Connecting Visual Attention to Choice: Uncovering Nudge Mechanisms Through Eye-Tracking in Virtual Reality

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SHORT SUMMARY

This paper investigates how eye-tracking data can help explain why interventions work or don't. Using an immersive virtual reality experiment in which participants repeatedly chose between taxi and bus, we compare a series of multinomial logit (MNL) and Decision Field Theory (DFT) models under static and dynamic specifications, with and without gaze-based information. The results show that eye-tracking improves behavioural interpretation in two ways. First, it helps distinguish which specific intervention elements entered the decision process, showing that not all parts of a nudge are equally effective. Second, when incorporated into DFT, gaze data provide a direct link between observed attention and preference formation. Across models, the dynamic structure better captures repeated decision making, and DFT offers a modest but consistent improvement in model fit. The findings provide useful guidance for policy makers by showing how intervention design can be improved through attention-based behavioural insights.

Keywords: Eye tracking; Decision Field Theory; Virtual Reality; Nudge; Dynamic Decision Making

1. INTRODUCTION

As conventional infrastructure-based demand management is costly and regulatory measures may face public and political resistance, policymakers have increasingly paid attention to psychological "soft" interventions, such as nudges, to influence travel behaviour (Thaler & Sunstein, 2021). Although nudges have shown promise in some transport contexts, their effects remain inconsistent and occasionally counterproductive (Kristal & Whillans, 2020). Much of the existing evidence relies on stated preference surveys that abstract decision-making from lived contexts and offer limited insight into underlying cognitive processes (Cherchi & Hensher, 2015), while field trials are constrained in capturing the full range of decision alternatives and behavioural mechanisms (Dixit et al., 2017). As a result, policy design and scale-up often remain trial-and-error processes rather than mechanism-informed interventions (Bhargava & Loewenstein, 2015).

Virtual reality (VR) offers a promising tool by immersing participants in controlled yet realistic travel scenarios (Yin & Cherchi, 2024; Choudhury et al., 2025; Wang et al., 2026). By overcoming behavioural incongruence and limited intervention flexibility, VR enables the testing of complex policies in a controlled and replicable environment (Farooq et al., 2018). Its value is further enhanced by instrumented experiments that integrate physiological measures, such as eye tracking, which provide direct insight into attention and preference formation and help uncover the decision making process (Shimojo et al., 2003; Krucien et al., 2017). This provides a new perspective for uncovering the mechanisms underlying interventions. Despite extensive use in experimental economics and marketing (Lahey & Oxley, 2016; Genie et al., 2023).

In transportation research, eye-tracking data have been used mainly to examine how travellers allocate visual attention in complex environments (Zhai et al., 2025; Rayner, 2009). Existing

applications can be broadly grouped into: safety assessment, wayfinding and navigation evaluation, and comfort or interface assessment in transport spaces (Zhai et al., 2025). These studies show that eye tracking has been particularly useful for identifying what attracts attention, what creates visual difficulty, and which environmental features influence travel behaviours in specific transport settings. Although, as far as we know, no studies have applied eye-tracking data directly to transport policy analysis, the existing studies still provide useful support for policy research by showing how attention is allocated, how information is processed, and which environmental cues are most likely to shape behavioural responses.

Most eye-tracking studies in choice analysis rely on summary measures such as fixation counts and fixation duration, which are typically analysed using correlation, ANOVA, or regression-based approaches (Genie et al., 2023; Hancock et al., 2022). In many cases, eye-tracking data are treated as supplementary explanatory information rather than being embedded directly in the choice formation process (Hancock et al., 2022). For transport policy research, this is a limitation, because the key issue is not only where travellers look, but also how attention to different cues develops and translates into behavioural responses to interventions.

Decision Field Theory (DFT) offers a useful way to address this gap. Unlike conventional one-off utility evaluation, DFT represents choice as a process in which preferences are updated over time through repeated attention to different attributes (Hancock et al., 2018). This makes it well suited to linking observed visual attention to preference formation and to examining how interventions influence behaviour through the decision process itself. However, to our knowledge, no study has yet incorporated eye-tracking data into a DFT choice model in a transport policy context.

Against this background, taking nudge1 as a case study. This paper uses eye-tracking data collected in an immersive VR experiment designed to test innovative nudge interventions in realistic but controlled travel scenarios (Wang et al., 2026). We incorporate gaze-based measures of attention to both SP attributes and intervention elements into a DFT framework, thereby linking observed visual attention directly to preference formation. We also leverage the sequential structure of the experiment to extend the analysis from a static setting to a dynamic framework across repeated tasks. The study addresses three research questions:

(1) RQ1 (Method-related): How can eye-tracking data collected in a VR experiment be incorporated into and contribute to the choice modelling framework?
(2) RQ2 (Behaviour-related): How can eye-tracking data help understand the deliberation process of decision makers?
(3) RQ3 (Policy-related): How can eye-tracking data help to explain whether an intervention is effective?

2. METHODOLOGY

A summary of the experiment procedure is presented here. For details of the experimental setup, please see Wang et al. (2026).

[1] Nudge is a soft intervention that guides individuals' behaviour by influencing perceptions, beliefs, attitudes, values, and norms (Thaler & Sunstein, 2021).

Experiment design and data

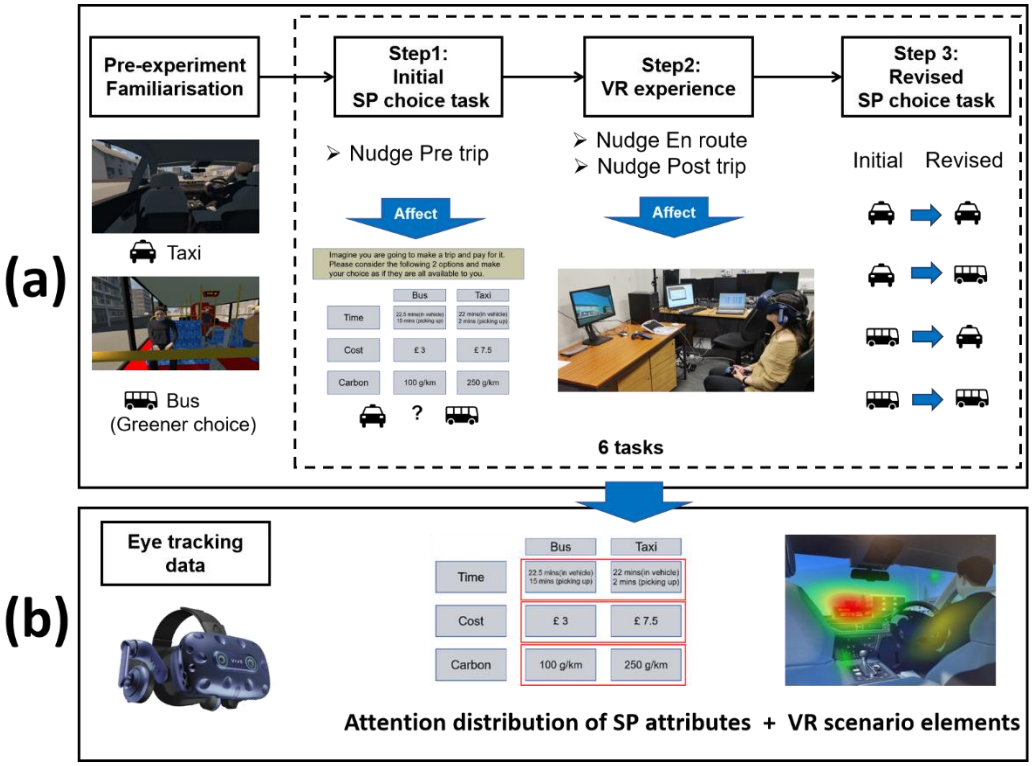


Figure 1 Experiment procedure diagram

As shown in Figure 1 (a), with a real-money budget, participants each completed six travel-choice tasks, where cost, time, and carbon emissions systematically varied between the two travel modes: high-carbon taxis to lower-carbon buses. Before the formal experiment, participants experienced bus and taxi scenarios to familiarise themselves with the VR environment. In each 3-steps task, participants first made a stated choice (Step 1), then experienced their chosen mode in an incentive-compatible VR scenario (Step 2). The VR scenario building was directly linked to the SP choice settings. For example, the time attribute was scaled so that one minute in the SP task was represented by ten seconds in VR. This preserved a meaningful connection between stated and VR experienced travel time, while keeping the overall experiment length practical. After the VR trip, participants were requested to choose the same mode or switch their choice for a hypothetical return trip with the same attribute level (Step 3). Therefore, for each participant, the six tasks produced 12 choice observations ($2 \times 6 = 12$). Once these 6 tasks were completed, participants answered a post-experiment questionnaire. This survey covered socio-economic characteristics and included an open-ended question asking participants to explain the factors that shaped their choices.



Figure 2 VIVE Pro Eye headset

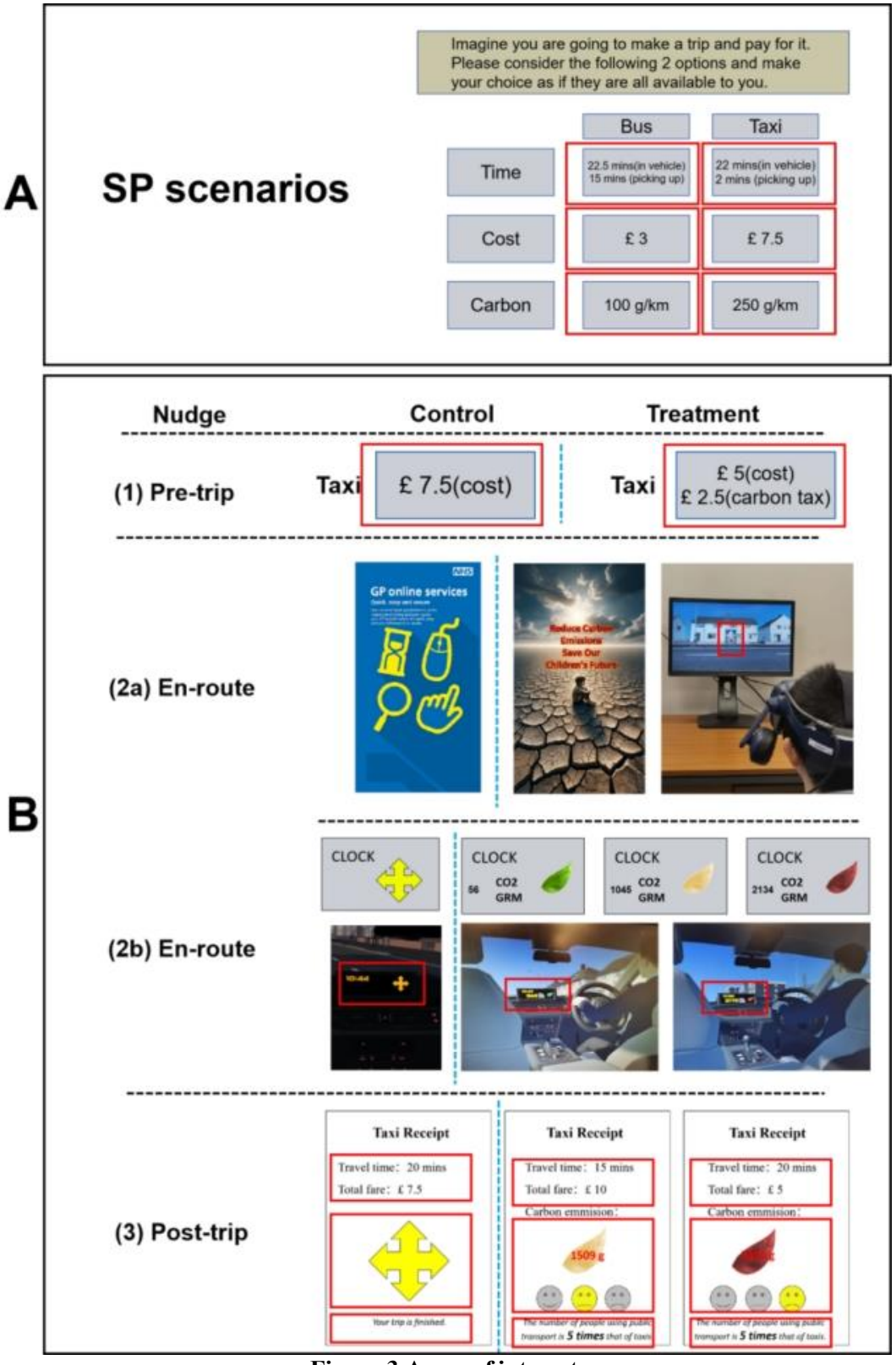


Figure 3 Areas of interest

Note: In Figure A, the main AOIs are the bus and taxi attributes. In Figure B, Panel (1) focuses on the taxi-cost attribute; Panel (2a) on the poster; Panel (2b) on the carbon meter; Panel (3) on the travel information, the label and the text.

Nudges were introduced at different stages to encourage a shift from high-carbon taxis to lower-carbon buses. As shown in Figure 3, there were three distinct nudges introduced at various points (pre-trip, en-route, and post-trip), allowing us to capture both immediate and repeated decision-making effects. The Nudge-pre trip was embedded in the SP choice screen before participants chose between bus and taxi. Rather than presenting the taxi option as a single fare, the cost was divided into the standard fare and a separate carbon tax. The Nudge-en route was delivered during the VR taxi journey and combined two interventions: a static poster shown while participants were waiting for the taxi, and a dynamic carbon meter displayed once they were inside the vehicle. The poster served as an initial prompt about the environmental consequences of travel, while the carbon meter provided continuous feedback throughout the journey. The Nudge-post trip appeared at the end of the VR taxi journey as a receipt-style summary. It combined two elements: carbon-emission feedback and a social-norm message.

In addition, as shown in Figure 1 (b), during the experiment, eye-tracking data were collected to record when and where the participants looked and paid attention. Eye-tracking data were collected using the VIVE Pro Eye headset2, shown in Figure 2, the eye-tracking data were collected across three main experimental scenarios: the SP scenarios for the initial choice, the SP scenarios for the revised choice, and the VR trip scenarios. Within each scene, we identified specific elements relevant to the decision-making process and defined the corresponding areas of interest for analysis. The areas of interest are shown in Figure 3.

Before the main study, a pilot session was run to check whether the experimental platform worked reliably and whether the task materials and parameter settings were appropriate. The full data collection was subsequently carried out in the Virtuocity Laboratory at the University of Leeds over the period from March to May 2024. The final eye-tracking dataset contains 104 participants and 1,248 associated choice observations, which were used in the subsequent estimation.

Models

In this section, we introduce the modelling specification used to analyse how eye-tracking information can be incorporated into travel choice behaviour analysis.

On the one hand, we estimate a series of DFT models alongside the conventional multinomial logit (MNL) model. The purpose is not simply to apply an alternative behavioural framework, but also to examine whether a DFT specification can better use the eye-tracking information collected in this study. Whereas the MNL models treat attention-related variables as inputs to the choice outcome, the DFT models allow them to be linked more directly to the internal formation of choice through preference updating (Hancock et al., 2022). Estimating both MNL and DFT models, therefore, provides a basis for comparing whether eye-tracking data contribute differently under an outcome-based framework and a process-based framework.

[2] https://www.vive.com/uk/product/vive-pro-full-kit/

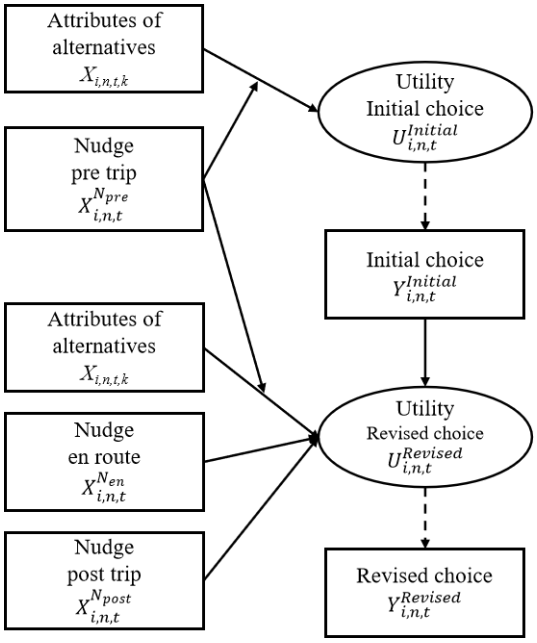


Figure 4 The structure of the static model: example of MNL

On the other hand, our data structure also supports two related model specifications for incorporating eye-tracking information. In the static specification (shown in Figure 4), we retain the two-stage structure within each task, so that the initial choice can affect the revised choice made after the VR experience. This captures within-task insistence and allows us to model how participants reassess their decision after experiencing the chosen mode. Furthermore, the dynamic specification extends this framework by introducing links across the six consecutive tasks (shown in Figure 5). In particular, it allows later choices to depend on earlier choices and experiences, thereby capturing learning effects over the repeated experiment sequence.

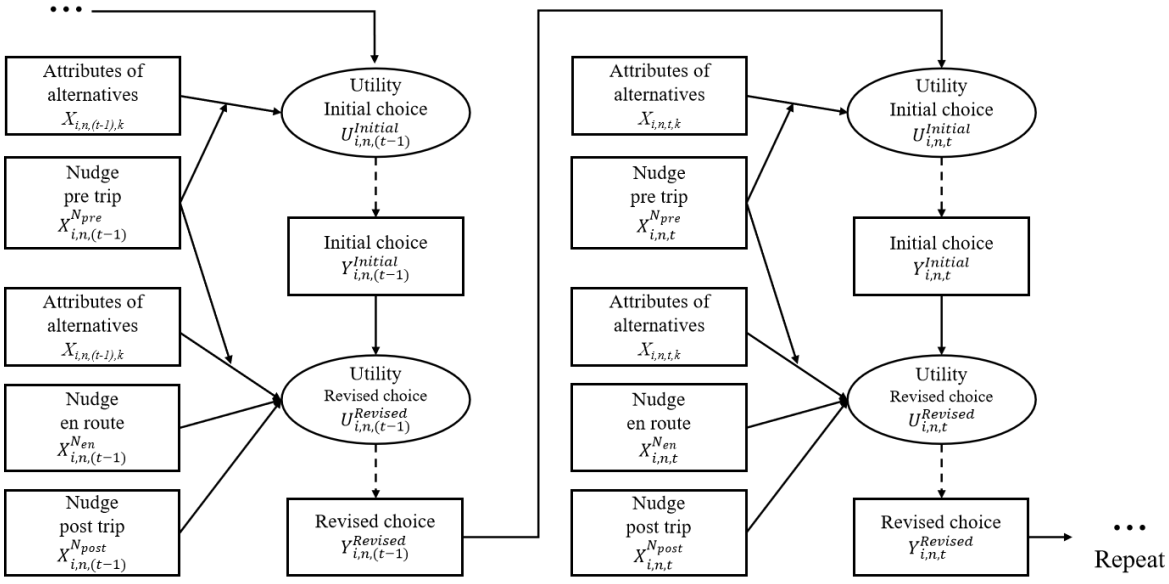


Figure 5 The structure of the dynamic model: example of MNL

Eye-tracking data are incorporated in two ways, shown in blue and green in Figure 6. First, for the intervention variables, the original nudge dummy terms are replaced with gaze-based measures reflecting visual attention to the specific nudge elements. In the baseline models, each intervention enters as a binary indicator, meaning that all content within the same intervention is

treated as a single effect. With eye-tracking data, however, this treatment can be refined. Instead of using only whether a nudge is present, we use the proportion of visual attention allocated to the relevant nudge element within its corresponding scene. Second, eye-tracking data are used in the DFT model to inform attention allocation across the SP attributes. In the baseline DFT specification without eye-tracking data, attribute attention is not directly observed. Once eye-tracking data are introduced, the attention-weight parameters can instead be linked to the observed proportion of gaze directed to each SP attribute.

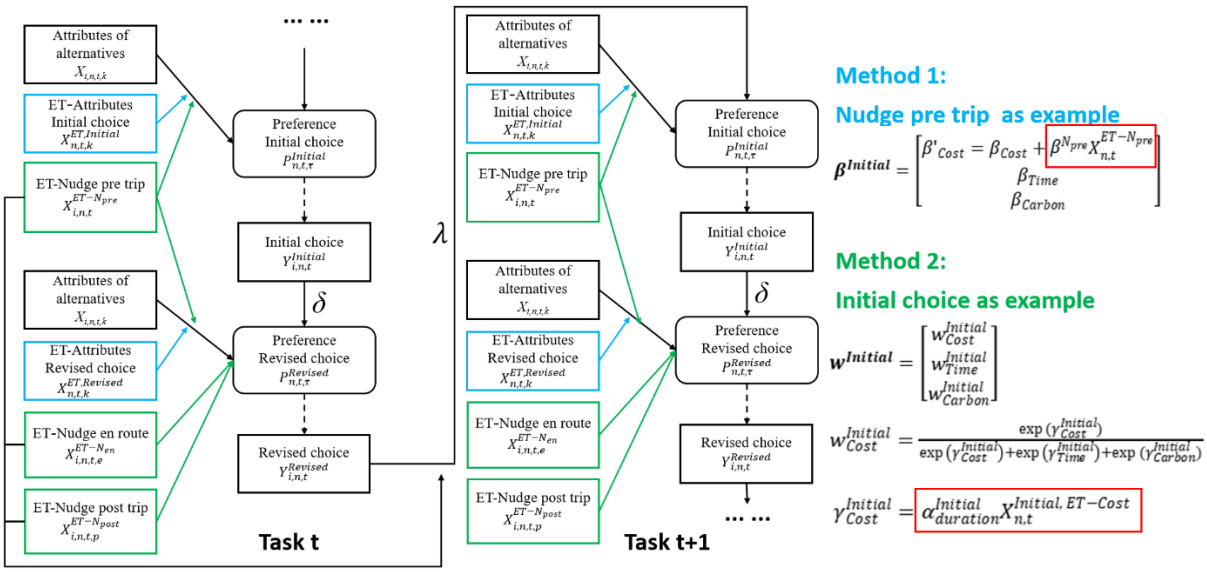


Figure 6 Incorporating eye tracking data: example of dynamic DFT

Note: We display two examples here. (1) For method 1, the Nudge-pre trip does not introduce a new attribute, but changes the salience and interpretation of the existing cost attribute. It is therefore reasonable to model its effect through an interaction with cost. (2) For method 2, $X_{n,t}^{Initial,ET-Cost}$ is the proportion of time a participant spent looking at the cost attributes (bus and taxi) before making a decision in the initial SP task t. α captures the relationship between eye tracking attention and the model attention weights. The model consists of six sub-modules corresponding to the six tasks, each of which includes two decision sub-models that are linked through a stickiness parameter (δ). Interactions across tasks are captured through a learning parameter (λ). These parameters are, in turn, influenced by the interventions.

Overall, we estimate a total of eight models: 2 model specifications (MNL and DFT) × 2 data structures (static and dynamic) × 2 data settings (without and with eye-tracking information).

3. RESULTS AND DISCUSSION

We conducted a series of model comparisons; due to space limitations, only some example results are presented here for illustration.

(1) Answer to RQ1: Comparing eight models compared above, the DFT models perform slightly better overall than the corresponding MNL models. The differences are modest, but fairly consistent across the model pairs. Incorporating eye-tracking data improves model fit and provides richer behavioural insights. Using adjusted rho-squared as an example, the static DFT model improves from 0.2329 to 0.237 after including eye-tracking data. Moreover, incorporating the dynamic structure further enhances model performance, taking DFT as an example, with adjusted rho-squared increasing from 0.2329 to 0.2593.

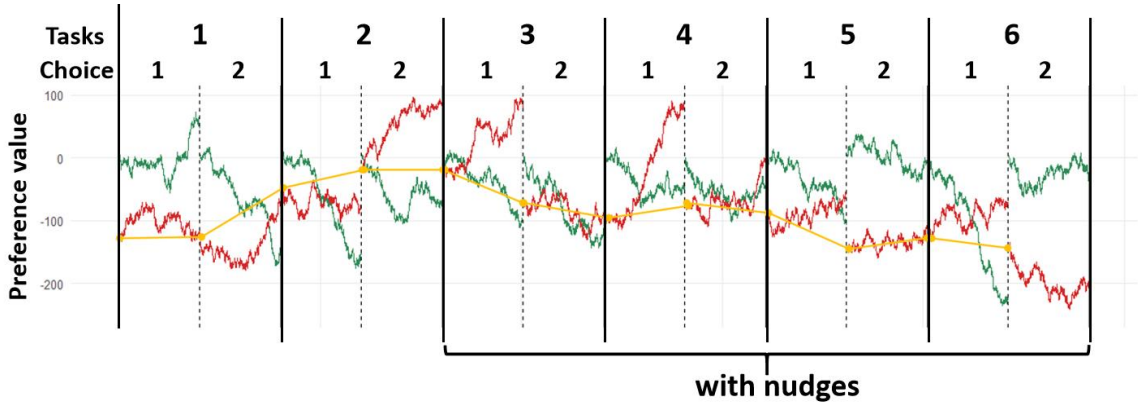


Figure 7 A simulated dynamic decision-making process

Note: This figure illustrates a DFT preference updating process based on the model results. There are interventions only for task 3/4/5/6. The red line represents the preference updating of the taxi, and the green line represents the bus. The yellow line traces the starting preference for taxis in each choice.

(2) Answer to RQ2: On the one hand, eye-tracking data effectively capture travellers' attribute weighting (Figure 6; $\alpha = 0.3570$, robust t-ratio = 2.45), reflecting how attention is allocated across decision dimensions. On the other hand, as shown in Figure 5, although the parameter δ/λ indicates that participants are more inclined to stick with their previous choices, increased exposure to nudge information reduces the initial preference for taxis in sequential decisions. For example, the carbon meter (an element of the en-route nudge) shows a significant negative effect (-374.6493, robust t-ratio = −3.18), lowering the likelihood of choosing taxis. As shown in Figure 7, to illustrate the preference updating process more clearly and to show how nudges affect decision-making over repeated tasks. The introduction of nudges lowers the starting preference for taxi and therefore reduces its probability of being chosen.

(3) Answer to RQ3: Compared with Wang et al. (2026), which assessed intervention effects at the treatment level, the present study uses detailed AOIs to distinguish between specific nudge elements and relate them to observed visual attention (such as, within the en-route intervention, the static poster is not significant, while the dynamic carbon meter shows a significant effect.). The results suggest that behavioural response depended less on the formal presence of an intervention than on whether a particular element could attract attention and enter the decision process. This allows policymakers to design and refine interventions with greater confidence before real-world deployment.

4. CONCLUSIONS

This paper examined how eye-tracking data can be used to uncover the mechanisms through which nudge interventions influence travel choice. Using an immersive VR experiment with repeated taxi–bus decisions, the study combined two modelling frameworks, MNL and DFT, under both static and dynamic specifications, and compared models with and without gaze-based information. The results show that eye-tracking contributes value in two distinct ways. First, it helps reveal why some intervention elements are more effective than others by distinguishing whether they actually entered the decision process. Second, when linked to a process-based framework such as DFT, it helps connect observed attention to the formation of preferences during choice. Across the model comparisons, the dynamic structure more effectively captured the experiment's repeated and staged nature, while the DFT framework yielded a modest but consistent improvement in explanatory fit and a more direct process-based interpretation of attention. Overall, these

findings suggest that eye-tracking is useful not only for evaluating whether an intervention works, but also for showing how it works and which parts of it matter behaviourally.

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