Nudging Travellers Towards Greener Modes: A Virtual Reality Experiment

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SHORT SUMMARY

The growing carbon footprint of transportation calls for new travel demand management strategies. The effectiveness of soft Nudge mechanisms in different fields makes them a potentially effective TDM measure. However, implementing Nudges in real-world transport involves technological and flexibility challenges. This study uses virtual reality to evaluate the effectiveness of different Nudges that provide explicit carbon information (pre-trip, en route, and post-trip) in realistic travel scenarios. Data from 105 participants facing six choice tasks yield 1,260 observations are analysed with a dynamic repeated choice model. Results show that en-route and post-trip Nudge interventions effectively encourage participants to shift from taxi to bus travel, with both immediate and potentially lasting effects. Pre-trip nudge on the other hand had mixed effects. The novelty of this research lies in its immersive data collection approach, innovative modelling, and policy implications. These findings highlight the promise of psychologically based interventions as a TDM and offer policy-makers insights on promoting more sustainable travel behaviour in the real world.

Keywords: Nudge, Virtual reality experiment, Dynamic repeated choice, Green travel behaviour

INTRODUCTION

According to the IPCC's 2023 Synthesis Report, drastic reductions in carbon emissions must occur before 2050. Road transportation ranks as the second-largest contributor, mainly due to light-duty vehicles whose emissions have increased steadily (Statista, 2023). This makes the sector a strategic target for climate-change mitigation (Wadud et al., 2024; Winkler et al., 2023; Lu et al., 2022). While technological solutions, such as electric vehicles, can reduce the environmental impact of transportation (Isik et al., 2021), high costs and slow adoption will impede significant emission cuts in the coming decades (Singh et al., 2024; Wang et al., 2023). Thus, from the demand side, governments and authorities need to leverage travel demand management (TDM) measures to motivate travelers toward lower-emission modes (Wang et al., 2022).

Traditional TDMs often involve significant resources and, when they rely on legal or infrastructural changes, may face resistance from the public (Saleh, 2007). In response, policymakers are increasingly considering "soft" or psychological interventions, collectively termed Nudge—strategies that influence perceptions, beliefs, and norms (Thaler & Sunstein, 2021). Nudge has proved effective in many contexts (Bhargava & Loewenstein, 2015), but its impact on travel behavior remains uncertain, with both successes and failures reported (Kristal & Whillans, 2020; Su et al., 2020). They are usually tested by field experiments. Field experiments yield real-world behavioral responses but often lack granularity in capturing all decision attributes or explaining why a given Nudge fails or succeeds (Su et al., 2020). Meanwhile, traditional stated preference (SP) surveys allow for the collection of controlled hypothetical scenarios at low cost (Cherchi & Hensher, 2015) but may suffer from hypothetical biases (Hensher, 2010).

Virtual reality (VR) experiments present an innovative approach that combines the control of SP with enhanced realism (Dixit et al., 2017; Bogacz et al., 2021). In VR, participants make travel choices in immersive environments that mimic real-world conditions, allowing for the testing of more complex interventions that might be difficult to implement in conventional field studies. This method addresses some limitations of field experiments and SP surveys—particularly the lack of detailed decision processes and biases linked to self-reported data (Dixit et al., 2017). Despite its promise, few studies have used VR to evaluate the effectiveness of policy measures, including Nudge.

To bridge these gaps, the present study employs a VR experiment to simulate realistic travel scenarios and test the effectiveness of Nudge interventions. 105 participants were recruited, yielding 1,260 observations used to estimate a repeated choice model. This model measure how sensitive travelers are to Nudge compared to time and cost, accounting for potential learning effects over multiple trials. Findings indicate that Nudge can effectively encourage a shift from taxis to buses, both in the short term and potentially beyond. By offering proof-of-concept for policymakers, this study highlights the value of integrating Nudge-based interventions with more traditional TDM tools, demonstrating which mechanisms could be most effective in real-world settings.

METHODOLOGY

Experiment procedure

Figure 1. VR equipment setting

This experiment used in the VR setup. Participants wore VR equipment as shown in Figure 1. They first tried a practice scenario (bus and taxi) to get familiar with VR. Each participant then completed six choice tasks (in two blocks), with a 30-second rest between tasks. As shown in Figure 2, each task proceeded in three steps: (1) an SP scenario where participants chose between taxi and bus (green mode) based on time, cost, and carbon emissions, potentially receiving pre-trip NUDGE interventions; (2) a VR experience of the chosen mode, scaled so that one minute of SP time equaled ten seconds in VR; (3) a subsequent SP choice (return trip) with the same attributes, to observe any shift in choice. After all tasks, participants filled out a post-survey on green attitudes, daily travel behaviors, socio-economic details, and an open-ended question on factors influencing their choices.

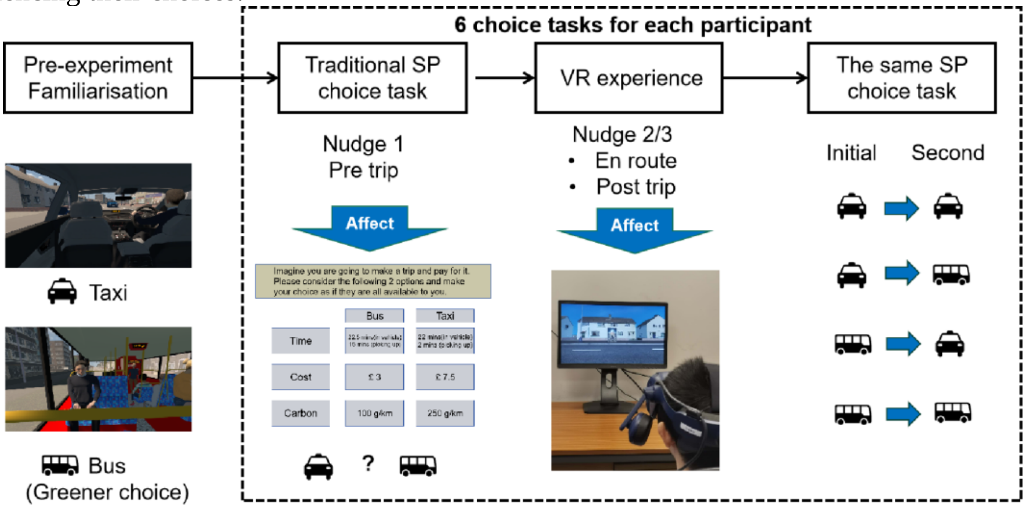

Figure 2. The steps of the experiment

Treatment design

This experiment employs three NUDGE interventions to highlight the carbon emissions from taxi travel and encourage bus use.

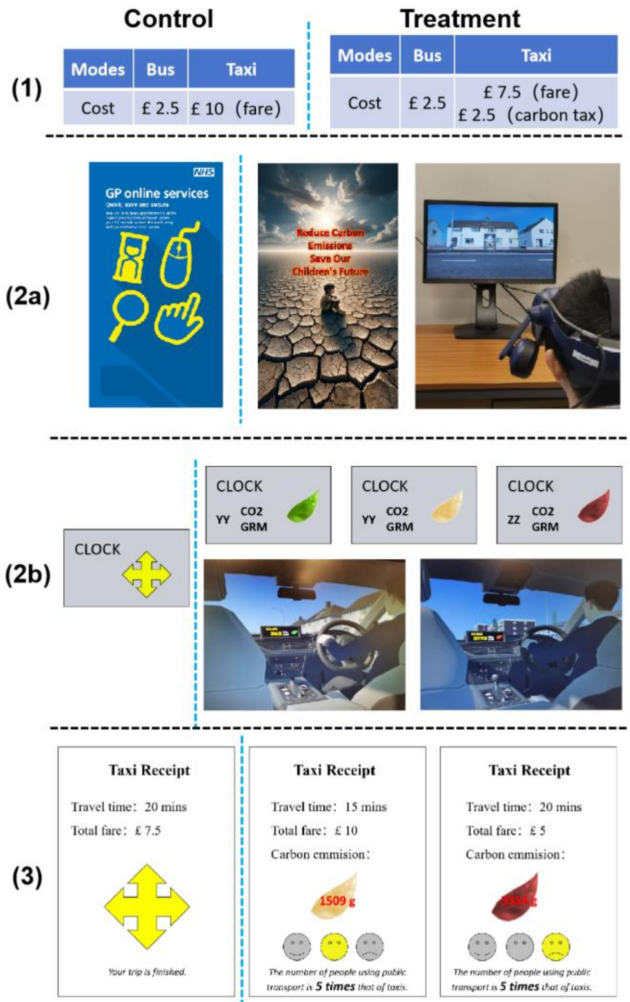

Figure 3. Treatment design

Nudge-pre trip (Figure 3-1): Before participants make their choice, taxi fare is split into a regular cost and a separate "carbon tax," maintaining the same total cost as the control condition. This underscores environmental costs and nudges travelers toward greener options by increasing the visibility of carbon impacts (Kahneman, 2011).

Nudge-en route (Figure 3-2): Two elements comprise this intervention: (a) a poster at the taxi stand proclaiming "Reduce carbon emission, save our children's future," and (b) a carbon meter in the taxi that displays real-time emission feedback. The poster appeals to social norms and moral suasion, while the meter changes colour as emissions accumulate (Andor et al., 2020).

Nudge-post trip (Figure 3-3): At the end of the journey, participants see a carbon receipt detailing cost, time, and emissions, alongside a social norm message. This reflective component helps them consider the environmental impact of their choices and fosters socially responsible behaviour (Allcott & Rogers, 2014). The control group receives a traditional receipt without emission data.

To test the impact of the different types of Nudges, different combinations of nudges are presented in different choice tasks. Further, to analyse the potential learning process, the participants received increasing amounts of intervention. In each group's six choice tasks (S1-6), the first two tasks always have no nudge interventions, whilst the Nudge-post trip always appears only in the last two tasks.

Data collection and sample composition

The experiment took place at the VirtuoCity Laboratory at the University of Leeds. 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 got 1,260 observations of task choices (2 choices for each task).

Model

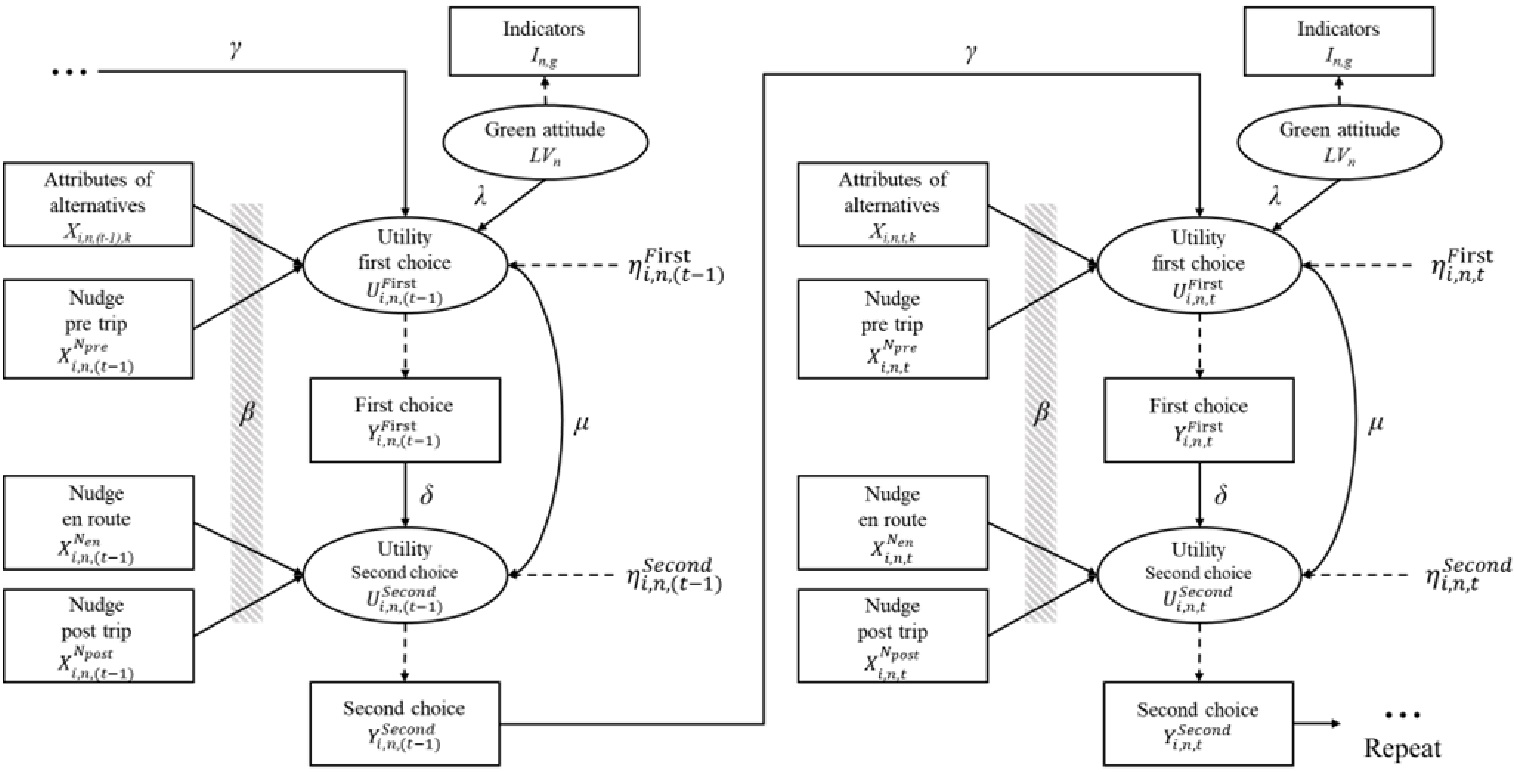

Figure 4. Structure of the model

As shown in Figure 4, a dynamic model considering the interdependencies among the six choice tasks was developed. Specifically, we acknowledge a potential learning process occurring throughout the six tasks, where the experiences from earlier tasks influence subsequent task choices.

In the first choice, participants evaluate the utility of each alternative based on the SP scenario. After choosing, they experience that option in VR, then re-evaluate the choice. Status quo bias often leads them to stick with their initial selection. The updated "second choice utility" is influenced by the first choice through a stickiness parameter δ, the initial systematic utility scaled by μ, and any Nudge interventions encountered in the VR trip.

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 first choice:

$$
\begin{aligned}
V_{n,t}^{First-taxi} = {} & ASC^{First-taxi} \\
& + \beta^{Cost} X_{n,t}^{Taxi_{cost}} + \beta^{Time} X_{n,t}^{Taxi_{time}} + \beta^{Carbon} X_{n,t}^{Taxi_{carbon}} \\
& + \beta^{N_{pre}} X_{nt}^{N_{pre}} \\
& + \gamma Y_{n,(t-1)}^{Second} \\
& + \left(\gamma^{N_{pre}} + \beta^{N_{pre}-Male} X_{n}^{Male}\right) Y_{n,(t-1)}^{Second} X_{n,t}^{pre_{pre}} \\
& + (\gamma^{N_{en}} + \beta^{N_{en}-Male} X_{n}^{Male}) Y_{n,(t-1)}^{Second} X_{n,t}^{pre_{en}} \\
& + \left(\gamma^{N_{post}} + \beta^{N_{post}-Male} X_{n}^{Male}\right) Y_{n,(t-1)}^{Second} X_{n,t}^{pre_{post}} \\
& + (\beta^{acu_{pre}} + \beta^{acu_{pre}-Male} X_{n}^{Male}) X_{n,t}^{acu_{pre}} \\
& + (\beta^{acu_{en}} + \beta^{acu_{en}-Male} X_{n}^{Male}) X_{n,t}^{acu_{en}} \\
& + \beta^{order2} X_{n,t}^{order2} + \beta^{order3} X_{n,t}^{order3}
\end{aligned} \tag{1}
$$

$$
\begin{aligned}
V_{n,t}^{First-Bus} = {} & ASC^{First-bus} \\
& + \beta^{Cost} X_{n,t}^{Bus_{cost}} + \beta^{Time} X_{n,t}^{Bus_{time}} + \beta^{Carbon} X_{n,t}^{Bus_{carbon}} \\
& + \lambda LV_{n}
\end{aligned} \tag{2}
$$

For the second choice:

$$
\begin{aligned}
V_{n,t}^{Second-taxi} = {} & ASC^{Second-taxi} \\
& + \mu V_{n,t}^{First-taxi} \\
& + \delta Y_{nt}^{First} \\
& + \beta^{N_{en}} X_{n,t}^{N_{en}} + \beta^{N_{post}} X_{n,t}^{N_{post}}
\end{aligned} \tag{3}
$$

$$
\begin{aligned}
V_{n,t}^{Second-bus} = {} & ASC^{Second-bus} \\
& + \mu V_{n,t}^{First-bus}
\end{aligned} \tag{4}
$$

Where *ASC* is the alternative specific constraint. β^{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. γ is related to the learning effect of inter-task choice. It captures the potential effect of the choice of previous task on the subsequent one. $\gamma^{N_{pre}}$, $\gamma^{N_{en}}$ and $\gamma^{N_{post}}$ represent the moderating effect of nudges on the learning effect between choice tasks, while we interact the constants with gender, allowing for differences in the sensitivities for male participants. In addition, $\beta^{acu_{pre}}$ and $\beta^{acu_{en}}$ capture the residual effect of the nudges. It describes when making the first choice in task t, how many times of a specific Nudge the subject experienced from task 1 to task t-1. Further, β^{order2} and β^{order3} capture any potential ordering effects/.

RESULTS AND DISCUSSION

Exploratory analysis

As shown in Figure 5, the results show that for all task observations with at least one nudge (366), the proportion of choosing the bus on the second choice (overall 76.78%) is higher than on the first choice (overall 54.64%). Meanwhile, for tasks without any nudges (364), there is no substantial difference in the proportion of choosing the bus between the first (overall 65.15%) and second (overall 66.29%) choice.

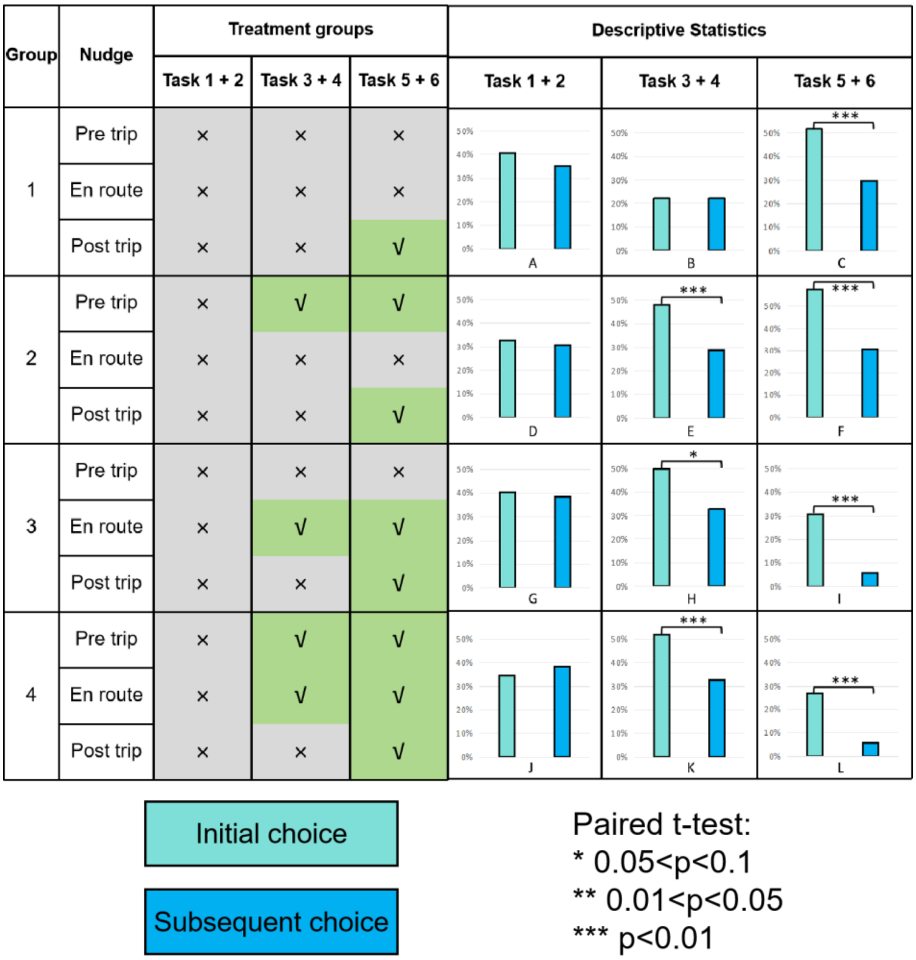

Figure 5. The proportion of choice tasks in which bus is chosen.

Note: There is significantly less bus choices in all seven conditions in which there are a nudge (highlighted by green boxes in the treatment group columns) and no significant changes in the other five conditions.

Model results

The model results are shown in Figure 6. The coefficients are marked on the arrow to show the relationships between each part.

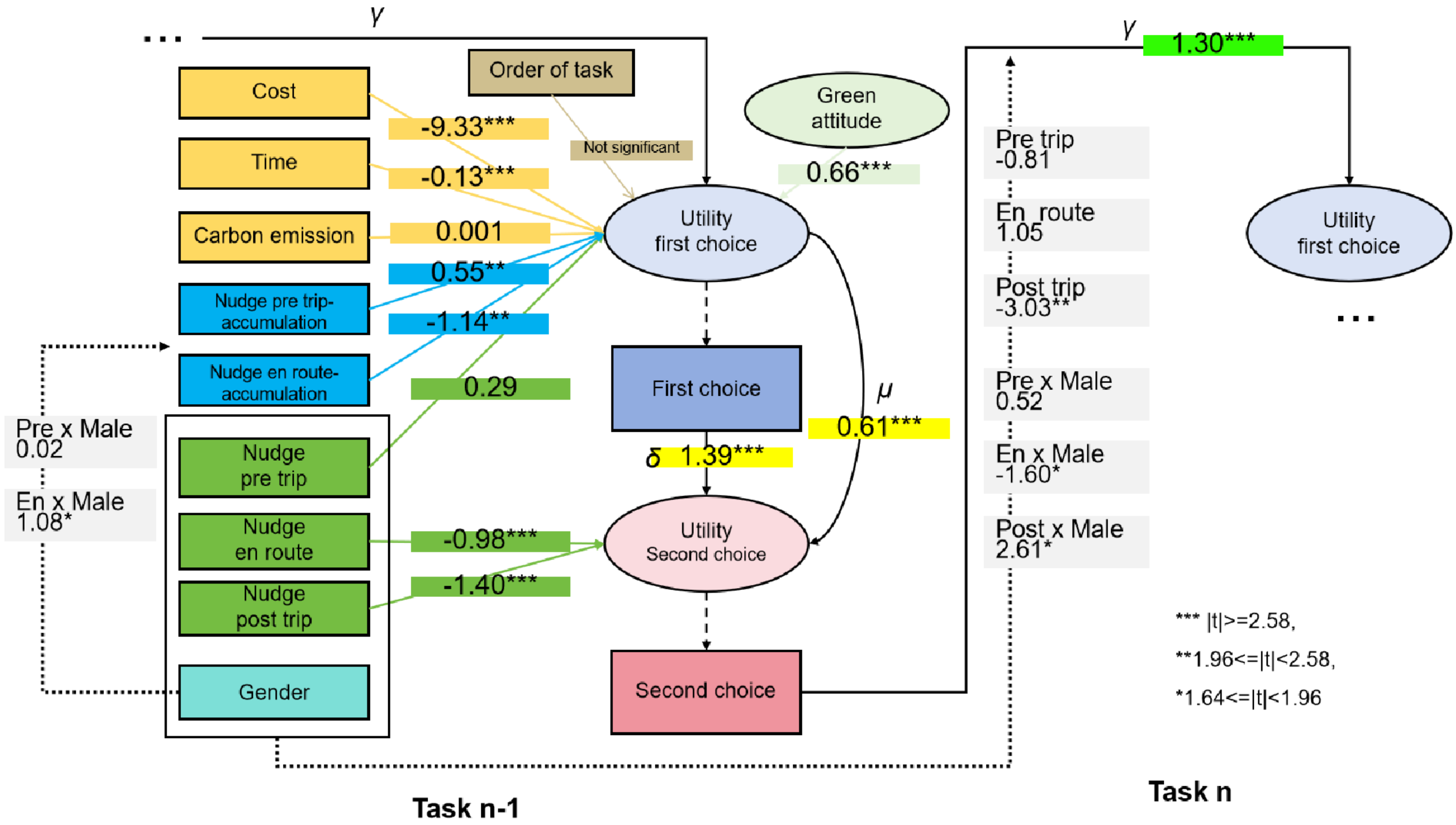

Figure 6 Model results

Our findings indicate that participants place greater emphasis on time and monetary costs than on carbon emissions when making travel choices, suggesting that carbon-related information may be insufficiently salient in the immediate decision-making context. Nonetheless, two of our NUDGE interventions—Nudge-en route and Nudge-post trip—significantly reduce taxi utility, indicating that real-time and post-trip feedback can effectively heighten awareness of environmental consequences and promote greener travel.

From the intra-task perspective, the scale parameter (μ) being less than 1 shows that systematic utility becomes less influential in the second choice. Meanwhile, the positive and significant stickiness parameter (δ) confirms a status quo bias, as participants tend to adhere to their initial choice. Even so, the en route and post-trip nudges can curb the attractiveness of a previously chosen taxi, demonstrating that targeted psychological interventions have the potential to interrupt habitual decision-making.

Inter-task results underscore that participants learn over multiple choice tasks. A positive γ coefficient implies that if a participant sticks with a taxi on one task, they are more likely to do so again subsequently—unless moderated by Nudge-post trip. This intervention weakens habitual taxi use, highlighting the potential for longer-term behavioural shifts. Heterogeneity analysis shows this moderating effect varies across gender: it is weaker among male participants, but in contrast, Nudge-en route more effectively persuades male participants to reconsider repeated taxi use.

Interestingly, Nudge-pre trip has an unintended "crowding out" effect: the more carbon tax participants pay up front, the more likely they later revert to taxi travel, hinting at a moral licensing phenomenon. By contrast, Nudge-en route exerts a residual effect, though again weaker among males, suggesting demographic-specific differences in how nudges carry over to subsequent choices.

Overall, the absence of a significant order effect indicates that the sequence of tasks is not driving results, and instead, the interventions themselves and participants' prior experiences play dominant roles.

These findings reinforce the notion that making carbon emissions more concrete—especially through real-time and reflective feedback—can drive pro-environmental behaviour, whereas purely monetary signals risk triggering moral licensing. Policymakers may therefore want to integrate continuous or post-travel feedback mechanisms into transportation planning tools and apps, providing timely environmental information and reinforcing learning over repeated trips. In designing such interventions, careful attention to demographic heterogeneity is also warranted: male participants, for instance, appear more influenced by certain types of nudges than others. Lastly, the use of VR highlights its potential for testing policy scenarios and refining behavioural interventions before scaling them up in real-world applications, offering a valuable resource for future transportation research and practice.

CONCLUSIONS

This study leverages a VR experiment to examine the effectiveness of Nudge interventions in shifting travel mode choices from taxi to bus, offering three key contributions. First, by integrating VR technology into the experimental design, it creates a realistic yet controlled environment to test complex Nudge strategies—an approach that overcomes the limitations of traditional field experiments and stated preference studies. This level of realism enables policymakers and researchers to explore interventions in detail before implementing them in actual transport systems, reducing risks and refining strategies for greater impact. Second, the results confirm that Nudge-en-route and Nudge-post trip substantially increase the likelihood of selecting greener travel modes, and these interventions exhibit both immediate and enduring effects. Third, a dynamic modelling framework reveals learning processes, whereby prior travel choices influence subsequent decisions, further highlighting how well-crafted nudges can disrupt habitual behaviours over multiple trips.

These findings underscore the potential of VR as a vital pre-deployment testing platform for travel demand management measures and underscore how real-time and reflective feedback mechanisms can effectively promote sustainable travel behaviour. Moreover, demographic-specific variations in response to nudges point to the importance of tailoring interventions to different user segments. Overall, this research offers valuable insights to policymakers seeking to implement targeted interventions, demonstrating the utility of VR as a powerful tool for designing, testing, and refining interventions that can be scaled to real-world applications.

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