological features selection

The GSR measured for each participant was aggregated by experience, after subtracting the mean of the GSR measured before the choice task (i.e. the baseline GSR). Then, different features were extracted: the mean, median, minimum, maximum, logsum, variance, skewness, kurtosis, and minmax. The selection of features was based on previous studies in this field (Henríquez-Jara et al., 2023; Paschalidis et al., 2019; Braithwaite et al., 2013). Two of these features deserve further explanation: the minmax and the logsum. The first is based on Paschalidis et al. (2019) and Braithwaite et al. (2013). It represents the variance of the GSR observed in task t, scaled by the variance observed in the complete time series H:

$$Minmax_{nt} = \frac{max_{t'\in t}(GSR_{t'n}) - min_{t'\in t}(GSR_{t'n})}{max_{t'\in H}(GSR_{t'n}) - min_{t'\in H}(GSR_{t'n})}, \tag{13}$$

where t' represents a single observation of GSR. Recall that the GSR was measured at a rate of 120 Hz. On the other hand, the $logsum$ is given by:

$$Logsum_{nt} = ln(\sum_{t'\in t} exp(GSR_{t,n})). \tag{14}$$

Castro et al. (2020) proposed the use of the logsum to aggregate physiological measures, since it represents the expected maximum value if the true physiological measure associated with the experience t diverges from the signal observed at each instant $t' \in t$ with an EVI error.

The resultant features were normalised (subtracting the mean and scaling by the standard deviation). Then an exploratory factor analysis (EFA) was performed for each wave of participants. The EFA helps identify which features explain a larger portion of the variance of the data, as it is desirable that the selected features explain the largest portion of it. In this case, the EFA was conducted with one factor as we only have a hypothesis about one underlying latent factor (i.e. stress). Based on the EFA results (Table 1) and the literature review, we selected the mean, maximum, and logsum for the first and third waves; and the logsum, maximum and minmax for the second wave.

To illustrate the differences in GSR observed across modes and waves of the experiment, we show in Fig. 11 the mean of the maximum value of the GSR observed in the VR experiences with each mode. From this analysis, it can be observed that driving a car in VR caused significantly higher levels of GSR relative to experiencing other modes.

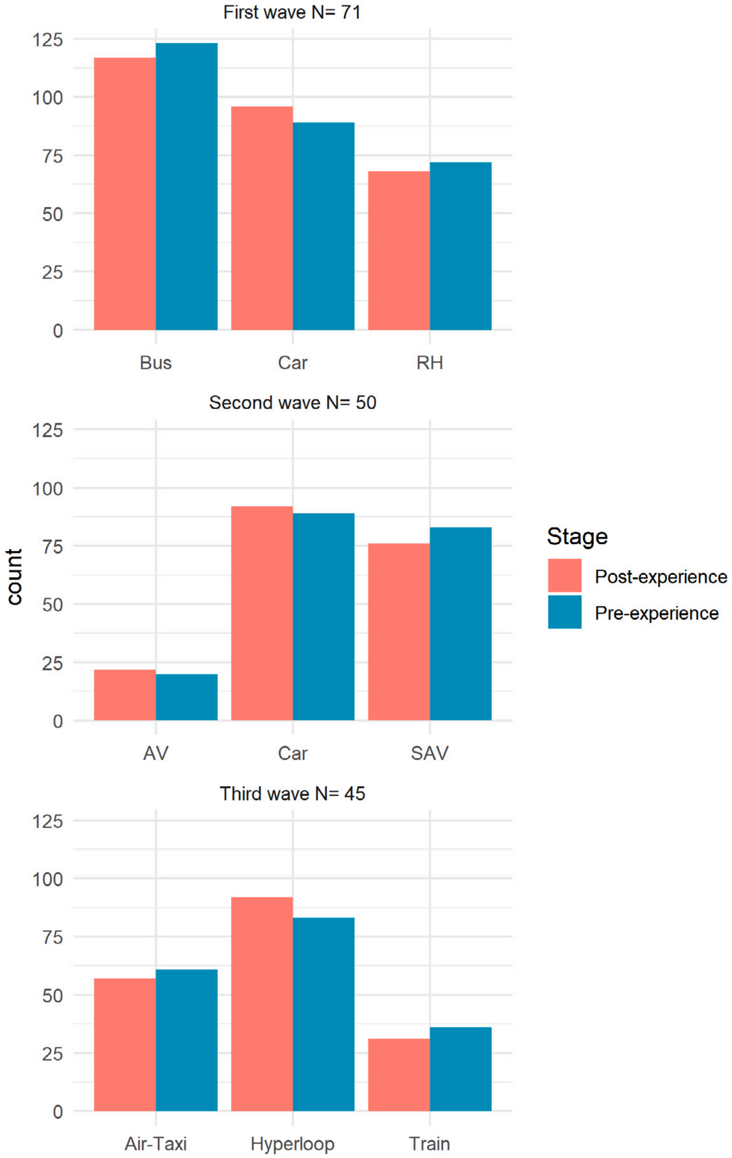


Fig. 9. Choices frequency by mode in each wave.

Table 1
Exploratory Factorial Analysis loadings (one factor) by wave.

Feature	Wave 1	Wave 2	Wave 3
Mean	0.984	0.681	0.942
Summation	0.933	0.665	0.938
Minimum	0.67	0.254	0.847
Maximum	0.72	0.998	0.841
Variance	0.209	0.756	0.237
Logsum	0.812	0.734	0.994
Minmax	0.379	0.829	0.335
Skewness	0.105	0.304	0.172
Kurtosis	−0.123	0.185	−0.192
SS loadings	3.261	3.889	4.414
Proportion of variance	0.409	0.432	0.49

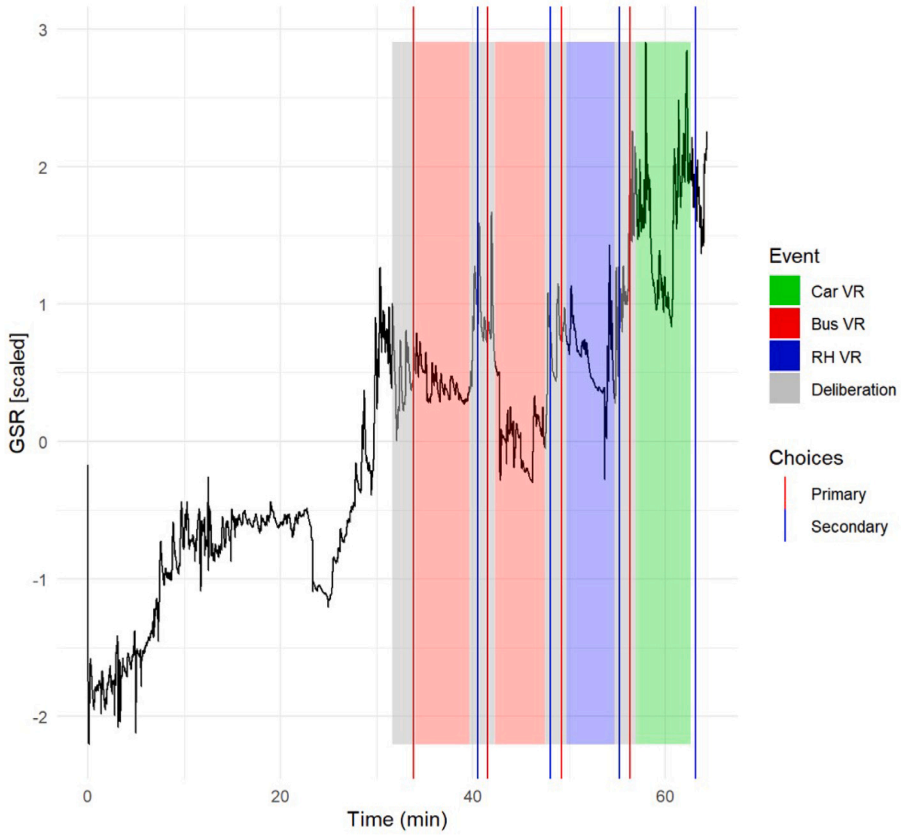


Fig. 10. Example of GSR profile of a subject. Coloured areas indicate the mode being used in VR. Vertical lines indicate the instants where the participant made a choice.

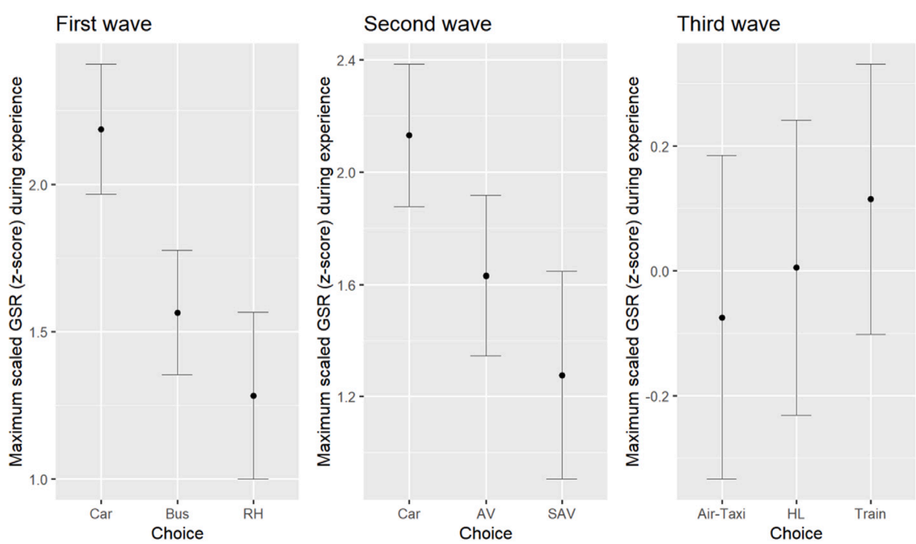


Fig. 11. Maximum scaled GSR measured during the VR experience. Points indicate the mean value and bars denote a 95% confidence interval. AV = autonomous vehicle, SAV = shared autonomous vehicle, HL = hyperloop.

5. Results

In this section, we show the results of the models presented in Section 3 (see Fig. 8). We divide the presentation of the results by wave and by model. In all models, all variables that were part of the experimental design were retained, even those that were not significant. Non-significant demographic variables were removed, except for age and gender, which we consider relevant as controls.

5.1. First wave

In the first wave, the consideration set consisted of: car, bus, and ride-hailing. The results of the structural equations are presented in Table 2, and the results of the measurement equations are presented in Table 3. On average, participants did not consider most of the information provided in the SP survey, and the inertia effect is negative in MNL1 and MNL2. From the point of view of inertia, this is interpreted as exploratory behaviour. This exploratory behaviour and the lack of consideration of the provided information hinders the fit of the models, as can be observed in Table 2. The role of inertia is less relevant when the latent stress variables are added, and the fit of the model increases.

As it is shown in the following sections, the exploratory behaviour was not observed in the following two waves. This might be a result of participants having a relatively low level of engagement in the first wave due to it presenting current travel modes, while the futuristic modes of the next two waves may have captured the interest of the participants in the experiment, which was demanding in terms of time and cognitive attention. However, interesting behavioural insights are obtained from the influence of experienced stress on the choice process. We now analyse the results of the different components of the models in turn.

Pre-experience choice

At the pre-experience choice stage, the travel time is significant in all models and the cost does not have a significant effect. On the other hand, waiting and walking time parameters are significant but do not have the expected sign in any model. According to MNL1 and MNL2, the bus was preferred when the weather was bad, i.e. foggy weather, rather than normal ($\beta_{Badweather} > 0, p\text{−}value < 0.01$), however, this effect is less significant in both dynamic hybrid models. No mode was significantly preferred for work trips. Before the experiment started, participants experienced each mode considered in the corresponding wave once for training (e.g. participants in the first wave only tested car, bus and RH). We controlled for the mode that was chosen first during this training stage, assuming the participant has some endogenous preference for that mode. We found a significant effect caused by experiencing ride-hailing first. That is, if a participant experienced ride-hailing as the first test mode, then it was more likely that they would also choose ride-hailing during the experiment. The inertia parameters are negative and significant in MNL1 and MNL2. This implies that choices are mostly exploratory, i.e. individuals tend to change their previous choices. Note that the inertia effects disappears when the lagged latent stress is added (that is in LS-Full). This is because the tendency to change to new alternatives is not solely caused by exploratory tendencies, but influenced by the experienced level of stress. Notably, latent stress has a significant effect only on the car ($\omega_{car} = -0.79, p - value < 0.01$ in LS and $\omega_{car} = -0.678, p - value < 0.05$ in LS-Full), which is perhaps not surprising given the additional demand on attention that is required when the participant has to drive.

Post-experience choice

The post-experience choice aimed to test if travel attributes gained importance after being experienced. We observed that participants showed little tendency to revise their initial choice during the pre-experience choice stage (the pre-experience choice was changed only in 22% of cases). The μ parameter was not significantly different from zero in any model (meaning that participants did not consider the SP information at the post-experience choice), and the stickiness parameter is positive and significant in all models with large effect size. In addition, the latent stress perceived after the pre-experience choice does not have a significant effect. A more detailed analysis could be done considering only the participants who change their pre-experience choice (as they are more likely to have changed their preferences), but the sample size does not allow for this analysis.

Latent stress

Regarding the latent stress parameters, travel time did not have a significant effect, the stated perception of realism of the VR scenario decreased the stress (low significance), and travelling with good weather conditions also decreased the stress (low significance). Travel by car was the most important factor in inducing stress. Travel by bus has a lower effect, which is not significantly different from the effect of travelling by ride-hailing. No other attribute caused significant changes in the latent stress. Table 3 shows the results of the four measurement functions. The first three are the PPIs' features (estimated with a normal density function) and the fourth is the stated satisfaction (estimated as an ordered logit). The three features of GSR increased with the latent stress, but also with the elapsed time in the experiment. There was no significant relationship between latent stress and the reported satisfaction with VR experience.

Despite driving a car was shown to be the most important factor in inducing stress, it cannot be ruled out that this was an artefact of the experiment itself. Driving implied a more active participation of the subject, as participants had to use the steering wheel, drive, and park the car. In other modes, participants only observed the VR environment but did not actively participate in it. Further work is needed to ensure that these effects can be replicated in the real world.

5.2. Second wave

In the second wave, the consideration set consisted of: car, AV, and SAV. The results of the structural equations are presented in Table 4. Measurement equations results are shown in Table 5.

Table 2
Comparison of structural equations first wave's models. Consideration set: car, bus and ridehailing.

Component	Parameter	MNL1 Estimate (Rob.t.test)	MNL2 Estimate (Rob.t.test)	LS Estimate (Rob.t.test)	LS-Full Estimate (Rob.t.test)
Pre-experience choice (β)	ASC, car	1.151 (2.105)	1.369 (1.968)	0.93 (1.857)	1.144 (2.028)
	ASC, bus	0.974 (1.552)	1.444 (1.659)	0.656 (1.716)	1.001 (1.706)
	Cost	0.044 (0.551)	0.007 (0.091)	0.045 (0.559)	0.015 (0.183)
	Travel time	−0.25 (−2.02)	−0.299 (−2.557)	−0.259 (−3.08)	−0.29 (−2.747)
	Walking time	0.52 (3.475)	0.517 (3.154)	0.408 (1.723)	0.484 (2.853)
	Waiting time	0.369 (2.435)	0.377 (2.176)	0.347 (2.482)	0.425 (2.799)
	Crowding	0.08 (0.48)	0.095 (0.597)	0.219 (1.503)	0.149 (0.922)
	Comfort	−0.087 (−0.196)	−0.299 (−0.718)	0.368 (1.556)	−0.07 (−0.143)
	Bad weather, car	0.448 (0.796)	0.66 (1.244)	0.425 (1.196)	0.634 (1.105)
	Bad weather, bus	1.471 (2.129)	1.5 (2.199)	0.943 (1.467)	1.455 (1.779)
	Work trip, car	−0.507 (−1.449)	−0.547 (−1.519)	−0.514 (−0.906)	−0.536 (−1.4)
	Work trip, bus	−0.355 (−0.869)	−0.447 (−1.14)	−0.455 (−1.078)	−0.374 (−1.007)
	Carbon	−0.026 (−0.25)	−0.102 (−0.936)	−0.08 (−0.6)	−0.096 (−0.776)
	Female, car	−0.26 (−0.441)	−0.223 (−0.32)	0.036 (0.103)	0.005 (0.008)
	Age young, car	−0.228 (−0.65)	−0.352 (−1.055)	−0.081 (−0.534)	−0.249 (−0.81)
	Female, bus	0.344 (0.645)	0.305 (0.506)	0.068 (0.243)	0.266 (0.471)
	Age young, bus	0.06 (0.251)	0.029 (0.124)	0.076 (0.622)	0.065 (0.346)
	First test choice, RH	1.083 (2.171)	1.379 (2.434)	0.867 (3.379)	1.258 (2.478)
	Inertia (γ^v)	−0.524 (−1.765)	−0.651 (−2.705)		−0.522 (−1.332)
	Dummy Inertia (γ^d)	−0.356 (−2.037)	−0.32 (−1.877)		−0.201 (−0.844)
	Car Stress (ω_{car})			−0.79 (−2.404)	−0.678 (−1.882)
	Bus Stress (ω_{bus})			−0.056 (−0.3)	−0.08 (−0.356)
	RH Stress (ω_{RH})			0.354 (0.661)	0.131 (0.227)
Post-experience choice	ASC, car		0.584 (1.703)	0.706 (1.219)	0.749 (1.276)
	ASC, bus		0.605 (1.694)	0.758 (1.11)	0.839 (1.244)
	Scale (μ)		−0.409 (−3.728[a])	−0.564 (−1.916[a])	−0.354 (−2.766[a])
	Stickiness (δ)		2.032 (12.327)	2.11 (8.029)	2.072 (8.272)
	Car Stress (ω'_{car})			−0.121 (−0.373)	−0.119 (−0.343)
	Bus Stress (ω'_{bus})			0.411 (1.567)	0.422 (1.56)
	RH Stress (ω'_{RH})			−0.131 (−0.175)	−0.113 (−0.173)
Latent stress (γ)	Constant			−0.205 (−0.354)	−0.222 (−0.393)
	Travel time			0.001 (0.002)	0.008 (0.028)
	Good weather			−0.496 (−1.746)	−0.493 (−1.726)
	Realism			−0.824 (−1.61)	−0.806 (−1.6)
	Age			0.115 (0.748)	0.114 (0.748)
	Female			0.178 (0.496)	0.172 (0.469)
	Car			1.91 (3.712)	1.852 (3.655)
	Bus			0.798 (1.483)	0.783 (1.493)
	Work trip			0.181 (0.653)	0.2 (0.748)
	Environmental cue			−0.275 (−1.296)	−0.271 (−1.296)
	Comfort			0.028 (0.122)	0.026 (0.121)
	Crowding			−0.175 (−0.733)	−0.17 (−0.713)
	Parking space			−0.067 (−0.249)	−0.069 (−0.245)
	σ_S			1 (–)	1 (–)
$LL(0)$ pre-experience choice		−304.32	−304.32	−275.75	−275.75
$LL(final)$ pre-experience choice		−278.19	−279.04	−252.15	−249.71
$LL(0)$ post-experience choice			−304.32	−275.75	−275.75
$LL(final)$ post-experience choice			−186.24	−171.25	−170.41
$LL(final)$ whole model		−278.19	−465.28	−1793.52	−1792.34
$\bar{\rho}^2$ pre-experience choice		0.02	0.02	0.1	0.1
$\bar{\rho}^2$ post-experience choice			0.37	0.41	0.42

[a] Denote a t-test against 1, otherwise the t-tests are against 0.

Pre-experience choice

The travel attribute parameters have the expected sign in the pre-experience choice component. However, in the baseline MNL1, the travel time is not significant. This significance of the travel time turns out to be higher when incorporating the post-experience choice (MNL2). That is, the joint estimation of the pre-experience and post-experience choice, helps in finding the true value of the travel time parameter. This may be explained by an underestimation of the importance of this attribute by the participants at the pre-experience choice, which is reverted after experiencing the travel time in the VR environment. In addition, the comfort

Table 3
Measurement equations parameters first wave's models. Consideration set: car, bus and ridehailing.

Component	Parameter	LS Estimate (Rob.t.test)	LS-Full Estimate (Rob.t.test)
Mean GSR (θ)	Alcohol	−0.021 (−0.343)	−0.014 (−0.229)
	Exp. Time	0.152 (1.386)	0.155 (1.412)
	Stress	0.414 (6.75)	0.417 (6.566)
	σ	0.833 (18.99)	0.834 (18.767)
Logsum (GSR)	Alcohol	0 (0.006)	0.005 (0.107)
	Exp. Time	0.143 (1.553)	0.146 (1.566)
	Stress	0.365 (4.261)	0.374 (4.123)
	σ	0.878 (3.886)	0.874 (3.899)
Max (GSR)	Alcohol	−0.033 (−0.655)	−0.028 (−0.53)
	Exp. Time	0.067 (0.641)	0.069 (0.662)
	Stress	0.346 (4.465)	0.351 (4.417)
	σ	0.897 (18.151)	0.896 (18.324)
Stated Satisfaction	Stress	−0.131 (−0.496)	−0.129 (−0.487)
	τ_1	−2.266 (−11.391)	−2.262 (−11.435)
	τ_2	−0.626 (−3.382)	−0.623 (−3.364)
	τ_3	0.868 (4.481)	0.871 (4.475)

parameter is significant and positive in all models. The inertia parameters are not significant in any of the models. However, similar to the first wave, LS-Full shows that the stress caused only significant effects on the utility of the car. This means that participants were less likely to choose a car after experiencing a stressful car trip ($\omega_{car} = -0.489, p-value < 0.1$). We also controlled for the mode that was experienced first during this training stage, but no significant effect was found and the variable was dropped from the reported models.

Post-experience choice

Regarding the post-experience choice, the μ parameter is not significantly different from 1, which means that the informed value of the attributes of the alternatives had an effect on the post-experience choice, i.e. participants revise their pre-experience choice and do not just stick to it. However, there is still a tendency to stick to their pre-experience choice (stickiness $\delta > 0$ and significant). Recall that in this wave the participants changed their pre-experience choice in 25% of the tasks. The experienced latent stress did not have a significant effect at this stage, despite the stress being significant in the pre-experience choice component. Note that this result might be explained by the presence of confirmation bias, i.e. people tend to think their initial beliefs or intuitions were correct and therefore have no intrinsic motivation to state they would like to have chosen an alternative experience (Mercier, 2022; Mynatt et al., 1977).

Latent stress

In the latent stress component, the variance was mainly explained by the use of the car, which is consistent with the results of the first wave. Also, the perceived level of realism of the experience, and the comfort level of SAV and AV turned out to be relevant variables. Again, the car triggered the highest levels of stress during the VR experience ($\gamma_{car} = 2.122, p-value < 0.01$), and the level of realism increases the stress ($\gamma_{realism} = 0.974, p-value < 0.01$). However, the comfort level does not have the expected sign ($\gamma_{comfort} = 0.428, p-value < 0.01$), suggesting that higher comfort (normal driving) increases the stress in comparison to low comfort (aggressive driving). This fact is counter-intuitive and deserves further investigation. A possible explanation is that aggressive driving could have been perceived as *faster*, which would imply that *normal* driving made participants more anxious or stressed. Also, note that from GSR we can only infer the level of arousal of the underlying emotion, however it is hard to disentangle the valence of it (i.e. if the emotion is positive or negative). Also participants are exposed to a level of comfort they freely chose, as it was informed in the pre-experience choice stage. This potentially alters the effect of the stimuli. Future research should test the effect of experiencing unexpected stimuli.

Table 5 shows the results of measurement equations. Latent stress increased the three features of GSR (logsum, maximum and minmax). However, these measures were also affected by the elapsed time on the experiment and the amount of alcohol consumed by the participant before the experiment. There is previous evidence suggesting that alcohol may increase the GSR measures (Li et al., 2022; Enewoldsen, 2016), however, it is not clear why this effect was found only for the second wave of participants. The stated satisfaction with the VR experience was not significantly correlated with the latent stress.

5.3. Third wave

In the third wave, the consideration set was: air-taxi, hyperloop and train. The results of structural equations are presented in Table 6. The estimates of the measurement equations are shown in Table 7.

Table 4
Comparison of structural equations second wave's models. Consideration set: car, bus and ridehailing.

Component	Parameter	MNL1 Estimate (Rob.t.test)	MNL2 Estimate (Rob.t.test)	LS Estimate (Rob.t.test)	LS-Full Estimate (Rob.t.test)
Pre-experience choice (β)	ASC, car	−0.942 (−0.997)	−0.532 (−0.644)	−0.33 (−0.445)	−0.365 (−0.437)
	ASC, SAV	−0.162 (−0.185)	0.197 (0.217)	0.587 (0.702)	0.498 (0.504)
	Cost	−0.17 (−3.535)	−0.136 (−3.2)	−0.143 (−2.907)	−0.137 (−2.905)
	Travel time	−0.037 (−0.701)	−0.079 (−2.089)	−0.075 (−1.954)	−0.067 (−1.634)
	Waiting time	−0.107 (−0.846)	−0.016 (−0.188)	−0.014 (−0.177)	−0.019 (−0.224)
	Crowding	−0.047 (−0.222)	0 (0.003)	−0.06 (−0.41)	−0.037 (−0.266)
	Comfort	0.542 (3.686)	0.524 (4.235)	0.613 (5.25)	0.588 (5.028)
	Weather, car	0.399 (0.569)	0.279 (0.531)	0.095 (0.213)	0.251 (0.467)
	Weather, SAV	0.519 (0.878)	0.739 (1.495)	0.62 (1.267)	0.703 (1.422)
	Work trip, car	0.505 (0.921)	0.366 (0.931)	0.467 (1.195)	0.46 (1.174)
	Work trip, SAV	0.203 (0.273)	−0.014 (−0.028)	−0.028 (−0.061)	0.021 (0.044)
	Female, car	−0.243 (−0.447)	0.08 (0.153)	0.019 (0.039)	0.019 (0.039)
	Age young, car	1.084 (1.104)	1.28 (1.41)	0.947 (1.356)	1.165 (1.336)
	Female, SAV	−0.139 (−0.235)	0.01 (0.018)	−0.031 (−0.065)	−0.074 (−0.145)
	Age young, SAV	1.118 (1.321)	0.847 (0.872)	0.469 (0.596)	0.66 (0.646)
	Inertia (λ^v)	−0.172 (−0.501)	−0.163 (−0.677)		−0.165 (−0.724)
	Dummy Inertia (λ^d)	0.035 (0.11)	0.173 (0.727)		0.231 (0.902)
	Car Stress (ω_{car})			−0.356 (−1.404)	−0.446 (−1.65)
	AV Stress (ω_{AV})			−0.074 (−0.218)	0.041 (0.102)
	SAV Stress (ω_{SAV})			−0.288 (−0.95)	−0.171 (−0.555)
Post-experience choice	ASC, car		−0.173 (−0.372)	0.003 (0.005)	−0.037 (−0.054)
	ASC, SAV		−0.369 (−0.774)	−0.399 (−0.542)	−0.437 (−0.616)
	Scale (μ)		0.812 (−0.774[a])	0.864 (−0.412[a])	0.863 (−0.417[a])
	Stickiness (δ)		1.321 (6.777)	1.27 (4.738)	1.265 (4.62)
	Car Stress (ω'_{car})			−0.364 (−1.078)	−0.355 (−1.008)
	SAV Stress (ω'_{SAV})			−0.538 (−1.322)	−0.559 (−1.298)
	AV Stress (ω'_{AV})			−0.235 (−0.573)	−0.212 (−0.496)
Latent stress (γ)	Constant			−1.836 (−3.403)	−1.82 (−3.384)
	Travel time			0.471 (2.364)	0.47 (2.332)
	Good weather			−0.013 (−0.041)	0.003 (0.009)
	Age			0.113 (0.804)	0.112 (0.787)
	Female			−0.142 (−0.415)	−0.134 (−0.392)
	Car			2.122 (4.605)	2.134 (4.566)
	SAV			−0.069 (−0.148)	−0.079 (−0.168)
	Realism			0.974 (2.517)	0.957 (2.438)
	Work trip			−0.055 (−0.215)	−0.075 (−0.285)
	Environmental cue			−0.227 (−1.049)	−0.23 (−1.072)
	Comfort			0.773 (2.262)	0.777 (2.211)
	Crowding			−0.229 (−1.082)	−0.216 (−0.988)
	Parking space			−0.253 (−1.069)	−0.267 (−1.106)
	σ_S			1 (–)	1 (–)
$LL(0)$ pre-experience choice		−208.74	−208.74	−208.74	−208.74
$LL(final)$ pre-experience choice		−149.56	−151.45	−151.73	−151.43
$LL(0)$ post-experience choice			−208.74	−208.74	−208.74
$LL(final)$ post-experience choice			−121.66	−120.04	−119.99
$LL(final)$ whole model		−149.56	−273.1	−1247.34	−1246.69
$\bar{\rho}^2$ pre-experience choice		0.2	0.19	0.19	0.18
$\bar{\rho}^2$ post-experience choice			0.4	0.39	0.39

[a] Denote a t-test against 1, otherwise the t-tests are against 0.

Table 5
Measurement equations parameters second wave's models. Consideration set: car, AV and SAV.

Component	Parameter	LS Estimate (Rob.t.test)	LS-Full Estimate (Rob.t.test)
Logsum GSR (θ)	Alcohol	0.173 (2.138)	0.172 (2.149)
	Exp. Time	0.225 (3.143)	0.225 (3.132)
	Stress	0.362 (4.344)	0.364 (4.327)
	σ	0.867 (16.049)	0.866 (16.06)
Max GSR (θ)	Alcohol	0.194 (4.477)	0.193 (4.345)
	Exp. Time	0.168 (2.337)	0.168 (2.332)
	Stress	0.445 (7.25)	0.445 (7.073)
	σ	0.818 (15.767)	0.817 (15.742)
Minmax GSR (θ)	Alcohol	0.104 (2.489)	0.104 (2.482)
	Exp. Time	0.222 (3.018)	0.222 (3.003)
	Stress	0.413 (6.864)	0.413 (6.748)
	σ	0.784 (15.368)	0.785 (15.349)
Stated Satisfaction (θ_E)	Stress	0.169 (0.81)	0.165 (0.793)
	τ_1	−2.027 (−8.73)	−2.025 (−8.79)
	τ_2	−0.461 (−2.068)	−0.458 (−2.059)
	τ_3	1.218 (5.228)	1.219 (5.216)

Pre-experience choice

The utility of each alternative at the pre-experience choice was affected the most by cost and travel time. Air-taxi and hyperloop were preferred over the train, possibly due to the novelty of those alternatives. No other travel attribute played a role in these models. Note that the only significant dynamic effect is the inertia dummy in the model MNL1 ($\lambda^d = -0.604, p - value < 0.01$). However, this effect disappears with the inclusion of the post-experience choice in MNL2 and the latent stress in the following models. In this wave, the latent stress did not cause significant effects in utility in the pre-experience choice stage. As explained next, no travel mode caused significant variations in the latent stress. This may be explained by how travel modes are simulated, as previously discussed. In the first and second wave, participants were asked to drive the car in the VR environment. In this wave, no mode required participants to actively engage in the task. We also controlled for the mode that was experienced first during this training stage, but no significant effect was found and the variable was dropped from the reported models.

Post-experience choice

In the post-experience choice stage, information about each alternative was still considered (scale $\mu < 1$, not significantly different from 1). However, they also tended to maintain their pre-experience choice (stickiness $\delta > 1$ with $p - value < 0.01$ in all models). In this wave, the measured latent stress did not cause participants to regret their pre-experience choices.

Latent stress

In the third wave, latent stress was mainly explained by the age of the participants, with older participants experiencing a lower stress ($\gamma_{age} = -1.096$ in LS and $\gamma_{age} = -1.056$ in LS-Full with $p - value < 0.01$), and the purpose of the trip (a work trip caused higher stress in LS and $LS - Full$).

Regarding the measurement equations of the latent stress (Table 7), it was obtained that the three GSR features increased with the latent stress. However, the GSR also increases consistently with the elapsed time in the experiment. Finally, the stated satisfaction with the experience was not significantly correlated with the latent stress.

6. Discussion and final remarks

It has not yet been shown how physiological measures can help to estimate the effect of latent psychological states perceived in travel experiences on travel mode choice. This paper addresses this question by analysing data from a VR experiment and estimating the latent stress associated with travel experience and decision-making using skin conductance data. In the three waves of the experiment, participants were exposed to different consideration sets, which included common and novel travel modes (AV, hyperloop and air-taxi). Each participant completed four choice tasks. In each, they first chose a mode from a SP survey (pre-experience choice), then experienced that mode, and finally were asked if they regretted that choice by choosing another mode (post-experience choice). This is the first experiment analysing psychological states and modal choice inside a VR environment, and the first study in using physiological data to analyse the effect of experienced psychological states on future choices.

We compared four models, with different intertemporal effects. To capture the effect of: inertia as a function of the difference between chosen and non-chosen alternatives, only as a function of; the carrying-over effect, the tendency to repeat the same choice across tasks; and the effect of a lagged latent stress variable, to test the effect of stress in travel mode choices. In general, the inclusion of latent stress did not improve the fit of the models in all waves of the experiment. However, in this experimental context, travelling by car as a driver was shown to trigger the highest levels of stress, making participants less likely to choose the car in the next choice task. Travel modes different from the car did not significantly increase the latent stress. Our finding supports our main hypothesis:

Table 6
Structural equations parameters third wave's models. Consideration set: air-taxi, hyperloop (HL), and train.

Component	Parameter	MNL1 Estimate (Rob.t.test)	MNL2 Estimate (Rob.t.test)	LS Estimate (Rob.t.test)	LS-Full Estimate (Rob.t.test)
Pre-experience choice (β)	ASC, air-taxi	0.509 (0.891)	0.667 (1.118)	0.604 (0.995)	0.653 (1.017)
	ASC, HL	0.885 (1.85)	0.849 (1.901)	0.758 (1.695)	0.84 (1.81)
	Cost	−0.664 (−3.452)	−0.575 (−3.182)	−0.566 (−3.103)	−0.571 (−3.109)
	Travel time	−0.298 (−2.55)	−0.315 (−2.997)	−0.308 (−2.819)	−0.323 (−2.891)
	Walking time	0.019 (0.172)	−0.079 (−0.763)	−0.082 (−0.822)	−0.073 (−0.694)
	Waiting time	−0.182 (−1.502)	−0.127 (−1.23)	−0.134 (−1.344)	−0.126 (−1.227)
	Crowding	−0.395 (−1.267)	−0.353 (−1.327)	−0.312 (−1.187)	−0.354 (−1.283)
	Comfort	−0.177 (−0.637)	0.007 (0.031)	0.017 (0.076)	0.022 (0.092)
	Work trip, air-taxi	−0.322 (−0.444)	−0.696 (−1.075)	−0.732 (−1.127)	−0.684 (−1.023)
	Work trip, HL	0.198 (0.313)	0.115 (0.212)	0.106 (0.202)	0.137 (0.251)
	Carbon	−0.098 (−0.694)	−0.133 (−1.075)	−0.126 (−1.009)	−0.128 (−1.019)
	Age, air-taxi	0.155 (0.567)	0.131 (0.472)	0.169 (0.592)	0.141 (0.49)
	Age, HL	0.179 (0.664)	0.13 (0.544)	0.165 (0.684)	0.171 (0.674)
	Gender, air-taxi	−0.116 (−0.255)	−0.331 (−0.699)	−0.362 (−0.739)	−0.357 (−0.725)
	Gender, HL	−0.27 (−0.599)	−0.224 (−0.533)	−0.228 (−0.546)	−0.252 (−0.575)
	Inertia (λ^v)	0.107 (0.966)	0.057 (0.485)		0.042 (0.347)
	Dummy Inertia (λ^d)	−0.696 (−2.201)	−0.465 (−1.533)		−0.442 (−1.458)
	Air-taxi Stress ($\omega_{air-taxi}$)			0.033 (0.083)	0.083 (0.205)
	HL Stress (ω_{HL})			−0.261 (−0.434)	−0.281 (−0.41)
	Train Stress (ω_{Train})			−0.573 (−1.091)	−0.586 (−1.167)
Post-experience choice	ASC, air-taxi		−0.118 (−0.239)	−0.099 (−0.161)	−0.088 (−0.146)
	ASC, HL		0.739 (1.507)	0.789 (1.867)	0.807 (2.012)
	Scale (μ)		0.722 (−1.182[a])	0.755 (−0.903[a])	0.725 (−1.031[a])
	Stickiness (δ)		2.618 (6.26)	2.659 (5.084)	2.634 (5.238)
	Air-taxi Stress ($\omega'_{air-taxi}$)			−0.122 (−0.286)	−0.149 (−0.347)
	HL Stress (ω'_{HL})			−1.027 (−0.363)	−1.017 (−0.351)
	Train Stress (ω'_{Train})			0.148 (0.166)	0.137 (0.158)
Latent stress (γ)	Constant			0.265 (1.097)	0.261 (1.086)
	Travel time			0.124 (1.456)	0.124 (1.451)
	Age			−0.831 (−4.282)	−0.83 (−4.303)
	Female			0.385 (1.2)	0.385 (1.189)
	Air-taxi			0.256 (0.875)	0.259 (0.883)
	HL			0.127 (0.589)	0.129 (0.595)
	Realism			−0.032 (−0.223)	−0.031 (−0.221)
	Work trip			0.253 (2.179)	0.253 (2.175)
	Environmental cue			−0.09 (−0.855)	−0.09 (−0.851)
	Comfort			−0.071 (−0.896)	−0.071 (−0.89)
	Crowding			−0.044 (−0.742)	−0.044 (−0.743)
	σ_S			1 (–)	1 (–)
$LL(0)$ pre-experience choice		−196.65	−196.65	−196.65	−196.65
$LL(final)$ pre-experience choice		−124.59	−126.09	−128.86	−126.58
$LL(0)$ post-experience choice			−196.65	−196.65	−196.65
$LL(final)$ post-experience choice			−54.39	−53.43	−54.23
$LL(final)$ whole model		−124.59	180.48	−860.44	−859.09
$\bar{\rho}^2$ pre-experience choice		0.28	0.27	0.25	0.25
$\bar{\rho}^2$ post-experience choice			0.70	0.69	0.69

[a] Denote a t-test against 1, otherwise the t-tests are against 0.

individuals who perceive higher levels of stress are less likely to choose the same alternative again, which can be identified using psychophysiological data. However, further research is needed to generalise this finding to a broad range of transport modes and to validate it out of the laboratory.

Regarding our second research question, our results suggest that the joint estimation of the pre- and post-experience choices helped to identify the effects of travel attributes. Importantly, the effect of travel time on the second wave was only significant after adding the post-experience choice to the model. This finding suggests that at the pre-experience stage, participants underweighted the displeasure they expected to feel per unit of time during the VR experience. Then, after the experience, they updated their marginal utility of the travel time. However, the overall tendency observed was to stick to the mode chosen in the pre-experience choice stage.

Regarding the third question, both inertia variables were significant only in the first wave, showing a negative effect, which means that the participants tended to explore the available alternatives. However, no inertia variables were significant when latent stress was present in the model. This means that the tendency to switch to other alternatives was mediated by the latent stress associated with previous experience, rather than only being explained by exploratory behaviour.

Table 7
Measurement equations parameters third wave's models. Consideration set: air-taxi, hyperloop (HL), and train.

Component	Parameter	LS Estimate (Rob.t.test)	LS-Full Estimate (Rob.t.test)
Mean GSR (θ)	Alcohol	−0.012 (−0.211)	−0.012 (−0.212)
	Exp. Time	0.372 (7.509)	0.372 (7.523)
	Stress	0.986 (5.224)	0.986 (5.217)
	σ_p	0.508 (15.467)	0.507 (15.44)
Max GSR (θ)	Alcohol	0.073 (0.944)	0.072 (0.929)
	Exp. Time	0.349 (6.061)	0.349 (6.068)
	Stress	0.786 (3.827)	0.786 (3.823)
	σ_p	0.695 (14.762)	0.695 (14.78)
Logsum GSR (θ)	Alcohol	0.02 (0.418)	0.02 (0.392)
	Exp. Time	0.291 (6.943)	0.291 (6.954)
	Stress	0.808 (5.19)	0.808 (5.179)
	σ_p	0.418 (15.82)	0.419 (15.843)
Stated satisfaction (θ_E)	τ_1	−4.488 (−6.312)	−4.488 (−6.311)
	τ_2	−1.731 (−7.246)	−1.731 (−7.244)
	τ_3	0.24 (1.015)	0.24 (1.014)
	Stress	0.158 (0.74)	0.159 (0.743)

Despite the fact that car driving was the more stressful choice in our experiment, this does not necessarily imply that in real life driving is more stressful. The external validity of transport-related stimuli in VR experiences deserves further research. That is, it is not completely clear which attributes related to transport alternatives generate psychophysiological effects in VR environments that can be compared to the real-life effects. In addition, the stress caused by the experiences can be affected by the fact that the participants where informed about the expected value of the attributes and they freely chose to be exposed to that experience. For example, a passenger that chooses to travel under high crowding conditions, may be less emotionally affected than an individual under unexpected levels of crowding. This is supported by evidence from neuroscience, showing that changes in physiological signals and emotions depend on exposure specifically to *unexpected* stimuli (Lerner et al., 2021). A relevant point of this study, is how the attributes were mapped from the SP survey to the VR experience (Tables A.2–A.4). Although most attributes area easy to map, subjectives attributes (as the comfort level) are challenging since it is no possible to anticipate how people interpret them in order to adjust the VR experience to the expected level.

We found some unexpected results in the parameters of the pre-experience utility, for example not significant waiting time parameters, not significant cost parameter (only in first wave) and positive walking time parameters (only in first wave). In particular in the case of the first wave (where all modes were familiar to the participants) this could have been influenced by endogenous preferences or low level of engagement in the task. In the first wave, no novel travel mode was presented, which could have made the experiment less interesting for the participants and decreased their engagement, which is consistent with our results that show strong exploratory behaviour. In the second and third wave, the participants were presented with novel alternatives (AV, air-taxi, and hyperloop). This may have served to keep participants attentive and engaged with the experiment, which was demanding in terms of time and attention. In light of our results, future experiments should be designed with the following considerations in mind (a) the inclusion of unexpected stimuli, (b) to have an equivalent level of reality of the different alternatives, (c) to capture in the VR all stimuli presented in the SP survey, (d) to add novelty to the simulations in order to keep participants engaged and attentive during the experiment, and (e) to consider the use of multisensory VR technology, which could help increase the ecological validity (Melo et al., 2022a,b). Future models should consider machine learning approaches to extract embedded representations of the physiological data that allow for the extraction of as much variance as possible and better explain behaviour without the need to compute features that may be arbitrary and context dependent, which is common practice when working with PPI (e.g. Shukla et al., 2021), as there is not likely to be a best practice to consistently integrate the data into a model (Hancock and Choudhury, 2023). This is a promising avenue for future work, given recent advances in the integration of machine learning with discrete choice models (Sifringer et al., 2020).

Our results contribute significantly to this emerging field, as it is the first experiment to integrate VR technology, travel mode choice, and physiological sensors. So far, the potential of VR has mainly been discussed in the context of travel satisfaction analysis. In contrast, this article highlights the potential of VR for the analysis of the effects of travel satisfaction on demand, which is necessary to capture the true benefit of transport projects and to move towards the evaluation of projects aimed at maximising subjective well-being (Henriquez-Jara and Guevara, 2025).

CRediT authorship contribution statement

Bastián Henríquez-Jara: Writing – review & editing, Writing – original draft, Visualization, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Thomas O. Hancock:** Writing – review & editing, Supervision, Methodology, Conceptualization. **Albert Solernou:** Software, Methodology. **Jorge Garcia:** Software, Methodology. **C. Angelo Guevara:** Writing – review & editing. **Charisma Choudhury:** Writing – review & editing, Supervision, Resources, Methodology, Investigation, Funding acquisition, Conceptualization.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix. Sample composition and attributes levels in SP and VR

The full details of the 'Future Modes Study' of the 'Next Generation Travel Behaviour Models Project' are available at Choudhury et al. (2025). The key tables are reproduced below for the sake of completeness of the current paper.

Table A.1
Sample composition.

Socio-demographic attributes		Number
Gender	Male	46
	Female	25
Job	Students	42
	Employed	26
	Other	3
Age	18–24	27
	25–34	23
	35–44	15
	45–54	4
	55+	2
Household annual income (Before reduction)[a]	Below £10,000	7
	£10,000–£25,000	18
	£25,000–£50,000	18
	Above £50,000	19
	Prefer not to say	3
	I do not know	5
Highest level of education[a]	High School diploma	10
	College/University certificate	11
	Bachelor's degree	17
	Master's degree	19
	Doctorate degree	13
Ethnicity[a]	Arab	2
	Asian - East Asian	10
	Asian - South Asian	9
	Black or African heritage	3
	White	40
	Mixed	3
	Any other ethnic group	2
	Prefer not to say	1

[a] One respondent did not report.

Table A.2
First wave: Attributes values and how they were incorporated into VR.

Attribute	Private Car	Ride-hailing	Bus/Train	Incorporation into VR
Trip type		Work or recreational		The time was shown on a dashboard, and displayed in red to highlight urgency for work trips.
Traffic/weather conditions		Good or bad		Bad conditions shown as 'nighttime' in VR
In-vehicle time	12 or 20 mins + up to 10 mins		20–30 mins + up to 10 mins	Average times used for trip duration
Pickup time	–	2 or 5 mins	5 or 10 mins	Proportional waiting time simulated
Parking	1, 5 or 10 mins	–	–	Parking space availability varied
Petrol/fare	£2.50 or £5	£7.50 or £10	£2.50 or £5	Participants were
Parking	£2.50, £7.50 or £12.50	–	–	incentivised to make choices as they would in the real-world
Occupancy	Always alone	Alone or with 1–3 passengers	10%–90% full	Bus passenger numbers vary based on SP task
Comfort	N/A	1 or 3 stars		Noise levels (bus) and driving smoothness (ridehail)
Carbon Emissions	50, 175 or 245 g/km		50 or 105 g/pkm	Green/orange/red leaf displayed

Table A.3
Second wave: Attributes values and how they were incorporated into VR.

Attribute	Private Car	Autonomous vehicle (shared)	Autonomous vehicle (personal)	Incorporation into VR
Trip type		Work or recreational		The time was shown on a dashboard, and displayed in red to highlight urgency for work trips.
Traffic/weather conditions		Good or bad		Bad conditions shown as 'nighttime' in VR
In-vehicle time	5 or 10 mins + up to 10 mins	7–15 mins + up to 10 mins	5 or 10 mins + up to 10 mins	Average times used for trip duration
Pickup time	–	2 or 5 mins	2 or 5 mins	Displayed on arrival board
Parking	1, 5 or 10 mins	–	–	Time searching for a parking space varied
Petrol/fare	£2.50 or £5	£12 or £15	£16 or £20	Participants were
Parking	£2.50, £7.50 or £12.50	–	–	incentivised to make choices as they would in the real-world
Occupancy	Always alone	1–3 passengers	Always alone	The number of AV passengers varied in line with number given in the SP task
Comfort	N/A	1 or 3 stars		'Smooth' or 'jerky' versions of each drive

Table A.4
Third wave: Attributes values and how they were incorporated into VR.

Attribute	Air taxi	Hyperloop	Train	Incorporation into VR
Trip type		Work or recreational		The time was shown on a dashboard, and displayed in red to highlight urgency for work trips.
Traffic/weather conditions		Good or bad		Bad conditions shown as 'nighttime' in VR
In-vehicle time	6 or 10 mins	2 or 5 mins	45–70 mins	Average times used for trip duration
Wait time	10 or 15 mins		5 or 10 mins	Proportional waiting time simulated
Fare	£45 or £65	£35–50	£11–£20	Participants were incentivised to make choices as they would in the real-world
Occupancy	50%–75% full	50%–90% full	10%–90% full	Passenger numbers varied based on SP task
Comfort	3 stars	3 stars	1 or 3 stars	Noise levels vary

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