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Nudging urban travellers towards greener travel modes: A virtual reality experiment☆

Yu Wang [a], Thomas O. Hancock [a,*], Albert Solernou [b], Jorge Garcia de Pedro [b], Yacan Wang [c], Charisma F. Choudhury [a]

[a] Institute for Transport Studies, University of Leeds, Leeds, UK
[b] Virtuocity, Institute for Transport Studies, University of Leeds, UK
[c] School of Economics and Management, Beijing Jiaotong University, Beijing 100044, China

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ABSTRACT

Cities worldwide face increasing pressure to reduce carbon emissions from transportation systems, yet implementing new transport policies often involves high costs and uncertainties. This study introduces an immersive virtual reality (VR) tool as a flexible, low-cost approach for evaluating travel demand management (TDM) strategies before real-world deployment. In a repeated discrete choice experiment (1,260 observations), participants chose between a taxi (high carbon) and a bus (low carbon) across multiple scenarios, each featuring variations in cost, travel time, and carbon attribute levels. Three nudge interventions were designed to highlight environmental impacts at three different decision points. The findings demonstrate that strategically timed nudges offer policymakers a scalable tool to promote sustainable urban mobility by integrating salient environmental feedback into decision-making contexts. These results underscore VR's potential to simulate realistic policy interventions and generate inputs to quantify the impact of different types of interventions alongside travel attributes.

1. Introduction

Drastic reductions in carbon emissions must take place in the current half-century, and the high emission contribution of road transportation makes it a strategic sector for policymakers interested in mitigating climate change (Wadud et al., 2024; Winkler et al., 2023; Lu et al., 2022). Road transportation is the second-largest contributor to global carbon emissions, where the primary source of transportation emissions is light-duty vehicles, i.e., passenger cars, whose emissions have increased by an average of one per cent per year since 2010 to more than 3.5 Gt CO_2 (Transportation emissions worldwide - statistics & facts, 2025). Technological innovations such as electric vehicles could reduce the environmental impact of transportation (Isik et al., 2021). However, it seems unlikely that these technologies will scale quickly enough to have a sufficient impact on carbon emissions in the following decades as the high cost of the technology makes widespread adoption challenging (Singh et al., 2024; Wang et al., 2023). Therefore, from the demand side, governments and authorities need to rely on travel demand management (TDM) interventions to motivate travellers to reduce high-carbon emission behaviours, such as driving, and instead adopt more environmentally friendly modes (Wang et al., 2022).

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* Corresponding author.
E-mail addresses: Y.Wang4@leeds.ac.uk (Y. Wang), t.o.hancock@leeds.ac.uk (T.O. Hancock), a.solernou@leeds.ac.uk (A. Solernou), jgarciadepedro@gmail.com (J.G. de Pedro), ycwang@bjtu.edu.cn (Y. Wang), c.f.choudhury@leeds.ac.uk (C.F. Choudhury).

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Traditional TDMs typically require substantial resources while coercing behaviour through modifications of the physical environment or legal policies. These may also involve political costs, as such measures can be met with opposition from the public (Saleh, 2007). As a result, policymakers have increasingly considered the so-called "soft" or psychological interventions. This includes nudges, which are strategies aimed at influencing individuals' perceptions, beliefs, attitudes, values, and norms (Thaler & Sunstein, 2021). Nudge has been proven to effectively change behaviour in many fields and can serve as an effective complement to traditional administrative or monetary policies (Bhargava & Loewenstein, 2015).

In the field of transportation, the effectiveness of nudge interventions remains uncertain. As shown in Table 1, many studies have demonstrated that nudges can be effective in shifting the behaviours of travellers under specific contexts, but there are also failures (Kristal & Whillans, 2020; Gravert & Collentine, 2021). However, as far as the authors are aware, these studies have always been based on field experiments. Researchers often find it difficult to capture all the decision alternatives (and or attributes) available to participants and do not observe detailed decision-making processes (Su et al., 2020). This results in a limited understanding of the mechanism of why certain nudge interventions fail or succeed. Moreover, limited by technological and policy inflexibility in the real world, nudge designs in past research have often had to be quite simple, such as sending social norms messages or letters related to travel information (Gravert & Collentine, 2021; Kristal & Whillans, 2020). To address the above challenge, traditional stated preference choice (SP) experiments can help capture the trade-off process of travellers in a controlled environment where researchers trial many policy scenarios at relatively low cost and with high flexibility (Cherchi & Hensher, 2015). However, the weakness of the SP approach lies in the lack of actual consequences, which is likely to lead to both noise and biases in responses (Dixit et al., 2017; Hensher, 2010). These issues make it challenging for policymakers to design and promote nudge interventions based on research findings of SP studies in real-world applications.

Combining the relative advantages of SP experiment data and field experiments, virtual reality (VR) has become an emerging tool to capture the behaviours of respondents under a more immersive and realistic environment (compared to SP) but in a more controlled setting (compared to field experiments) (Yin and Cherchi, 2024; Patterson et al., 2017; Dixit et al., 2017; Anthes et al., 2016). Research has demonstrated that immersive VR can create a natural and familiar environment, offering 'field cues' or 'hints' similar to those in the real world (Farooq et al., 2018; Fiore et al., 2009). This immersive experience encourages individuals to behave as they would in real-world situations. Therefore, this approach potentially allows researchers to capture less biased preferences of participants, while maintaining the flexibility of designing diverse experiment scenarios and treatment conditions (Jin et al., 2024; Bogacz et al., 2021; Sobhani & Farooq, 2018).

There is an increasing number of studies in the transportation field using VR to analyse individual decision-making processes, such as travel mode choice (Yin and Cherchi, 2024), bike riding behaviours (Bogacz, et al., 2021), pedestrian walking behaviour (Neider et al., 2010), interaction behaviours between pedestrians and vehicles (Camara et al., 2021; Farooq et al., 2018), etc. This method is also widely used for observing other decision behaviours, such as neighbourhood choice (Patterson et al., 2017), heroic behaviour analysis (Jin et al., 2024), healthy food choice (Blom et al., 2021), etc. Moreover, these studies indicate that VR not only helps us observe individual behaviour from a new perspective but also assists in capturing variables or behaviours that are difficult to identify in traditional datasets. For example, risk perception is traditionally analysed through surveys or lab experiments (Slovic, 1987). Bogacz et al. (2021) innovatively developed a hybrid choice model that jointly employed dynamic data on cycling behaviour in VR and neural data collected during the experiment to evaluate how the fluctuations in momentary risk perception influence the behaviour of cyclists. Jin et al. (2024) constructed VR scenarios to study heroic behaviour, which poses challenges and ethical concerns in traditional experimental set-ups due to its association with physical risks. Specifically, in VR, participants unexpectedly witnessed a criminal event, allowing observation of their tendency to physically intercept a thief. These advantages expand the possibilities of behavioural modelling. However, few studies have used VR tools to evaluate the effectiveness of policy instruments, particularly nudges. To our

Table 1
Nudging travel behaviours.

Paper	Treatment	Target	Effect
Steffen et al. (2024)	Moral nudges	Improving public, active, and shared travel modes	Effective for public transport and especially active travel
Hollenstein and Wittmer, (2024)	Carbon emission information using different framings	Reducing personal air travel	Insignificant effect.
Franssens et al. (2021)	Card with social label	Increasing public transport use	1.18 rides per day greater on experimental lines than on control lines
Gravert and Collentine, (2021)	Positive social norms message	Public transport usage	Insignificant effect
Su et al. (2020)	Social norm poster	Orderly bike parking	Effective for males
Riggs (2017)	Social norm message	Increasing non-automotive travel behaviour	Social nudge had a high degree of effectiveness when compared to both the financial incentives and gifts.
Kormos et al. (2015)	Descriptive social norm information	Reduce private vehicle use	A decrease in commuting-related private vehicle use by approximately five times, compared with baseline
Kristal and Whillans, (2020)	The salience of cost; Personalised travel information	Reducing single-occupancy vehicle commutes	Insignificant effect
Tørnblad et al. (2014)	Tailored travel information	Reduce private car use	Insignificant effect
Thøgersen and Møller, (2008)	Reminder travel plan	Breaking car use habits	In the short run, the effect of the intervention is significant
Lu et al. (2016)	Warning messages	Reducing violations	Insignificant effect

knowledge, only Blom et al. (2021) used VR experiments to investigate the effect of nudge tool salience on healthy food choices. However, this study did not focus on innovative nudge designs but rather employed a classic nudge design in the study context, focusing on the choices of individuals under different time pressures. Moreover, no studies have yet used the VR method to test policy in the context of travel or sustainable choice behaviour, specifically to investigate the potential effectiveness of nudging travellers towards greener modes.

Another advantage of VR is that it allows researchers to observe the dynamic decision-making processes of participants. For example, on the one hand, the dynamic characteristics of the data enable the modelling of individuals' continuous behaviour, such as pedestrian crossing behaviour (Velasco et al., 2019; Farooq et al., 2018), continuous bike riding behaviour (Bogacz, et al., 2021), etc. On the other hand, this also provides more opportunities to study the dynamic repeated discrete choice behaviour and learning process of individuals (Henríquez-Jara et al., 2025). Unlike one-shot choices, with repeated decisions, decision-makers can learn from their own experiences (Ben-Elia & Shiftan, 2010). Previous research has primarily relied on controlled laboratory experiments to capture repeated choice behaviour of individuals for modelling the learning process (Ben-Elia et al. 2013; Ben-Elia and Shiftan, 2010; Brouwer et al., 2010). For example, Ben-Elia et al. (2013) and Ben-Elia and Shiftan (2010) set up a laboratory experiment to collect repeated route choice data and construct learning-theory-based choice models. However, their experimental choice tasks were traditional SP choice tasks which have the limitations discussed above. Additionally, there is research indicating that repeated choices in SP do not identify any significant impact of learning effects on parameter estimates or variance across choice tasks (Brouwer et al., 2010). The key fact here is that these choices in SP or laboratory settings are not experienced; hence, there is no real scope for 'learning'. To solve the reality bias, some studies use field experiments to model the learning effect of subjects under the accumulation of repeated intervention context (Byrne et al., 2022; Kaur et al., 2015). For example, Byrne et al. (2022) studied the learning process of developing water-saving habits of users through repeated information feedback. However, these studies have primarily observed the final choices of subjects rather than the attributes of their choice sets. The lack of detailed information makes it difficult to analyse the trade-off processes in decision-making during modelling.

Based on the above discussion, to fill the aforementioned research gaps, this study leverages the flexibility of VR to test a more complex and dynamic set of nudge interventions than previously explored. 105 participants each completed six travel-choice tasks, where cost, time, and carbon emissions systematically varied between the two travel modes. The experiments were incentive compatible, and each participant had a real-money budget. In each of the six repeated tasks, participants first made an initial choice under an SP scenario and then experienced their chosen alternative in a virtual environment. After the VR phase, they were offered an opportunity to revise their choice. Nudges were introduced at different stages to encourage a shift from high-carbon taxis to low-carbon buses. Participants were randomised to four experimental groups, each exposed to different combinations of nudges across the six consecutive choice tasks. This combinatorial experimental design is an efficient allocation mechanism of both between-subject and within-subject conditions. This allows us to test a wide range of parameters capturing the impact of both the intra/inter task learning process and the interventions in our sample. In total, we collected 1,260 observations. A dynamic integrated choice and latent variable model is constructed, incorporating both choice sub-models to analyse the dynamic decision-making process and a latent variable model to measure the influence of green attitudes. The model framework identifies which policies most effectively promoted greener decisions after controlling for travel attributes, carbon emission variations and green attitudes. To the best of our knowledge, this is the first study to apply a VR experiment to decision-making in urban transportation to evaluate the effectiveness of potential sustainability policy instruments. By simulating real-world conditions in a controlled setting, VR not only facilitates repeated exposure to nuanced interventions but also helps capture the learning process of the subjects. This allows policymakers to refine TDM strategies with greater confidence before real-world deployment.

The remainder of this paper is structured as follows: Section 2 outlines the study design and methodology. Section 3 presents the model structure. Section 4 shows the results. Section 5 discusses the policy implications. Finally, Section 6 summarises the findings, highlights limitations, and suggests directions for future research.

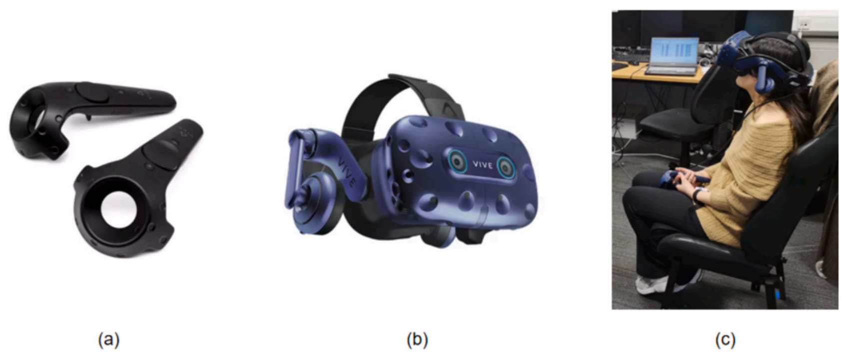

Fig. 1. VR equipment. Controller: Used to select options in the experiment. VR headset: Provides an immersive VR environment for the participants. A participant using the equipment.

2. Experiment design and data

This section will introduce the experimental design, data collection process, sample descriptive statistics and exploratory analysis.

2.1. Experiment procedure

The experiment is conducted using a VR setup. When participants enter the laboratory, they first read the experiment instructions to understand the basic procedure, duration, reward calculation rules, and data confidentiality and anonymisation guidelines. The participants signed the consent form after confirming that they were satisfied with the experimental and data handling protocol.

Before the experiment began, as shown in Fig. 1, the experiment assistant helped participants put on the VR equipment and performed device calibration. Before the formal experiment started, participants experienced a bus and a taxi scenario to help them adapt to the VR environment. This also reduced the propensity of potential variety-seeking behaviour, where subjects actively seek out different choices or experiences for the sake of variety and not necessarily because they are dissatisfied with their current options (McAlister & Pessemier, 1982).

Choice tasks were generated with an efficient design using Ngene (ChoiceMetrics, 2018). The a-priori parameter values and attribute ranges for the efficient design were adapted from Choudhury et al. (2025) and Henríquez-Jara et al. (2025). Because this study focuses on the behavioural impact of nudge interventions, we simplified their original design by reducing both the number of choice alternatives and attributes to keep the sample size requirements and model complexity within feasible limits. 12 choice tasks were divided into 2 blocks. Each participant completed 6 choice tasks and had 30 seconds of rest between each task. As shown in Fig. 2 (a), each choice task in the experiment includes three steps:

(1) Step 1: In stated preference scenarios, the participants were asked to imagine making a trip and choose their preferred mode between a taxi and a bus (green travel mode). The attributes included travel time, travel cost and carbon emission, where there are 3 levels for each mode attribute (as shown in Fig. 2 (b)). It should be noted that the additional time required to collect VR data limited our sample size, preventing us from adding further complexity to the choice scenarios, such as varying trip purpose

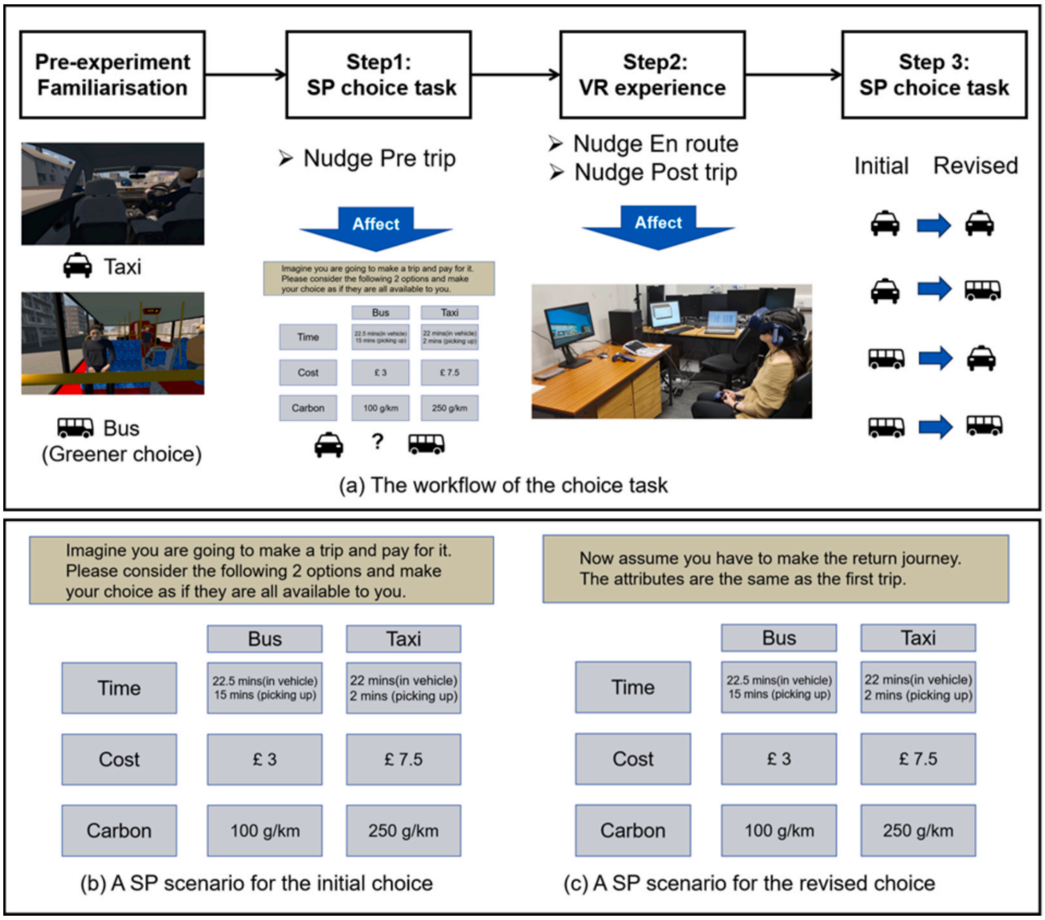

Fig. 2. The steps of the experiment.

or weather conditions, which would have reduced the number of observations per condition. Furthermore, we tested the effect of trip purpose and weather on mode choice in the context of future modes in a previous VR-based study (Choudhury et al., 2025), where the effect of purpose and weather (work vs leisure, good vs bad weather) was not found to be significantly different between taxi and bus (the effects were only significantly different in choice tasks with train and hyperloops in comparison with the other modes). We therefore focused on the core variables of interest. At this step, participants may receive Nudge-pre trip interventions.

(2) Step 2: The participants experienced their chosen mode from Step 1 in a VR scenario. The attributes of the VR scenario were related to those of the SP choice scenario. One minute in the SP scenario corresponded to ten seconds in the VR scenario. This ensured that the actual time spent by participants was related to their choices without making the experiment runtime excessively long. To control for other factors that may influence the choices of participants, the trip made by the same mode in different choice tasks shared several common elements. This included traffic flow on the road, fellow passengers, weather, background environmental sounds, etc. At the same time, there were differences between scenarios. For example, the number of stops varied based on the duration of the bus journey. In addition, if participants choose the taxi, they may receive Nudge-en route and Nudge-post trip interventions. The details of the design of the treatments are given in Section 2.2;

(3) Step 3: The participants were asked to imagine making the return trip with the same attributes and make a choice again in the SP choice scenario (as shown in Fig. 2 (c)). This step allows us to observe the shifting behaviour of participants.

Following completion of the VR experiment, participants received £5 to spend on travel costs on top of the £10 they received for participation. To achieve incentive compatibility, the choices they made determined how much of the £5 they “spent”. After finishing the 6 choice tasks, the participants were asked to roll a die twice. Based on the first roll, a specific task from the 6 tasks was selected. Depending on the second roll, participants were expensed for the initially chosen mode (for 1, 3, 5) or were expensed for the chosen ’return’ mode (for 2, 4, 6). Then, half the cost of the chosen mode within that specific task was deducted from participants’ £5 travel budget. Through pilot testing, this value resulted in participants not always choosing the cheapest travel mode nor ignoring the cost altogether. For example, if a participant rolls a 3 and a 4, and in Task 3, the participant chooses a taxi as a return choice, which costs £6, then the remaining travel budget is £5 − (£6 * 1/2) = £2. The participant ends up with a total of £10 + £2 = £12.

After completing the above steps, participants were required to fill out a post-survey. This included questions about daily travel behaviours and socio-demographic characteristics of participants, statements to measure their green attitudes, and an open-ended question asking them to state what factors influenced their choices.

2.2. Treatment design

This experiment designed three types of nudges to highlight the salience of the high carbon emission attribute of taxi travel and encourage participants to choose a bus or shift from taxi travel to bus travel. Based on the timing of the nudge interventions, they are classified as ’Nudge-pre trip’, ’Nudge-en route’, and ’Nudge-post trip’.

During the design process, we referred to relevant successful cases of the nudge mechanism in other fields (Byrne et al. (2022), Allcott and Rogers (2014)) and adapted the interventions to the taxi-travel context. Using the flexibility of VR, innovative elements were added with inputs from an expert in behavioural economics. After pilot testing and adjustments, we developed the final intervention design. This process ensures that our intervention is grounded in prior empirical and theoretical work while remaining context-specific and innovatively designed.

(1) Nudge-pre trip.

As shown in Fig. 3, before participants made their travel choice, they were presented with the cost of taking the taxi, divided into the regular cost and a separate carbon tax (fixed amount £2.50), where the total cost remains the same compared with the control condition (where there is no carbon tax). This aims to add no additional monetary cost but only nudge participants towards greener

(a) Control

Your choice	Bus	Taxi
Cost	£ 2.5	£ 10 (fare)

(b) Treatment

Your choice	Bus	Taxi
Cost	£ 2.5	£ 7.5 (fare) £ 2.5 (carbon tax)

Fig. 3. Nudge-pre trip.

choices by simply changing the mode of presentation of the cost. This approach thus enhances the salience of the environmental cost associated with their choice. When information is presented in a more prominent and attention-attracted way, individuals are more likely to consider it in their decision-making (Kahneman, 2011).

Empirical studies have documented the importance of the salience of tax and attracting attention in a variety of economic contexts (Goldin, 2015; Chetty et al., 2009; Shafir et al., 1997). For example, Chetty et al. (2009) found that posting tax-inclusive prices reduced demand by roughly 8% among the treated products relative to control products. In this experiment, by structuring the cost information in the manner of separating the taxi fare into the regular cost and an explicit carbon tax, we emphasise the salience of the carbon tax and draw attention to the environmental consequences of choosing a taxi over a bus. This increased salience of the carbon tax was expected to trigger a sense of environmental responsibility among participants, thereby nudging them to opt for the more environmentally friendly option—taking the bus, which does not incur this additional tax.

(2) Nudge-en route.

There are two elements in the Nudge-en route: a nudge poster and a carbon meter. The poster serves to make participants more aware about the impact of carbon emissions, while the meter provides continuous real-time feedback, reinforcing the salience of their environmental impact throughout the journey.

As shown in Fig. 4, while participants wait for a taxi, they see a poster on the opposite side of the street with the message "Reduce carbon emission, save our children's future." For the control condition, an unrelated poster is shown. This visual poster uses social norms and moral suasion by appealing to the sense of social responsibility and the long-term impact of their actions on future generations (Andor et al., 2020; Ito et al., 2018; Allcott, 2011).

As shown in Fig. 5, once participants are in the taxi, they are provided with real-time feedback on the carbon emissions of their journey through a carbon meter. The meter includes a leaf-shaped indicator light that changes colour based on the amount of accumulated carbon emissions. The light transitions from green to yellow (at 1 kg of carbon) and then to red (at 2 kg of carbon) as these emission thresholds are reached. For the control condition, an unrelated symbol is shown on the meter. Real-time feedback has proven effective in altering the energy consumption behaviour of residents in energy-saving literature (Byrne et al., 2022; Lynham et al., 2016). Real-time feedback can allow individuals to learn about the energy consumption of various activities in time, and a constant reminder of energy use keeps the environmental impact prominent in their minds (Tiefenbeck et al., 2018; Lynham et al., 2016).

(3) Nudge-post trip.

As shown in Fig. 6, at the end of the VR journey, participants were shown a carbon receipt on the screen. This receipt includes not only the cost and time information of the trip as shown on a traditional taxi receipt, but also the carbon emissions associated with it. The carbon emissions are visualised using leaf icons with different facial expressions: a yellow leaf with a neutral expression indicates moderate emissions (1–2 kg carbon emission), and a red leaf with a sad face indicates high emissions (above 2 kg carbon emission). Alongside this, a piece of information on social norms is also displayed. The two elements always appeared together and jointly formed the Nudge-post trip. For the control condition, a traditional taxi receipt with an unrelated symbol and text was shown.

By providing detailed information about the carbon emissions of the trip and associating them with emotive icons, participants might reflect on the environmental impact of their choices. This approach utilises reflective learning, encouraging individuals to think about their past behaviour and its consequences (Allcott & Rogers, 2014; Allcott, 2011; Boyd & Fales, 1983). In addition, by showing information about the common practices or expectations regarding carbon emissions, participants may feel social pressure to conform to more environmentally friendly behaviour.

To test the impact of the different types of nudges, different combinations of nudges were presented in different choice tasks. These combinations of nudge scenarios are shown in Fig. 7. For each task block, participants were assigned to one of four experimental groups (Groups 1–4). To analyse the potential learning process, the participants received increasing amounts of interventions. In each group's six choice tasks (Task 1–6), the first two tasks always had no nudge interventions, whilst the post-trip nudge always appeared only in the last two tasks (and only if the participant initially chose a taxi).

(a) Control (b) Treatment

Fig. 4. Nudge-en route: Poster.

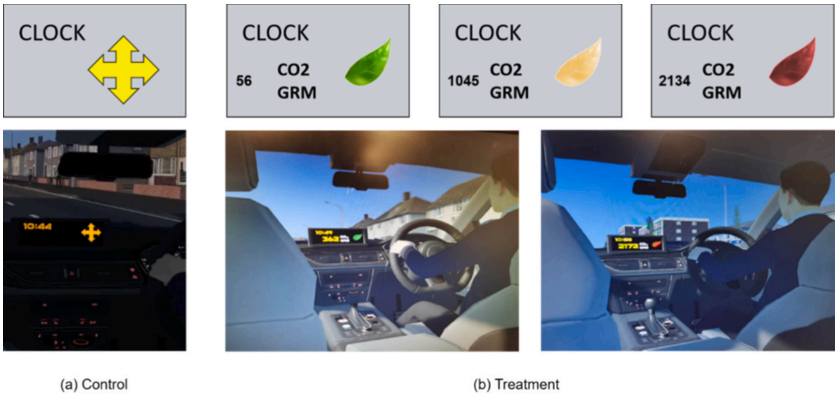

Fig. 5. Nudge-en route: Carbon meter.

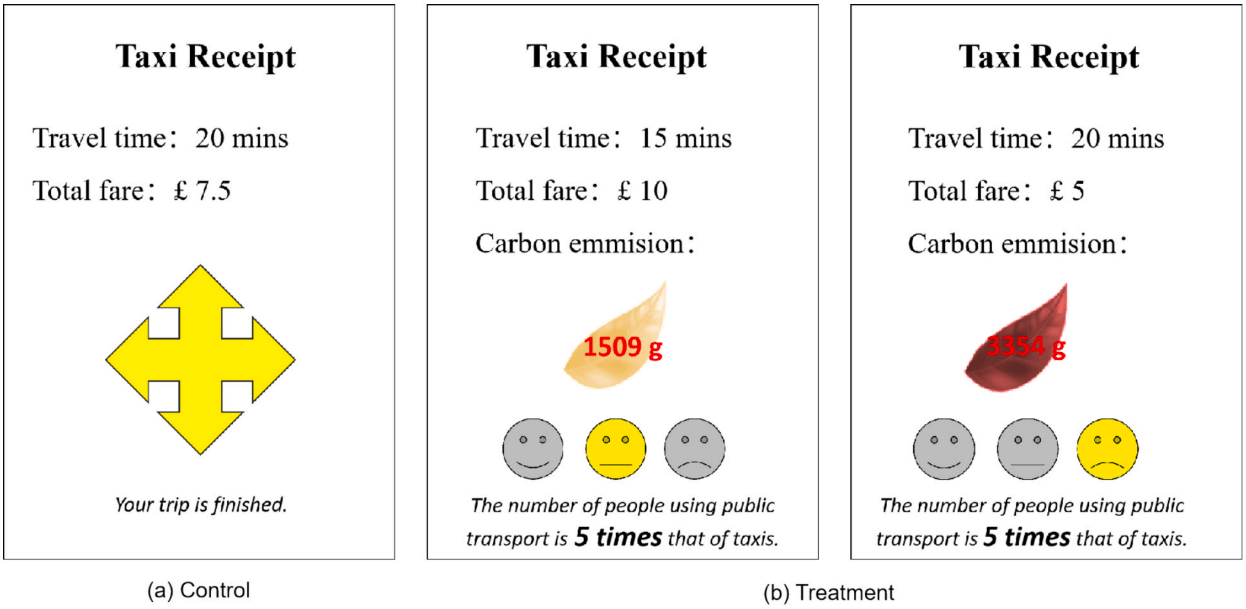

Fig. 6. Nudge-post trip.

Group	Nudge	Task 1	Task 2	Task 3	Task 4	Task 5	Task 6
1	Pre	×	×	×	×	×	×
	En route	×	×	×	×	×	×
	Post	×	×	×	×	√	√
2	Pre	×	×	√	√	√	√
	En route	×	×	×	×	×	×
	Post	×	×	×	×	√	√
3	Pre	×	×	×	×	×	×
	En route	×	×	√	√	√	√
	Post	×	×	×	×	√	√
4	Pre	×	×	√	√	√	√
	En route	×	×	√	√	√	√
	Post	×	×	×	×	√	√

Fig. 7. The combination of nudges that appeared in the different choice tasks.

It should be noted that considering the sample size limitations of the VR experiment, this study did not employ a randomised controlled trial design to analyse the causal effects of different nudge interventions. Instead, we utilised an approach focusing on the choices of participants across a series of controlled experimental tasks. This approach allows us to observe the impact of each intervention by modelling the effects of different nudges on choice probabilities (McFadden et al., 2005). This design also helped to more clearly capture the potential residual effect from the nudges.

2.3. Data collection and sample composition

A pilot of the experiment was conducted in February 2024 to test the stability of the experimental system, the design of the documentation, and the parameter settings. The formal experiment took place at the Virtuocity Laboratory, the state-of-the-art VR and city simulation experiment facility at the University of Leeds,. between March 13, 2024 and May 13, 2024. Participants were recruited through emails and offline posters, targeting mainly students and staff from the University of Leeds. 132 participants registered, and 105 showed up and completed the experiment. Finally, we recorded 1,260 observations of task choices (2 choices for each of the 6 tasks). Participants received an average reward of £12.45.

The descriptive statistics of the 105 respondents in the final sample are presented in Table 2. Due to the challenges associated with recruiting participants for VR experiments, we were unable to recruit a large, broadly representative sample. However, compared to other VR experiments related to travel behaviour, the sample size for this study is relatively large, with 71 participants in Henríquez-Jara et al. (2025), 48 in Bogacz et al. (2021), and 30 in Pawar et al. (2022). In addition, the gender ratio in our sample is relatively balanced. However, since recruitment was primarily conducted within the university, the sample is younger, has a higher proportion of students, and has a higher level of education compared to the general population.

2.4. Exploratory analysis

The main analysis of this work is on whether participants chose the bus and whether they change their choice after initially choosing a taxi in each task, following the experience of VR trips and nudge interventions.

In Fig. 8, the vertical axis represents the proportion of observations for which bus was chosen, and the horizontal axis represents tasks with different nudge combinations and the corresponding number of observations. The blue bar represents the proportion for the initial choice and the orange bar represents the revised choice. The x/x/x represents the combinations of the three nudges (pre trip/en route/post trip), where 1 indicates the presence of the corresponding nudge and 0 indicates its absence. The results show that for all task observations with nudges (366), the proportion of tasks in which the bus was chosen on the revised choice (76.78%) is higher than on the initial choice (54.64%). Meanwhile, for tasks without nudges (364), there is no substantial difference in the proportion choosing the bus between the initial (65.15%) and revised (66.29%) choice. However, for the first four nudge combinations (1/0/0, 0/1/0, 0/0/1 and 1/1/0), which always appear in order 3 or 4 (shown in Fig. 7), there is not much change in the proportion choosing the bus on the initial choice. This suggests that Nudge-pre trip may not be effective, given that Nudge-pre trip does not substantially increase the

Table 2
Sample composition.

Socio-demographic attributes		Number
Gender	Female	49
	Male	55
	Other	0
	Prefer not to say	1
Job	Students	69
	Employed	29
	Other	7
Age	18–24	40
	25–34	37
	35–44	16
	45–54	7
	55–64	4
	65 or above	2
Highest level of education	High School diploma	13
	College/University certificate	11
	Bachelor's degree	33
	Master's degree	41
	Doctorate degree	8
Ethnicity	Arab	4
	Asian – East Asian	35
	Asian – South Asian	16
	Black or African heritage	7
	Hispanic or Latino	1
	White	31
	Mixed	4
	Any other ethnic group	7

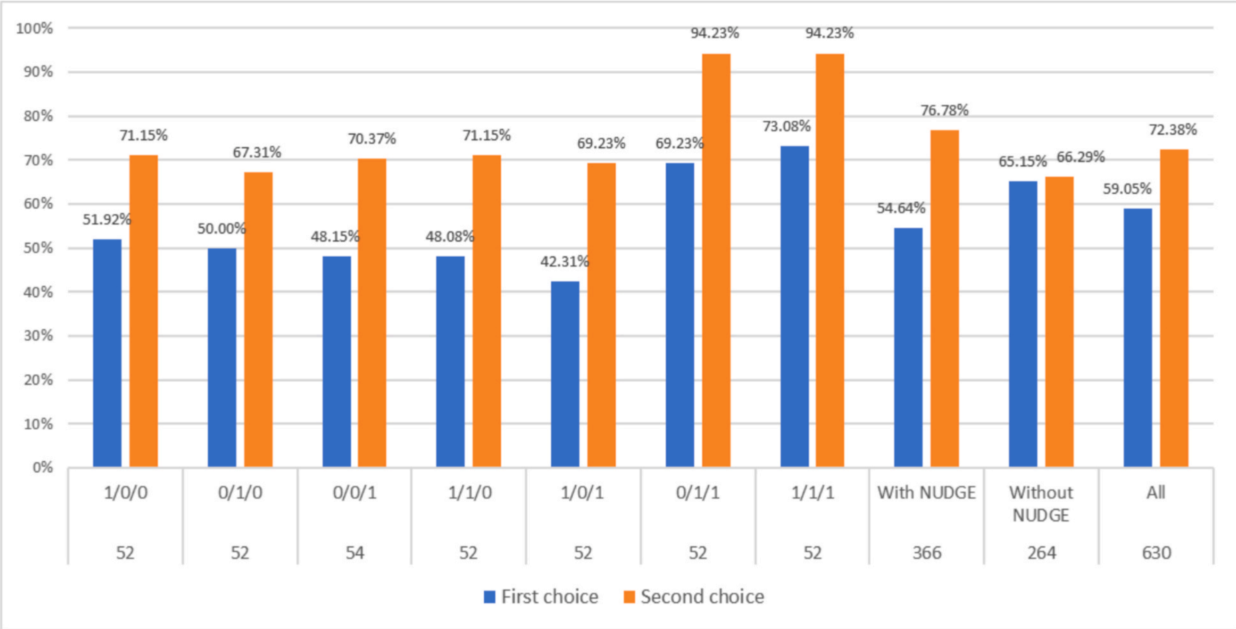

Fig. 8. The proportion of choosing bus.

proportion of bus in the initial choice. Additionally, this proportion is lower compared to tasks without nudges, which always appear in order 1 or 2. Compared to the (1/0/1) and (1/1/1) combinations, this proportion is also lower. This indicates that there might be an order effect. For example, participants may feel more tired due to the heavy VR headset, which could influence their choices. Furthermore, the (1/0/1) and (1/1/1) combinations have the highest proportion choosing the bus as the initial choice. This could be due to the order effect as well or the residual effect of previous nudge interventions influencing the choices in subsequent tasks. This has been discussed in further detail in the modelling section, which disentangles confounding factors through the use of a framework to model the dynamic decision-making process.

Fig. 9 shows the proportion of shifting choice behaviour. The horizontal axis represents different nudge combinations and the number of observations that initially chose a taxi as the initial choice, while the vertical axis represents the proportion of tasks where participants shifted to choosing the bus on the revised choice. The results show that for tasks with nudges, the shift proportion (59.04%) is substantially higher than for tasks without nudges (38.04%). Additionally, for tasks with only nudge-pre trip, the shift proportion (40.00%) is similar to that of tasks without nudge (38.04%). This further indicates that Nudge-pre trip may not be effective.

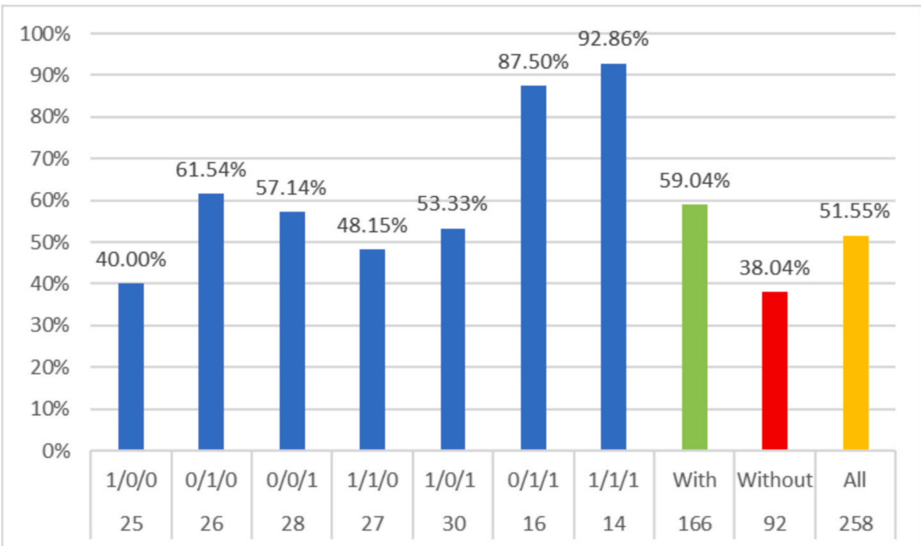

Fig. 9. The proportion of shifting choice behaviour. Note: Observations include only those who chose a taxi in the initial choice.

Furthermore, compared to the combination (0/1/0), the combination (1/1/0) shows a noticeable decrease (13.39% lower) in the shift proportion, which may be due to a crowding-out effect of the tax-related Nudge-pre trip[4]. Participants may believe that they have already paid a tax for their carbon emissions, thus reducing their concern for the negative externalities of conducting trips that produce higher carbon (Lu & Zhu, 2021).

3. Methodology

Given that participants made two choices in each task and completed six consecutive experiment tasks, a dynamic structure is implemented to provide additional flexibility in our model construction. In particular, this section presents two model structures based on the model structure proposed by Henríquez-Jara et al. (2025). The first is the static model, where we consider a combined structure in which the participant's initial choice in a scenario influences their revised choice. The second is a dynamic model, which builds upon the static model by considering the interdependencies among the six choice tasks. Specifically, we acknowledge a potential learning process occurring throughout the six tasks, where the experiences from earlier tasks influence subsequent task choices.

Before introducing the model specification, we first present the variables used in the models, as shown in Table 3. It is noted that the choice variables not only serve as the dependent variables for their corresponding choice tasks but can also act as explanatory variables influencing subsequent choices (Henríquez-Jara et al., 2025).

3.1. Base model

The structure of the static model is shown in Fig. 10. In the figure, ovals denote latent variables, rectangles indicate observed variables, solid lines represent structural equations, and dashed lines correspond to measurement equations. In this framework, we developed three static models: two single-stage models that consider only initial choices and revised choices of participants in each task, respectively (separately), and a combined model that accounts for both the initial and revised choices. In the initial choice of the task, the participant evaluates a utility associated with each alternative based on the alternative attributes provided in the SP choice scenarios. After making the initial choice, the participant experiences their chosen option in the VR environment. Then, the participant re-evaluates their initial choice. We account for the status quo bias during the dynamic decision-making process, where subjects prefer to stick with their current state to avoid the potential losses associated with change (Caplin et al., 2011). The revised utility is affected by the initial choice through the stickiness parameter δ, the systematic utility of the respective alternative in the initial choice, scaled by μ, and nudges experienced during the VR trip.

The specification of the utilities for the initial choice can be expressed as:

$$U_{n,t}^{Initial-taxi} = V_{n,t}^{Initial-taxi} + \sigma^{Initial}\xi_n^{Initial-taxi} + \eta_{n,t}^{Initial-taxi} \tag{1}$$

$$U_{n,t}^{Initial-bus} = V_{n,t}^{Initial-bus} + \sigma^{Initial}\xi_n^{Initial-bus} + \eta_{n,t}^{Initial-bus} \tag{2}$$

The utilities for the revised choice are:

$$U_{n,t}^{Revised-taxi} = V_{n,t}^{Revised-taxi} + \sigma^{Revised}\xi_n^{Revised-taxi} + \eta_{n,t}^{Revised-taxi} \tag{3}$$

$$U_{n,t}^{Revised-bus} = V_{n,t}^{Revised-bus} + \sigma^{Revised}\xi_n^{Revised-bus} + \eta_{n,t}^{Revised-bus} \tag{4}$$

Where n is the individual, t is the choice task. The η is the error term. ξ is an error component which is independently distributed Normal variate with a zero mean and a standard deviation of 1. 500 Halton draws are used. σ are scale parameters attached to the error-component terms. Estimating σ measures the magnitude of alternative-specific unobserved heterogeneity. V represents the systematic utility, which is expressed by the following equations.

For the initial choice:

$$\begin{aligned} V_{n,t}^{Initial-taxi} &= ASC^{Initial-taxi} \\ &+\beta^{Log(Cost)}X_{n,t}^{Taxi_{cost}} + \beta^{Time}X_{n,t}^{Taxi_{time}} + \beta^{Carbon}X_{n,t}^{Taxi_{carbon}} \\ &+\beta^{N_{pre}}X_{n,t}^{N_{pre}} \end{aligned} \tag{5}$$

$$\begin{aligned} V_{n,t}^{Initial-Bus} &= ASC^{Initial-bus} \\ &+\beta^{Log(Cost)}X_{n,t}^{Bus_{cost}} + \beta^{Time}X_{n,t}^{Bus_{time}} + \beta^{Carbon}X_{n,t}^{Bus_{carbon}} \\ &+\lambda LV_n \end{aligned} \tag{6}$$

For the revised choice:

$$\begin{aligned} V_{n,t}^{Revised-taxi} &= ASC^{Revised-taxi} \\ &+\mu V_{n,t}^{Initial-taxi} \\ &+\delta Y_{n,t}^{Initial} \\ &+\beta^{N_{en}}X_{n,t}^{N_{en}} + \beta^{N_{post}}X_{n,t}^{N_{post}} \end{aligned} \tag{7}$$

Table 3
The variables used for the model.

Categories	Variables	Description
Bus attributes	$X_{n,t}^{Bus_{cost}}$	The logarithm of the cost of the bus (in £).[a]
	$X_{n,t}^{Bus_{time}}$	The total travel time of the bus (waiting time + in-vehicle time) (the SP value, in mins).
	$X_{n,t}^{Bus_{carbon}}$	Carbon emissions per kilometre of bus trip (in g/km).
Taxi attributes	$X_{n,t}^{Taxi_{cost}}$	The logarithm of the total cost of the taxi (travel cost + carbon tax, in £).
	$X_{n,t}^{Taxi_{time}}$	The total travel time of the taxi (waiting time + in-vehicle time) (the SP value, in mins).
	$X_{n,t}^{Taxi_{carbon}}$	Carbon emissions per kilometre of the taxi trip (in g/km).
Green attitude	LV_n	Green attitude, which is a latent variable.
Nudge	$X_{n,t}^{N_{pre}}$	Nudge_pre trip: Whether there is a carbon tax on taxi (dummy, 0/1).
	$X_{n,t}^{N_{en}}$	Nudge_en route: Whether there is a nudge poster + carbon meter on the taxi (dummy, 0/1).
	$X_{n,t}^{N_{post}}$	Nudge_post trip: Whether there is areceipt with carbon emission and nudge text shown on the screen at the end of the taxi trip (dummy, 0/1).
Nudge pre	$X_{n,t}^{pre_{pre}}$	Nudge_pre_pre trip: When making the initial choice in task t, whether the subject experienced a Nudge_pre trip in the previous task (task t-1) (dummy, 0/1).
	$X_{n,t}^{pre_{en}}$	Nudge_pre_en route: When making the initial choice in task t, whether the subject experienced a Nudge_en route in the previous task (task t-1) (dummy, 0/1).
	$X_{n,t}^{pre_{post}}$	Nudge_pre_post trip: When making the initial choice in task t, whether the subject experienced a Nudge_post trip in the previous task (task t-1) (dummy, 0/1).
Nudge accumulation	$X_{n,t}^{acu_{pre}}$	Nudge_accumulation_pre trip: When making the initial choice in task t, how many times Nudge_pre trip the subject experienced from task 1 to task t-1.
	$X_{n,t}^{acu_{en}}$	Nudge_accumulation_en route: When making the initial choice in task t, how many times Nudge_en route the subject experienced (during the VR trip) from task 1 to task t-1.
Order	$X_{n,t}^{order2}$	Whether the order of the task is 3 or 4 (dummy, 0/1).
	$X_{n,t}^{order3}$	Whether the order of the task is 5 or 6 (dummy, 0/1).
Independent variables: Choices	$Y_{n,t}^{Initial}$	Whether the subject chooses the taxi in the initial choice (dummy, 0/1).
	$Y_{n,t}^{Revised}$	Whether the subject chooses the taxi in the revised choice (dummy, 0/1).

[a] This study applies a logarithmic transformation to the cost variable to capture travellers' diminishing marginal sensitivity to monetary cost (Batley, 2018; Daly et al., 2017; Rich & Mabit, 2016). Empirically, the log specification yielded a better model fit than the linear form.

$$V_{nt}^{Revised-bus} = ASC^{Revised-bus} + \mu V_{nt}^{Initial-bus} \tag{8}$$

Where ASC is the alternative specific constraint. $\beta^{Log(Cost)}$,β^{Time} and β^{Carbon} are estimated parameters related to alternative attributes. $\beta^{N_{pre}}$, $\beta^{N_{en}}$ and $\beta^{N_{post}}$ capture the influences of nudges. λ captures the impact of the participant's green attitude on the greener mode choice. δ is the stickiness parameter, which captures whether the participant will stick to the choice of taxi within a task. μ is the relative importance of the utility of the initial choice. Since both δ and μ influence participants' choices within the same task, they are collectively referred to as intra-task parameters.

For the latent variable measurement model, responses of the participant to the statements shown in Table 4 are included as indicators to express the green attitude.[1] Participants were asked to rate on a scale of 1 to 5 (1 being "strongly disagree" and 5 being "strongly agree") to what extent they (dis) agreed with each statement. This results in one equation for each indicator:

$$I_{n,g} = \zeta_g LV_n + \varepsilon_{n,g} \tag{9}$$

Where the vector I identifies the indicators of the latent variable. The latent variable loading matrix is represented by ζ, and ε is a normally distributed error term.

3.2. Dynamic model

Fig. 11 shows the dynamic model, which further considers three additional potential effects. On the one hand, a learning effect is introduced, such that participants learn from their previous choices and experiences and then apply this knowledge to future decisions in subsequent tasks. Therefore, the revised choice in $task_{t-1}$ might influence the initial choice in $task_t$. However, the presence of a nudge may moderate this effect in two ways: Firstly, each nudge can disrupt habitual behaviour by introducing new information or incentives. Further, the nudges may have residual effects, where nudge interventions from previous tasks continue to influence subsequent choices (Byrne et al., 2022). This residual effect suggests that the impact of a nudge is not confined to a single task but can extend over multiple tasks, reinforcing the desired behaviour over time. In addition, the order effect is controlled by adding two

[1] We tried to construct a hybrid model that incorporated a MIMIC structure, where socio-demographic variables were entered into structural equations to explain the latent variable. However, none of those socio-demographic predictors proved significant. The limited size and relatively homogeneous nature of our sample may be a potential reason for this.

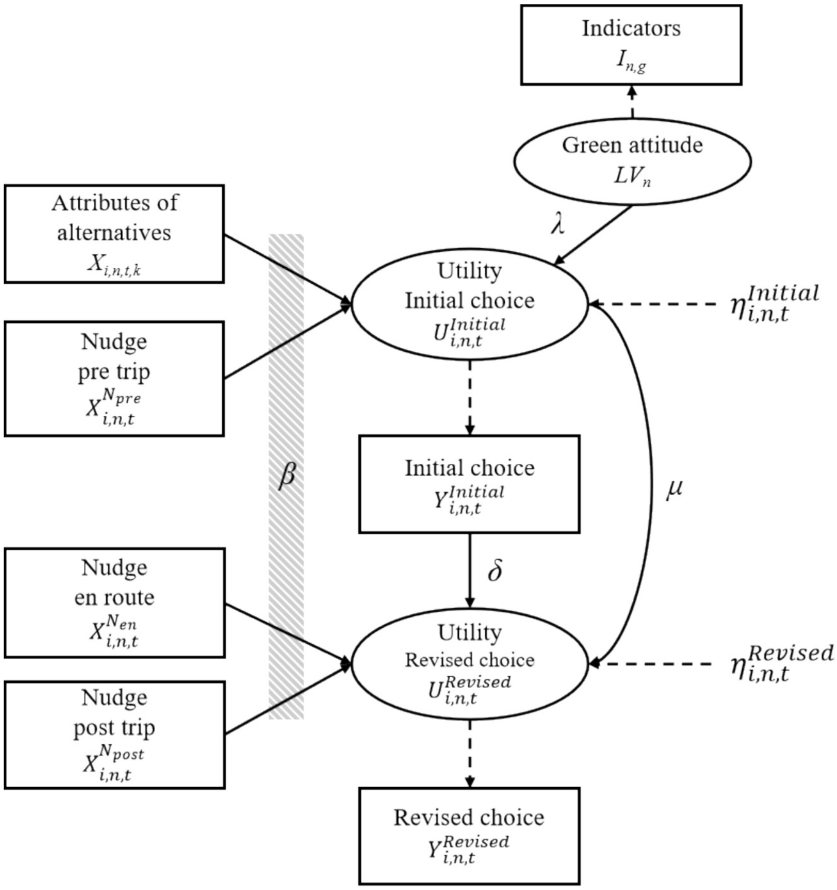

Fig. 10. The structure of the base model: static model.

Table 4
Indicators of the latent variable measurement model.

Indicators	Measurement items
I_1	Stricter actions should have been taken to curb climate change.
I_2	People should take the environmental impact into account in their daily choices.
I_3	Transport is a major contributor to climate change.
I_4	I limit using private car and use public transport or active modes (e.g. walking, cycling) where I can to reduce the carbon emissions produced from my travel.
I_5	I limit my flying to reduce carbon emissions.
I_6	I rarely consider the impact on the environment in my daily choices.[1]

[1]In model estimation, the responses to the measurement item of I6 are reversed to avoid the negative signs of the loading factor.

dummy variables related to the order of the tasks.

Given these considerations, the utility functions in the dynamic model are extended to include additional components that capture these effects. We constructed 12 sub-models corresponding to the 12 choices to analyse the dynamic process. Thus, for example, in task t, we have for the initial choice:

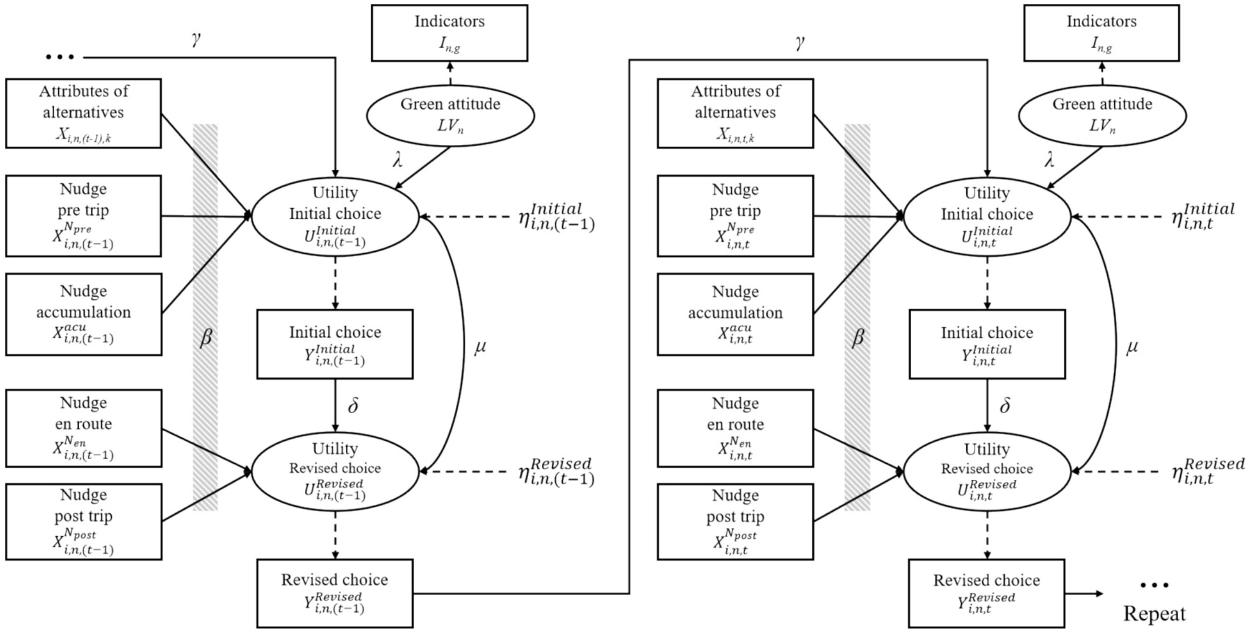

Fig. 11. The structure of the dynamic model.

$$\begin{aligned}
V^{Initial-taxi}_{n,t} &= ASC^{Initial-taxi} \\
&+\beta^{Log(Cost)}X^{Taxi_{cost}}_{n,t}+\beta^{Time}X^{Taxi_{time}}_{n,t}+\beta^{Carbon}X^{Taxi_{carbon}}_{n,t} \\
&+\beta^{N_{pre}}X^{N_{pre}}_{n,t} \\
&+\gamma Y^{Second}_{n,(t-1)} \\
&+\gamma^{N_{pre}}Y^{Revised}_{n,(t-1)}X^{pre_{pre}}_{n,t} \\
&+\gamma^{N_{en}}Y^{Revised}_{n,(t-1)}X^{pre_{en}}_{n,t} \\
&+\gamma^{N_{post}}Y^{Revised}_{n,(t-1)}X^{pre_{post}}_{n,t} \\
&+\beta^{acu_{pre}}X^{acu_{pre}}_{n,t} \\
&+\beta^{acu_{en}}X^{acu_{en}}_{n,t} \\
&+\beta^{order2}X^{order2}_{n,t}+\beta^{order3}X^{order3}_{n,t}
\end{aligned} \tag{10}$$

$$\begin{aligned}
V^{Initial-Bus}_{n,t} &= ASC^{Initial-bus} \\
&+\beta^{Log(Cost)}X^{Bus_{cost}}_{n,t}+\beta^{Time}X^{Bus_{time}}_{n,t}+\beta^{Carbon}X^{Bus_{carbon}}_{n,t} \\
&+\lambda LV_n
\end{aligned} \tag{11}$$

For the revised choice:

$$\begin{aligned}
V^{Revised-taxi}_{n,t} &= ASC^{Revised-taxi} \\
&+\mu V^{Initial-taxi}_{n,t} \\
&+\delta Y^{First}_{nt} \\
&+\beta^{N_{en}}X^{N_{en}}_{n,t}+\beta^{N_{post}}X^{N_{post}}_{n,t}
\end{aligned} \tag{12}$$

$$\begin{aligned}
V^{Revised-bus}_{n,t} &= ASC^{Revised-bus} \\
&+\mu V^{Initial-bus}_{n,t}
\end{aligned} \tag{13}$$

Where γ is related to the learning effect of inter-task choice. $\gamma^{N_{pre}}$, $\gamma^{N_{en}}$ and $\gamma^{N_{post}}$ represent the moderating effect of nudges on the learning effect between choice tasks. In addition, $\beta^{acu_{pre}}$ and $\beta^{acu_{en}}$ capture the residual effect of the nudges. Considering the post-trip nudge exists only in tasks 5 and 6 (see Fig. 7), there is only the residual effect of this nudge in task 6, which cannot be separately identified from the learning effect. Therefore, the residual effects of only the pre-trip nudge and en-route nudge are incorporated. Further, β^{order2} and β^{order3} capture the order effect. The above parameters are used to estimate the impact of variables across different tasks. Collectively, they are referred to as inter-task parameters.

For the initial and revised choice, the probability of participant n choosing an alternative i in task t is then given by:

$$P_{i,n,t}^{Initial} = \frac{\exp(V_{i,n,t}^{Initial})}{\sum_{j \in C} exp(V_{j,n,t}^{Initial})} \tag{14}$$

$$P_{i,n,t}^{Revised} = \frac{\exp(V_{i,n,t}^{Revised})}{\sum_{j \in C} exp(V_{j,n,t}^{Revised})} \tag{15}$$

The likelihood function with latent variables is calculated by:

$$L_t = \prod_{n=1}^{N} \int LV_n \int \xi_n \left(\prod_{t=1}^{T} P_{i,n,t}^{Initial} \right) f(LV_n) f(\xi_n) dLV_n \bullet \prod_{i,n} P_{i,n,t}^{Revised} \tag{16}$$

Where $\int LV_n$ accounts for the uncertainty in the latent variable. $f(LV_n)$ describes the distribution of the latent variable. 500 inter-individual standard Normal draws are made based on Halton draws.

Table 5
Estimation results.

Parameters		Static						Dynamic	
		Model (1)-Initial choice		Model (2) −Revised choice		Model (3)- Combined		Model (4)-Dynamic	
		Estimate	Rob.t-ratio(0)	Estimate	Rob.t-ratio(0)	Estimate	Rob.t-ratio(0)	Estimate	Rob.t-ratio(0)
ASC	$ASC^{Initial-bus}$	0.0000	NA	–	–	0.0000	NA	0.000	NA
	$ASC^{Initial-taxi}$	−0.2269	−0.44	–	–	−0.7840*	−1.73	−0.994*	−1.74
	$ASC^{Revised-bus}$	–	–	0.0000	NA	0.0000	NA	0.000	NA
	$ASC^{Revised-taxi}$	–	–	−3.0014***	−4.28	−1.2728***	−5.88	−1.291***	−5.48
Error component	$\sigma^{Initial}$	0.5803***	3.31	–	–	0.7136***	4.70	0.649***	3.57
	$\sigma^{Revised}$	–	–	0.6983***	5.07	0.3820	1.63	0.321	1.03
Scenario attributes	$\beta^{Log(Cost)}$	−9.7457***	−9.05	−4.6873***	−4.69	−9.3307***	−8.26	−9.956***	−8.70
	β^{Time}	−0.1197***	−4.83	−0.0998***	−3.94	−0.1318***	−6.05	−0.141***	−5.79
	β^{Carbon}	−0.0010	−0.37	0.0047*	1.68	0.0014	0.74	3.2337e-04	0.12
Nudge	$\beta^{N_{pre}}$	0.4700	1.57	−0.2282	−0.77	0.2854	1.10	−0.149	−0.35
	$\beta^{N_{en}}$	–	–	−0.9526**	−2.48	−0.9824***	−2.70	−0.861**	−2.37
	$\beta^{N_{post}}$	–	–	−1.4253***	−3.91	−1.4000***	−4.19	−1.451***	−4.39
Attitude	λ	0.6539***	4.12	0.4272**	2.27	0.6570***	3.44	0.724***	3.91
Parameters		**Static**						**Dynamic**	
		Model (1)-Initial choice		**Model (2) −Revised choice**		**Model (3)-Combined**		**Model (4)-dynamic**	
		Estimate	**Rob.t-ratio(0)**	**Estimate**	**Rob.t-ratio(0)**	**Estimate**	**Rob.t-ratio(0)**	**Estimate**	**Rob.t-ratio(0)**
Intra-task parameter	δ	–	–	1.9501***	5.52	1.4039 ***	4.20	1.450***	3.89
	μ	–	–	–	–	0.7280 **	−2.00[a]	0.574***	−3.55[a]
Inter-task parameter: Learn effect	γ	–	–	–	–	–	–	1.484***	4.79
	$\gamma^{N_{pre}}$	–	–	–	–	–	–	−0.374	−0.71
	$\gamma^{N_{en}}$	–	–	–	–	–	–	−0.706	−1.30
	$\gamma^{N_{post}}$	–	–	–	–	–	–	−1.739**	−1.98
Inter-task parameter: Residual effect	$\beta^{acu_{pre}}$	–	–	–	–	–	–	0.356*	1.65
	$\beta^{acu_{en}}$	–	–	–	–	–	–	−0.371	−1.17
Inter-task parameter: Order effect	β^{order2}	–	–	–	–	–	–	−0.261	−1.10
	β^{order3}	–	–	–	–	–	–	0.308	0.91
Sample size		105		105		105		105	
Number of modelled observations		1,260		1,260		1,890		1,890	
Model fitness	LL (final, whole model)	−1,208.2		−1,167.97		−1,487.07		−1,481.61	
	AIC	2,454.4		2,379.95		3,024.13		3,029.22	
	BIC	2,504.82		2,438.33		3,090.48		3,116.81	

Note: ***indicates $|t|>=2.58$, **indicates$1.96<=|t|<2.58$, *indicates $1.64<=|t|<1.96$; [a] Denote a Rob. t-test against 1, otherwise the Rob. t-tests are against 0.

The final log-likelihood for the joint 12 models is given by:

$$LL = \sum_{t=1}^{T} \log(L_t) \tag{17}$$

The model parameters are estimated by maximising this function. The Apollo choice modelling package (Hess and Palma, 2019) is used in this regard.

4. Results

Table 5 presents the results of the static models and the dynamic model. In the static models, model (1) and model (2) only the initial choices and the revised choices in the data are used, respectively. Model (3) combines both the initial choice and the revised choice in a static framework (i.e. ignores learning and ordering effects), while Model (4) is the dynamic version of the combined model (referred to simply as a dynamic model in the subsequent sections). Table 6 shows the estimation results of the measurement model of the latent variable.

4.1. Static models

The results show that travel costs and times negatively influence the choices of participants significantly, but carbon emission has no significant influence. This aligns with our expectations, as many participants indicated in the open-ended question at the post survey that they paid more attention to time and monetary costs when making choices and were less concerned about carbon emissions. However, the green attitude positively influences the choice of bus.

The statistically significant log form of cost implied that the value of time increased with travel cost, which was the result of declining sensitivity to cost. Given the log-transformation, the value of travel time is calculated using the following equation and plotted in Fig. 12:

$$VoT(X^{Cost}) = \frac{|\beta^{Time}|}{|\beta^{Log(Cost)}|} X^{Cost} * 60 \tag{18}$$

As seen in the figure, a higher willingness to pay for travel time savings is observed for more expensive travel (in comparison with cheaper travel).

Regarding the intra-task parameters in model (3), the scale parameter μ is significantly different from 1 and less than 1, which means that systematic utility becomes less important in the revised choice. Additionally, the significant and positive coefficient δ indicates that participants tend to stick to their initial choice.

Furthermore, the results of models (2) and (3) show that the treatment effect of the en-route nudge and post-trip nudge significantly reduces the utility of choosing a taxi. In other words, these two interventions significantly promoted the shift from taxi to bus among participants, while the pre-trip nudge had no significant effect.

4.2. Dynamic model

After extending the model to the dynamic structure, the results remain robust.

In model (4), the results of the inter-task parameters show that the choices of participants are also influenced by their previous experiences. For the learning effect, the γ is significantly positive, indicating that if participants choose the taxi as the revised choice for the previous task, they are more likely to stick with this choice in the next initial choice. Then, $\gamma^{N_{post}}$ is significantly negative. This parameter captures the moderating effect of experiencing the Nudge post-trip on the learning effect. If participants were subject to the post-trip nudge in one task, the learning effect was weakened.

For the residual effect, $\beta^{acu_{pre}}$ is positive and significant. This means that the more the participants experience the carbon tax, the more likely they are to choose the taxi.

In terms of model fit, the dynamic model offers a slight improvement over the static model. The relatively small improvement while moving from the static to dynamic model is likely attributable to the small sample size, meaning a larger, more representative sample is

Table 6
Estimation results of the measurement models.

Measurement model		Static						Dynamic	
		Model (1)-Initial choice		Model (2) −Revised choice		Model (3)-Combined		Model (4)-Dynamic	
		Estimate	Rob.t-ratio(0)	Estimate	Rob.t-ratio(0)	Estimate	Rob.t-ratio(0)	Estimate	Rob.t-ratio(0)
Parameters	ζ^1	0.5826***	5.04	0.5679***	5.44	0.5851***	5.46	0.5797***	5.35
	ζ^2	0.5510***	5.25	0.5825***	5.75	0.5617***	5.49	0.5479***	5.34
	ζ^3	0.3959***	2.70	0.4103***	2.98	0.4027***	2.92	0.3896***	2.70
	ζ^4	0.6946***	3.72	0.6335***	3.50	0.6736***	3.63	0.6978***	3.76
	ζ^5	0.6636***	4.10	0.6278***	4.10	0.6360***	4.03	0.6476***	4.09
	ζ^6	0.4108**	2.26	0.3873**	2.14	0.4010**	2.22	0.4093**	2.27

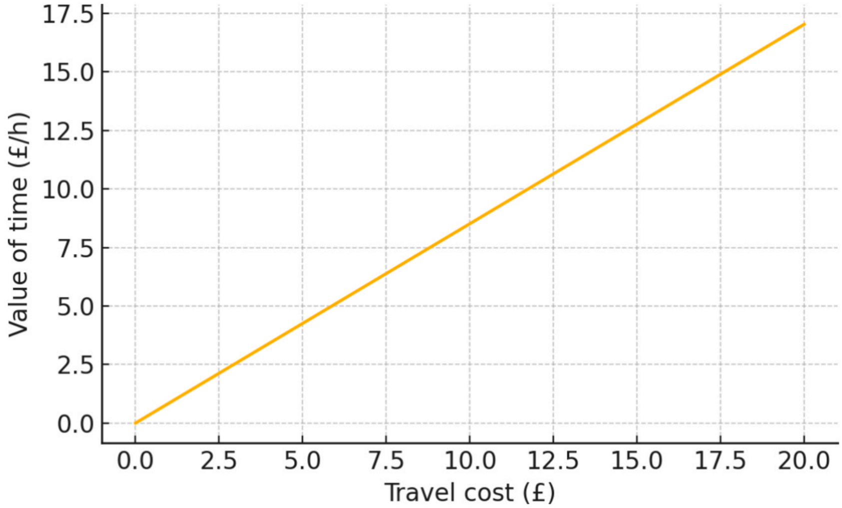

Fig. 12. Value of time as a function of travel cost.

required to more comprehensively understand the longer-term effects of the nudges.

Finally, the results do not show a significant order effect.

5. Discussion and implications

Our findings provide valuable insights into how different nudges influence urban travel behaviour within a realistic yet controlled setting. This section discusses the results through three key lenses: behavioural insights, policy implications, and methodological contributions.

5.1. Behavioural implications

In this experiment, participants' choices tend to be governed by cost and time. Even when carbon emissions are explicitly presented as a decision attribute, our quantitative results show that the coefficient for carbon intensity remains statistically insignificant. This aligns with prior studies indicating that travellers often view environmental impacts as secondary to immediate concerns such as price, convenience, and travel time (Choudhury et al., 2025; Henríquez-Jara et al., 2025; Javaid et al., 2020). One possible explanation is that climate costs are typically intangible and long-term, making them less compelling in short-horizon choices. In addition, this is not unexpected as in the real-world, choices tend to be dominated by level-of-service variables (Berger et al., 2022).

Despite the weaker direct effect of carbon emissions, we observed that interventions designed to enhance the salience of environmental costs can nevertheless shape behaviour. Both en-route and post-trip nudges significantly reduced taxi usage and prompted a switch to bus travel. Specifically, the real-time carbon feedback and the post-trip receipt make emissions tangible in ways that a generic carbon attribute might not. The in-time feedback of the en-route nudge, for instance, helps bridge the gap between an abstract climate cost and the user's immediate experience, consistent with research showing that timely visual or auditory cues can elevate environmental considerations in personal decisions (Byrne et al., 2022). Meanwhile, the post-trip receipt not only renders past behaviour in a more concrete manner but also provides a moment of reflection, tapping into a sense of social or moral responsibility.

Interestingly, the pre-trip carbon "tax" framing showed minimal effectiveness. In some cases, it generated an unintended result, potentially due to a 'crowding-out effect' (Pizzo et al., 2024). This suggests that participants who paid a carbon fee for a taxi felt justified in continuing or even repeating that mode, perceiving the tax as a form of moral absolution for their environmental impact. This aligns with existing evidence that monetary interventions can inadvertently license undesirable behaviour (Merritt et al., 2010; Wollbrant et al., 2022; Lu & Zhu, 2021). The findings underscore the complexity of cost-based nudges: while taxes are conceptually straightforward and widely used as a policy tool, their framing can backfire if individuals interpret them as a justification for high-carbon actions (Wollbrant et al., 2022).

The dynamic model reveals a strong tendency for participants to stick with their previously chosen mode across successive tasks, as well as within tasks. Such inertia has been widely documented in travel behaviour research, where past choices shape future preferences through habit formation and consistent mental shortcuts (Innocenti et al., 2013). Our data indicate that well-placed nudges can attenuate this learning effect and open a window for switching to a greener mode. Post-trip nudges, in particular, reduce the probability of carrying forward a high-carbon choice. These results highlight the potential importance of repeated or ongoing interventions to break entrenched routines, suggesting that a single prompt or message may be inadequate to shift ingrained behaviours.

5.2. Policy implications

Our results suggest that offering travellers continuous or real-time reminders of carbon costs can produce more enduring effects than imposing a simple charge at the outset. En-route nudges, for example, directly link ongoing emissions to the user's travel experience, prompting the traveller to reconsider a taxi ride in progress. Post-trip receipts similarly reinforce the behavioural feedback loop, enabling individuals to reflect on their choices and potentially shift mode on the next trip. In practice, policymakers could integrate such feedback into ride-hailing apps or public transport systems, for instance, by displaying carbon footprints on users' mobile phones during and after the trip.

Though carbon taxes remain a cornerstone of many climate policies, our evidence suggests that framing a portion of taxi fare as a "carbon charge" can sometimes backfire. If travellers view the tax as a license or moral offset, it may fail to encourage a shift to greener modes. This does not mean carbon taxes themselves are ineffective in the broader sense; indeed, many macro-level models show that internalising externalities can reduce overall emissions (Winkler et al., 2023). However, from a behavioural standpoint, the success of such pricing mechanisms may hinge on their framing and complementarity with other policies (Ben-Elia & Ettema, 2011). Governments might consider emphasising the ongoing negative impacts of driving even if a tax is paid. By doing so, they may avoid the perception that paying a fee absolves one from environmental responsibility.

The presence of a learning effect highlights that single or short-term campaigns may be insufficient to sustain greener travel habits. Over time, people tend to revert to familiar patterns in the absence of consistent reminders or structural changes (Byrne et al., 2022). Our results demonstrate that repeated exposure to en-route feedback can gradually chip away at a person's propensity to choose a high-carbon mode. Translating this into real-world policy means that implementing a one-off poster campaign or an isolated pilot is unlikely to yield large or lasting impacts. Instead, local governments or transport agencies could adopt an iterative approach whereby travellers receive regular updates on their cumulative carbon savings or repeated prompts about the benefits of lower-carbon modes. Consistent engagement may help normalise the new behaviour, strengthening the shift to public or active transport. It should be noted, however, that the information we use functions as an "emotional tax" and may impose a psychological burden on travellers, such as guilt (Thunström et al., 2018). Policymakers therefore need to calibrate both the amount and the presentation of the information to avoid reducing traveller welfare through information or emotional overload.

It should also be noted that the implementation of the policies may meet resistance from some transport stakeholders, for example, taxi drivers. However, though some groups may lose benefits, overall social welfare will rise. When promoting such policies, the government should keep the net welfare gain in view. At the same time, the government would need to consider potential welfare loss for the operators and introduce supporting measures to raise their acceptance of the new policy. They could, for instance, offer subsidies to help taxi drivers upgrade petrol cars to new-energy vehicles. The framing of the feedback could also be adapted to different vehicle types and trip contexts.

5.3. Methodological implications

The use of VR in this study highlights its potential as a powerful tool for policy research and behavioural studies. This method overcomes several limitations of traditional field experiments and stated preference studies, providing richer and more reliable data in testing the effect of treatments, which are hard to test in the real world. In this study, VR created a controlled yet dynamic environment that allowed us to test complex nudge interventions, such as real-time feedback and post-trip summaries, and assess their combined effects on behaviour. This flexibility is particularly valuable for developing and refining multifaceted policy tools to promote sustainable behaviours.

One of the significant advantages of using VR was the ability to test interventions in an incentive-compatible environment. This means that the decisions of participants had real consequences within the virtual setting, closely simulating real-world scenarios where choices affect outcomes. By ensuring that participants felt the impact of their decisions, we gathered more preference-reflecting data on their behaviour. This incentive compatibility is crucial for obtaining reliable insights into how different nudge strategies influence decision-making processes. It reduces the hypothetical bias often present in traditional surveys and experiments, leading to more reliable and actionable findings for policymakers.

Moreover, VR allows for detailed observation of decision-making processes. Unlike traditional methods, where researchers must infer decision-making steps from outcomes, VR enables direct observation of how participants navigate choices. This capability is crucial for understanding the underlying mechanisms of behaviour change and identifying the specific points where nudge interventions exert their influence. The detailed insights gained from VR were instrumental in uncovering learning effects and residual impacts, offering a deeper understanding of the long-term potential of these strategies.

Despite its advantages, VR also has drawbacks. For example, recruitment constraints can lead to a relatively small and less representative sample. Before any policy is rolled out more widely, its suitability for a broader population must be considered. In addition, VR cannot reproduce the scenarios with 100% complete reality, which may generate preferences that are different from those that lead to observed real-world behaviour (e.g., variable waiting times at bus stops may frustrate passengers but would be complex to simulate in VR). Nevertheless, the method provides valuable insight into travellers' decision making under incentive-compatible conditions and their potential responses to innovative policies. Future research could test the findings obtained from VR in real-world settings, thereby assessing the reliability, robustness and scalability of different experimental approaches. Moreover, the present work focuses on short-term effect of nudges. Although the potential lasting effect is discussed, whether the interventions endure over longer timeframes or trigger a possible "nudge-fatigue" or "fed-up" effect in the real-world remains an open question for future research.

6. Conclusion

This study employs a VR experiment to explore the impact of nudge interventions on travel mode choices, specifically aiming to shift participants from using taxis to buses. The results demonstrate that nudge interventions, particularly Nudge-en route and Nudge-post trip, significantly promote greener travel behaviours. The dynamic model reveals a learning effect, indicating that the previous experiences of participants influence their subsequent choices. Additionally, the study finds that these nudge interventions can have both immediate and lasting effects, reinforcing sustainable travel behaviours over time. The contribution of this research lies in its methodological innovation and practical implications. By integrating VR technology into the experimental design, this study provides a realistic and controlled environment to test complex nudge strategies, overcoming the limitations of traditional field experiments and SP choice experiment studies. The findings offer valuable insights for policymakers, demonstrating the potential of real-time feedback and reflective learning mechanisms in promoting environmentally friendly travel choices.

Looking ahead, VR's ability to simulate and test policy scenarios has significant implications for policy research. Beyond nudges, VR could assist policymakers in evaluating the integration of other TDM measures, such as comfort, reliability, or digital service enhancements in public transport. By adjusting these factors in VR, planners can identify which combinations resonate most with travellers and how they interact with behavioural cues. Implementing these insights in real-world settings could enhance policy efficiency and public acceptability, as the interventions would have already been tested in a realistic virtual environment.

While VR offers substantial immersion, it cannot yet fully replicate unpredictable factors such as traffic congestion, time pressure, or real-time crowding. As VR technology evolves, richer simulations incorporating these elements could provide additional insights into how travellers respond to complex scenarios. Future research could also explore multi-user interactions and more detailed urban environments, further bridging the gap between virtual and real-world decision-making.

CRediT authorship contribution statement

Yu Wang: Writing – original draft, Methodology, Formal analysis, Data curation, Conceptualization. **Thomas O. Hancock:** Writing – review & editing, Supervision, Methodology, Conceptualization. **Albert Solernou Crusat:** Software, Methodology, Data curation. **Jorge Garcia de Pedro:** Software, Methodology, Data curation. **Yacan Wang:** Supervision, Conceptualization. **Charisma F. Choudhury:** Writing – review & editing, Supervision, Methodology, Funding acquisition, Conceptualization.

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.

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Appendix

In Model (a), we estimate an MNL that includes only the three experimental attributes for the initial choice. Models (b) and (c) extend Model (3) and (4) by adding socio-demographic controls. Although the coefficients remain stable in value, sign and significance level, the overall fit does not improve significantly compared with Models (3) and (4).

Table A1. Estimation results.

Parameters		Model (a)-Reference		Model (b)- Combined		Model (c)-Dynamic	
		Estimate	Rob.t-ratio(0)	Estimate	Rob.t-ratio(0)	Estimate	Rob.t-ratio(0)
ASC	$ASC^{Initial-bus}$	0.0000	NA	0.0000	NA	0.0000	NA
	$ASC^{Initial-taxi}$	0.1145	0.31	−2.4406***	−5.05	−2.7719***	−4.25
	$ASC^{Revised-bus}$	–	–	0.0000	NA	0.0000	NA
	$ASC^{Revised-taxi}$	–	–	−1.2603***	−5.73	−1.2785***	−5.60
Error component[1]	$\sigma^{Initial}$	–	–	0.6295***	4.30	−0.5685***	−3.51
	$\sigma^{Revised}$	–	–	0.3471	1.46	−0.2997	−1.05
Scenario attributes	$\beta^{Log(Cost)}$	−7.9639***	−9.90	−9.2329***	−8.25	−9.8689***	−8.73
	β^{Time}	−0.0847***	−4.53	−0.1301***	−5.87	−0.1401***	−5.64

(continued on next page)

(*continued*)

Parameters		Model (a)-Reference		Model (b)- Combined		Model (c)-Dynamic	
		Estimate	Rob.t-ratio(0)	Estimate	Rob.t-ratio(0)	Estimate	Rob.t-ratio(0)
	β^{Carbon}	−0.0003	−0.14	0.0015	0.81	0.0005	0.21
Nudge	$\beta^{N_{pre}}$	–	–	0.2831	1.09	−0.1578	−0.37
	$\beta^{N_{en}}$	–	–	−0.9487**	−2.62	−0.8258**	−2.34
	$\beta^{N_{post}}$	–	–	−1.4156***	−4.29	−1.4712***	−4.47
Attitude	λ	–	–	0.6605***	3.48	0.7148***	4.53

Parameters		Model (a)-Reference		Model (b)-Combined		Model (c)-dynamic	
		Estimate	Rob.t-ratio (0)	Estimate	Rob.t-ratio (0)	Estimate	Rob.t-ratio (0)
Intra-task parameter	δ	–	–	1.3797***	4.13	1.4215***	3.96
	μ	–	–	0.7405*	−1.97[a]	0.5904***	−3.53[a]
Inter-task parameter:Learn effect	γ	–	–	–	–	1.4580***	4.82
	$\gamma^{N_{pre}}$	–	–	–	–	−0.3817	−0.74
	$\gamma^{N_{en}}$	–	–	–	–	−0.6304	−1.20
	$\gamma^{N_{post}}$	–	–	–	–	−1.7559**	−2.03
Inter-task parameter:Residual effect	$\beta^{acu_{pre}}$	–	–	–	–	0.3620*	1.71
	$\beta^{acu_{en}}$	–	–	–	–	−0.3472	−1.08
Inter-task parameter:Order effect	β^{order2}	–	–	–	–	−0.2612	−1.13
	β^{order3}	–	–	–	–	0.2946	0.88
Gender (non-female as base)	β^{Female}	–	–	−0.6571**	−2.42	−0.6575**	−2.52
Age (65 or above as base)	$\beta^{Age_{18-24}}$	–	–	−1.0869***	−3.51	−1.2299***	−3.33
	$\beta^{Age_{25-34}}$	–	–	−1.4910***	−5.21	−1.5838***	−4.43
	$\beta^{Age_{35-44}}$	–	–	−1.6598***	−4.34	−1.7783***	−3.83
	$\beta^{Age_{45-54}}$	–	–	−1.3613***	−2.65	−1.3298**	−2.31
	$\beta^{Age_{55-64}}$	–	–	−2.0289***	−7.54	−1.9691***	−4.86
Sample size		105		105		105	
Number of modelled observations		630		1,890		1,890	
Model fitness	LL (final, whole model)	−345.95		−1,481.68		−1,476.26	
	AIC	699.89		3,025.36		3,030.52	
	BIC	717.68		3,107.64		3,134.02	

[1]Since σ represents a standard deviation, it is reported as a positive value. Standard errors remain unchanged.

Note: ***indicates |t|>=2.58, **indicates1.96<=|t|<2.58, *indicates 1.64<=|t|<1.96; [a] Denote a Rob. *t*-test against 1, otherwise the Rob. t-tests are against 0.

Table A2. Estimation results of the measurement models.

Measurement model		Model (a)-Reference		Model (b)-Combined		Model (c)-Dynamic	
		Estimate	Rob.t-ratio(0)	Estimate	Rob.t-ratio(0)	Estimate	Rob.t-ratio(0)
Parameters	ζ^1	–	–	0.5991***	5.06	0.5913***	4.89
	ζ^2	–	–	0.5394***	5.18	0.5275***	5.06
	ζ^3	–	–	0.4048***	2.87	0.3951**	2.64
	ζ^4	–	–	0.6873***	3.81	0.7015***	3.64
	ζ^5	–	–	0.6269***	3.86	0.6357***	3.82
	ζ^6	–	–	0.3891**	2.17	0.3907**	2.15

Data availability

Data will be made available on request.

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