An adapted decision field theory model for capturing the impact of experiences on preferential change for new travel modes.

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Short summary

There have been limited applications using physiological sensor data to unpick the role of experience in preferential change under experimental conditions. We design a novel virtual reality (VR)–based data collection process that allows us to collect physiological sensor data to measure the effect of experience in a controlled setting. Specifically, we ask participants to complete a number of stated preference tasks on travel mode choice based on traditional stated preference (SP) scenarios. After each SP choice, the participant 'experiences' their chosen mode in Virtual Reality (VR). The participant then 're-evaluates' their choices. We develop and test different versions of a sequential sampling model (decision field theory) to evaluate how to best capture the impact of experiencing the chosen travel mode. We gain insights into the participants' relative preferences towards new travel modes and how experiencing the new modes may influence their uptake when they become available.
Keywords: Decision field theory, Futuristic travel modes, Preferential change, Virtual reality.

1 Introduction

Within the stream of mathematical psychology research, 'sequential sampling' (accumulator) models have been developed to represent the accumulation of preference over time, with the idea being that a model that better mirrors the decision-making process will also better predict the choice outcome. In particular, decision field theory (Busemeyer & Townsend, 1992, 1993; Roe et al., 2001) has recently made the transition into mainstream travel behaviour research, having initially been developed by cognitive psychologists for laboratory choice settings (i.e. often psychophysical data as opposed to preferential choice data). Recent work has demonstrated that the model can predict stated preference (SP) mode choice behaviour (Hancock et al., 2018, 2021) and can be adapted for revealed preference (RP) travel behaviour (Hancock, Choudhury, Hess, & Tsoleridis, 2023), often with better model performance than standard econometric choice models. It has also been demonstrated that the model can be adapted to incorporate physiological sensor data (Hancock, Choudhury, & Hess, 2023), specifically the use of eye-tracking data to better understand individual preferences for different attributes and the use of skin conductance data to better understand when people are making more attentive choices. At the core of the model is the assumption of a specific decision-making process. Under the DFT model, decision-makers sequentially (but stochastically) consider different attributes, comparing them across alternatives. Thus, after each 'preference updating step', the 'preference' (utility) for each alternative updates based on the currently considered attributes and the previous preference. After some amount of deliberation time, the decision-maker concludes the process by either reaching a point at which one alternative satisfices (an internal threshold) or they run out of time to make a decision (an external threshold). A representation of this process is shown in Figure 1. Depending on how long the decision-maker considers their alternatives, they may reach a different conclusion. In Figure 1, a decision-maker would choose ridehail if they were to stop after 12 preference updating steps (the blue dashed vertical line) but choose bus after 35 preference updating steps (the purple dashed vertical line).

However, whilst the model provides a conceptually appealing fit to modelling sequential choice behaviour, applications thus far have been almost entirely limited to datasets where all choices are treated as independent. In contrast, within the field of transportation research, modelling the role of experience in the formation of preferences is an increasingly popular topic, with an ever-expanding number of analysts studying the decision-making process and how it can be linked to

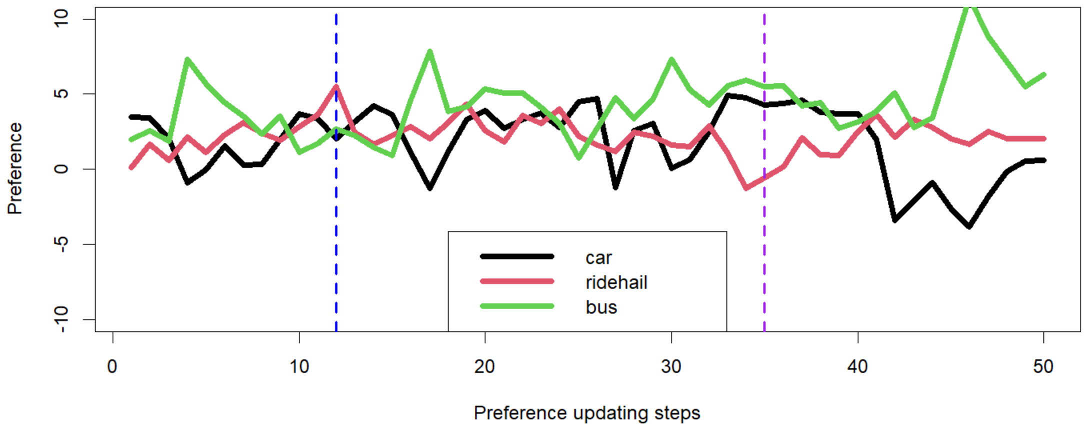


Figure 1: A simulated DFT process (preference on the y-axis). A different alternative may be chosen depending on the number of preference updating steps, as indicated by the dashed vertical lines.

choice outcomes. Some work has focussed specifically on preferential change through an intervention (Abou-Zeid et al., 2012; Palma et al., 2019; Harb et al., 2022), whilst others focus on the use of physiological sensor data to explain experiences (Henríquez-Jara et al., 2023). There has also been work on inertia (Cantillo et al., 2007; Cherchi & Manca, 2011; Bansal et al., 2022) and the development of preferences (Dekker et al., 2014; Bliemer et al., 2022). However, these applications are not based on models with psychological foundations and thus have rarely included consideration of the decision-making process itself and how it might change for sequential decisions. They have instead typically focussed on capturing the evolution of biases (underlying preferences) towards alternatives over time.

There has also been limited applications using physiological sensor data to unpick the role of experience in preferential change under experimental conditions, a particularly challenging task in real-world settings where the effect of an experience can be confounded with changes in other external factors. This motivates the work in the present study. If we are to stand by the hypothesis that better representing the decision-making process will lead to better predictions of chosen alternatives, there is significant scope for the development of a new sequential sampling model that specifically aims to capture sequential choices.

We aim to test this idea through the application of different versions of DFT models to data from a virtual reality (VR) experiment. Participants make mode choice decisions, experience their chosen travel mode, and then re-evaluate their preferred travel mode in the same choice context. The use of VR here allows the participant to experience hypothetical but immersive experiences (Patterson et al., 2017; Farooq et al., 2018; Bogacz et al., 2021) in a fully controlled setting, thus allowing them to 'experience' new travel modes such as air taxi and hyperloop. Electroencephalogram recordings, eye-tracking data, and skin conductance data are recorded to (a) better understand the initial decision-making process, (b) better evaluate the participant's experience within the virtual reality settings and (c) allow for the possibility of better predicting preferential change.

We aim to answer the following research questions:

- How can we best model the change in preference as a result of experiencing a choice?
- Can we better capture and explain behavioural change/preference reversals?
- Can we incorporate proxies of the decision-making process (eye-tracking, EEG, stress measurement data, etc.) into the model to better understand the unobserved processes behind decision-making?

The rest of this paper is organised as follows. First, we present an overview of the mathematics of decision field theory and how it might be adapted for sequential choice processes. Next, we introduce our data collection effort. We then discuss some preliminary model results. We conclude with steps to be taken and a list of hypotheses that will be tested ahead of the hEART conference in June 2025.

2 Modelling framework

Decision field theory background

We start by describing the base DFT model. It is currently designed to explain a single choice and simulates the evolution of preference in this single choice context. The preference value for each alternative is represented in the model by a vector, $\boldsymbol{P}_{nt,\tau}$, the preference after τ updating steps for decision-maker n for choice task t. The preference updating process is then represented by:

$$\boldsymbol{P}_{n,t,\tau+1} = S_{n,t} \cdot \boldsymbol{P}_{n,t,\tau} + C_{n,t} \cdot M_{n,t} \cdot \beta \cdot \boldsymbol{W}_{n,t,\tau+1} + \boldsymbol{\varepsilon}_{n,t,\tau+1}, \tag{1}$$

where:

- S is a feedback matrix that specifically controls how much the contextual effects (e.g. the similarity effect, Roe et al. 2001) impact the preferences and captures the relative importance of previous preferences through a memory parameter (i.e. more recently attended attributes will have more weight on the overall preference levels).
- C is a contrast matrix used to rescale the attributes such that they sum to zero.
- M is a matrix of size k (number of attributes) by J (number of alternatives) containing the full set of attribute values.
- $\boldsymbol{W}_{n,t,\tau+1}$ is a vector of zeros with a single 1 in the row that corresponds to the attribute k that is considered by the decision-maker in preference updating step $\tau + 1$.
- $\boldsymbol{\varepsilon}_{n,t,\tau+1}$ is an error term that is normally distributed identically and independently across alternatives, steps, individuals, and choice tasks.

In the absence of physiological sensor data or choice response time data, the decision-making process is assumed to stop after some number of preference updating steps (which are estimated by the model). Probabilities of choosing different alternatives under the model are calculated based on the expectation and covariance of $\boldsymbol{P}_{n,t,\tau+1}$ (Roe et al., 2001; Hancock et al., 2021) rather than simulation of the preference updating process itself.

Modelling sequential choices

There are many different possibilities for how to mathematically represent a sequential choice process within a DFT model. Four possibilities include:

- Decision-makers' preference at the start of the second deliberation process will match the value at the end of the first deliberation process (see the top left panel of Figure 2).
- Decision-makers' preference remains unchanged for the chosen alternatives, but continues to update for the alternative that they are currently experiencing (top right panel).
- Decision-makers' preference will fully 'reset' back to initial preference values (lower left panel).
- Decision-makers' preference at the start of the second deliberation process will be different to those at the start of the first process, as a consequence of the experience of the chosen alternative (lower right panel).

3 Experimental setup

The data collection effort is part of the wider 'NEXUS' project in which one key aim is to study the preferences for new travel modes across different countries. The first data collected were online survey data (Hancock, Song, et al., 2023), where we demonstrated that amongst 1,015 respondents from the East (China, Singapore), Middle East (UAE), and the West (Sweden, UK, USA), the largest driver of preference heterogeneity was the decision-maker's country, as opposed to standard sociodemographic variables such as age, gender and income. The work in this paper is based on the exact same choice scenarios, which additionally allows for the comparison of preferences from those who completed the study online to those who completed the study in Virtual Reality (VR) settings.

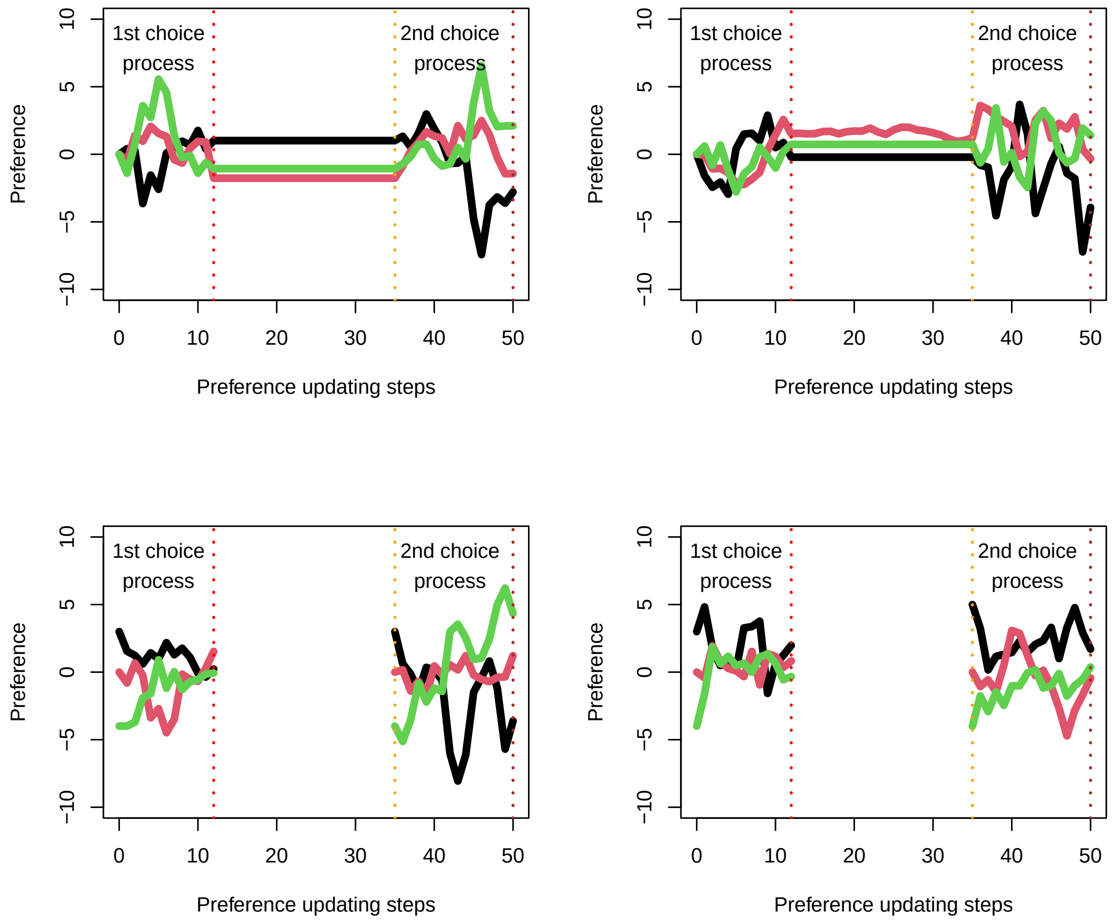


Figure 2: Four different possible preference updating processes that could occur at the point the decision-maker is experiencing their initial preferred mode in Virtual Reality. In this case, the participant had a positive experience of the alternative represented by the black line in the bottom right panel, resulting in an increased initial preference for this alternative at the start of the second period. This results in the decision-maker choosing this alternative, whereas they switched to the alternative represented by the green line in the example given in the lower left panel.

For the VR settings, participants completed up to a total of 12 choice tasks across three sessions. The sessions encompass four tasks each on current (car, train, bus), upcoming (shared autonomous car, private autonomous car vs. car), and future (hyperloop, air taxi vs. train) travel modes, respectively. Alternatives are described by attributes including travel cost, travel time, comfort, carbon emissions, and crowdedness (see Figure 3 for an example of a 'current' mode choice task, Figure 4 for 'upcoming' modes and Figure 5 for 'future' modes).
The crucial difference with the online setting is that participants in VR (in each choice scenario) make a choice, experience the choice, then make a choice again on the same scenario seen prior to the VR experience. The participant thus has an opportunity to make a different choice (i.e. state that they have changed their mind). The experimental process is visualised in Figure 6.
An additional advantage that the VR data has over the online version is that physiological sensor data is also recorded. Thus, for each participant, electroencephalogram recordings, eye-tracking data, and skin conductance data are recorded. Examples images from the VR process are given in Figure 7.

Scenario 1/12:

Imagine you are going to make a **Work** trip and pay for it.
Please consider the following 3 mode options and make your choice as if they are all available to you.
(to see the definition of an attribute, please hover the pointer over that attribute or* Click Here *)*

	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

Figure 3: Example choice task for current modes.

Scenario 6/12:

Imagine you are going to make a **Recreational** trip and pay for it.
Please consider the following 3 mode options and make your choice as if they are all available to you.
(to see the definition of an attribute, please hover the pointer over that attribute or* Click Here *)*

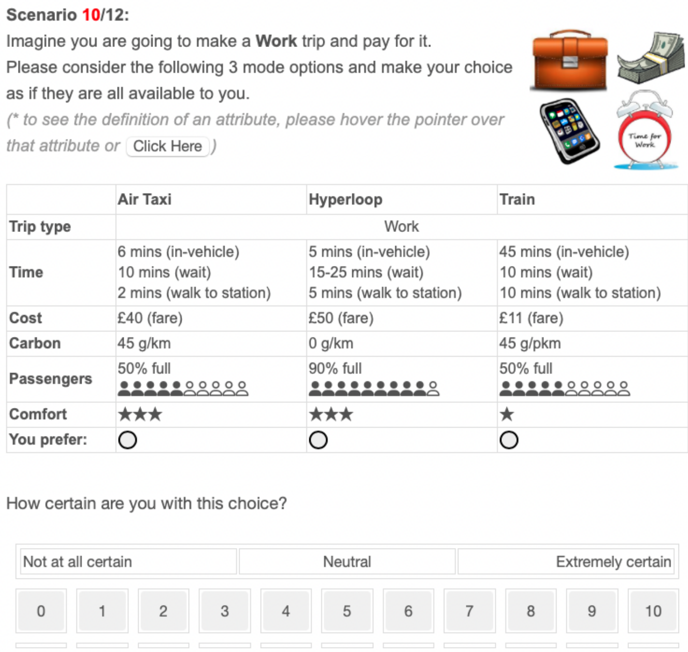
	Private Car	Self-driving car (shared)	Self-driving car (only you)
Trip type	Recreational		
Traffic/weather conditions	Good		
Time	5-10 mins (in-vehicle) 1 mins (parking and walk from parking)	7-12 mins (in-vehicle) 5 mins (pickup)	5-10 mins (in-vehicle) 5 mins (pickup)
Cost	£2.5 (petrol) £2.5 (parking)	£15 (hire)	£20 (hire)
Passengers	on your own	3 other passengers	on your own
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

Figure 4: Example choice task for upcoming modes.


Scenario 10/12:
Imagine you are going to make a **Work** trip and pay for it.
Please consider the following 3 mode options and make your choice as if they are all available to you.
(to see the definition of an attribute, please hover the pointer over that attribute or* Click Here *)*

	Air Taxi	Hyperloop	Train
Trip type		Work	
Time	6 mins (in-vehicle) 10 mins (wait) 2 mins (walk to station)	5 mins (in-vehicle) 15-25 mins (wait) 5 mins (walk to station)	45 mins (in-vehicle) 10 mins (wait) 10 mins (walk to station)
Cost	£40 (fare)	£50 (fare)	£11 (fare)
Carbon	45 g/km	0 g/km	45 g/pkm
Passengers	50% full	90% full	50% full
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

Figure 5: Example choice task for futuristic modes.

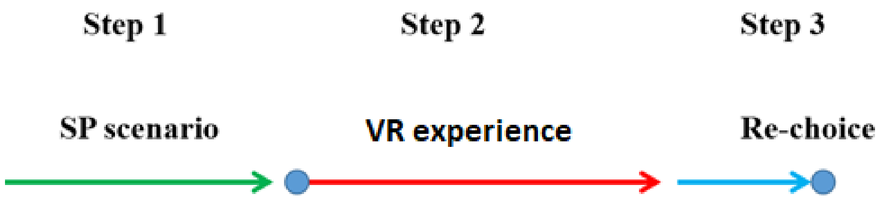


Figure 6: The process for each choice scenario in VR settings.

4 Data

71 participants complete choice tasks, with the modal shares and shifts given in Figures 8 and 9. The largest change appears to be between car and own AV in the 2nd setting. Shifting behaviour is less frequent in the third setting. This could be driven by the fact that experienced stress is highest for car (see Figure 10).

5 Results

For the modelling work in this paper, we use data from 71 participants. Each participant completes up to 12 VR choice scenarios and 12 online choice scenarios. They complete tasks before and after VR experiences, resulting in up to 36 choice tasks each. After data cleaning, a total of 2,111 choices remain (The difficulty of recruiting participants for VR sessions meant that only 50 completed all three sessions).
We develop several DFT models of increasing complexity. These are:

1. A *base* model that assumes that all choices are made under the same conditions.

2. A model that accounts for the *settings*, by estimating separate alternative specific constants for the online choices, the VR pre-trip choices and the VR post-trip choices. Separate timestep parameters are also estimated, to capture the fact that the choice processes may be different across settings.

Figure 7: The upper panel shows the lead author trialling the VR driving experience, the middle panel shows a screenshot from an example ridehail trip, and the bottom panel shows a screenshot from an example public transport trip.

3. A model that additionally accounts for the fact that participants are more likely to *stick* to their pre-trip VR choice. This is captured in the DFT model through an addition the P_0 in Equation 1 for the VR post-trip choices.
4. A model that captures *inertia* by recognising that participants may be more likely to choose alternatives they have already experienced. This again is implemented in the DFT model with a shift to the initial preference matrix, P_0.
5. A model that recognises the impact of *stress*. It does this by adjusting P_0 to account for the fact that individuals that have particularly stressful VR experiences (as indicated by GSR measurements) are more likely to switch away from their pre-trip chosen alternative in the post-trip choice task.

The performance of these models is given in Table 1.
The full parameter estimates of the final ('*Stress*') model are given in Figure 11.
A summary of these model results is given below:

Round 1

First choice \ Second choice	Car	Taxi	Bus
Car	24.0%	2.9%	4.4%
Taxi	4.0%	37.1%	3.3%
Bus	5.8%	2.2%	16.4%

Round 2

First choice \ Second choice	Car	Own AV	Shared AV
Car	36.5%	8.5%	1.6%
Own AV	7.9%	31.7%	2.6%
Shared AV	2.6%	0.5%	7.9%

Round 3

First choice \ Second choice	Car	Hyperloop	Train
Air taxi	29.3%	3.4%	0.6%
Hyperloop	0.6%	44.8%	0.6%
Train	1.1%	3.4%	16.1%

Figure 8: Choice shares across the participants.

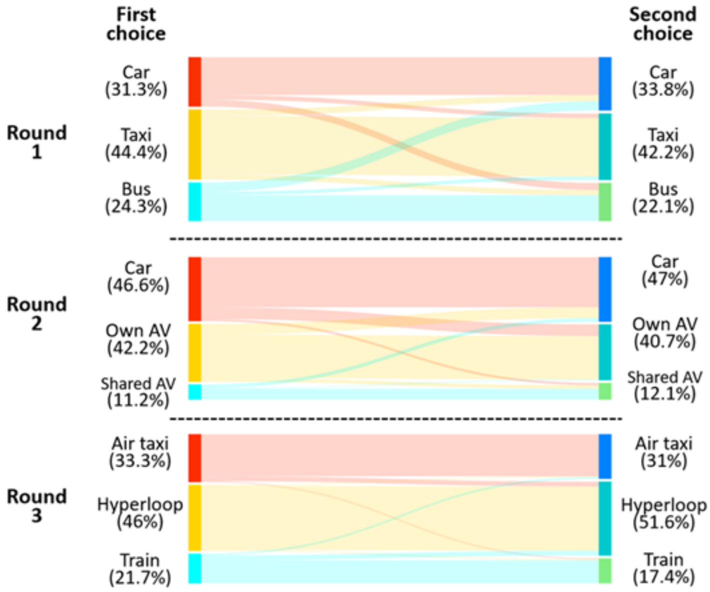


Figure 9: Preferential shifts.

	Base	Settings	'Stick'	Inertia	Stress
Estimated parameters	21	35	36	38	47
LL(online)	-731.00	-688.16	-686.54	-677.67	-677.58
LL(before experience)	-617.53	-604.38	-605.32	-599.78	-599.85
LL(after experience)	-612.32	-598.23	-381.40	-381.43	-372.03
LL(total)	-1,960.85	-1,890.77	-1,673.26	-1,658.87	-1,649.46
BIC(total)	4,054	3,972	3,549	3,531	3,565

Table 1: Log-likelihoods from the different types of choice tasks across the different models.

1. The parameter estimates that are common to all models ('Base') are of the expected sign. However, the influence of the number of passengers on buses or trains is insignificant. Some shifts are seen for work trips, with own AVs and air taxis less likely chosen.
2. Incorporating differences across settings significantly improves model performance. A notable clear difference is that there are positive estimates for the shift towards bus and train in online settings. Not actually experiencing these modes makes them more likely to be chosen, clearly demonstrating the role of hypothetical bias.
3. The incorporation of a single parameter in the initial preference matrix to account for the

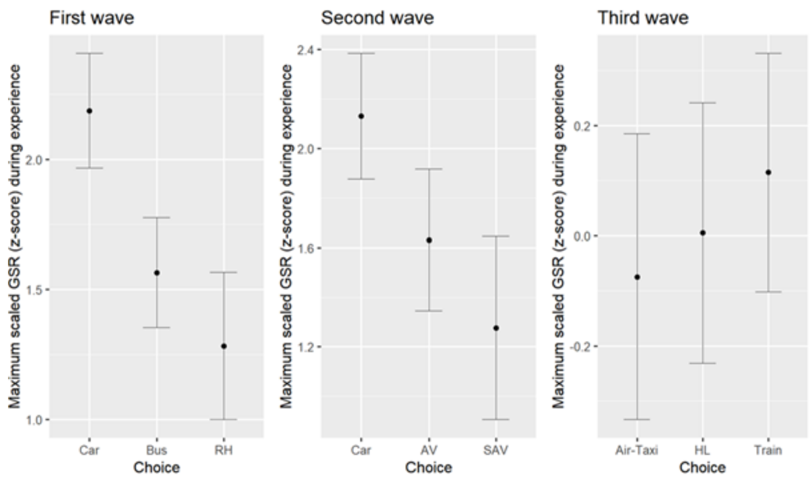


Figure 10: Mean of the maximum scaled GSR measured during the VR experiences, with the points indicating the mean values and bars denoting 95% confidence intervals.

BASE	Estimate	Rob.t-ratio(0)
delta_rh	0.0003	0.02
delta_pt	-0.0530	-2.42
delta_oav	0.0501	2.20
delta_sav	-0.0507	-2.29
delta_hy	-0.0550	-2.47
delta_tr	-0.2808	-6.63
b_condition_bad_rh	0.0259	1.45
b_condition_bad_pt	-0.0118	-0.72
b_condition_bad_oav	0.0245	1.51
b_condition_bad_sav	-0.0049	-0.25
b_work_rh	0.0132	0.76
b_work_pt	0.0209	1.26
b_work_oav	-0.0475	-2.53
b_work_sav	-0.0165	-0.90
b_work_hy	0.0528	2.25
b_work_tr	0.0309	1.69
b_ivt	-0.0008	-1.96
b_cost	-0.0079	-6.97
b_passenger	-0.0089	-1.54
b_passenger_pt	0.0000	-0.34
b_comfort	0.0090	2.50
p_timesteps	6.9068	NA

SETTING	Estimate	Rob.t-ratio(0)
delta_VR2_rh	-0.0750	-1.95
delta_VR2_pt	0.0167	0.44
delta_VR2_oav	-0.0495	-0.93
delta_VR2_sav	-0.0478	-0.61
delta_VR2_hy	0.0865	1.51
delta_VR2_tr	0.0017	0.03
delta_online_rh	-0.0692	-3.34
delta_online_pt	0.0343	2.01
delta_online_oav	-0.0487	-2.49
delta_online_sav	0.0025	0.08
delta_online_hy	0.0107	0.48
delta_online_tr	0.1073	4.44
p_timesteps_online	0.5103	1.17
p_timesteps_VR	-0.9323	-2.30
STICK	Estimate	Rob.t-ratio(0)
b_stick	33.4916	4.35
INERTIA	Estimate	Rob.t-ratio(0)
b_prev	16.8347	3.09
b_prevVR	-7.5416	-2.93

STRESS	Estimate	Rob.t-ratio(0)
b_stress_pc	-0.3989	-0.63
b_stress_rh	0.5503	0.97
b_stress_pt	-1.4065	-2.23
b_stress_pc2	-1.3566	-1.67
b_stress_oav	-0.6092	-0.81
b_stress_sav	0.5896	0.57
b_stress_at	0.7557	0.96
b_stress_hy	0.5689	0.44
b_stress_tr	0.8142	0.68

Figure 11: Parameter estimates from the 'stress' DFT model that accounts for the level of stress faced by decision-makers..

fact that individuals may more likely choose the same alternative pre and post VR experience has a substantial and significant impact on model performance. This manifests through the improvement in log-likelihood of the post-trip choices.

4. The addition of inertia terms also significantly improves model performance. Notably the estimate for this term in online settings is positive, demonstrating people are likely to choose the same alternative across choice tasks. Meanwhile, the estimate is negative for VR settings, implying a degree of variety seeking.

5. Finally, we note that individuals who find bus trip experiences in VR stressful are less likely to choose it in the post-trip choice.

6 Conclusions

In this work, we explored the development of a two-stage DFT model that has separate decision-making processes for repeated choice scenarios. We find that the model captures the tendency for participants to stick to their initial choices. Further considerations to be addressed include capturing:

The impact of choice deliberation time: If the participant has a good VR experience, then it is likely that they will not spend much time considering the attributes of the different alternatives the second time they make a choice. *Hypothesis 1:* Physiological sensor data will be able to show that a decision-maker has had a poor experience and will correlate with choice response time in the second choice.

Processing speeds: Through the use of the eye-tracking and EEG data, we will test whether a decision-maker's speed at which they process information can be inferred. *Hypothesis 2:* The estimated number of preference updating steps in a DFT model will be correlated with a decision-maker's 'processing speed'.

Preferential change: There will be smaller differences in preferences for individuals who complete the online survey version of the choice tasks closer to the time point at which they complete the VR choice scenarios. *Hypothesis 3:* There will be a greater extent of preferential change in the futuristic travel mode scenarios as (a) it will have been a longer timeframe between the online and VR choice scenarios for the futuristic modes and (b) participants will have less initial preference biases for new modes, thus may be more subject to change their preferences.

Eye-tracking data: Eye-tracking data will be used to infer which attributes are important to the different decision-makers. *Hypothesis 4:* If a participant chooses a different alternative in the re-evaluation stage, then it will be possible to infer what key factors led to the change based on eye-tracking data.

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