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Attitudes, Time Pressure, and Behavior Change Techniques Affect Route Journey Planning Decisions: Evidence from an RCT

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Abstract: Transport emissions are a major contributor to global CO_2 emissions, requiring interventions to promote sustainable travel behaviors. This study examines how behavior change techniques (BCTs), attitudinal and behavioral segmentation, and time pressure influence green route selection in a simulated journey-planning app. Using a randomized 2 × 3 × 3 factorial design, 600 UK participants completed travel booking tasks under three time-pressure scenarios (low, moderate, high) using either a control app or a BCT-enhanced intervention app. Participants were segmented based on environmental attitudes, public transport preferences, and travel needs. Multilevel logistic regression showed significant main effects for condition, segment, and time pressure. Participants using the intervention app were more likely to select green routes (5.39, $p < 0.001$). Segments with a more positive attitude to public transport demonstrated higher baseline green route selection compared to those with low public transport attitudes (odds ratio [*OR*] = 0.31, p = 0.020). Moderate time pressure facilitated the highest likelihood of green route selection, while low (*OR* = 0.16, $p < 0.001$) and high (*OR* = 0.48, $p < 0.001$) time pressures reduced green bookings. Interaction effects were non-significant, potentially reflecting the sample size. The findings highlight the potential of BCT-enhanced apps to promote sustainable travel, particularly when tailored to user segments and designed to address time pressure. Future research should explore real-world applications and intervention durability.

Keywords: sustainable mobility; environmental behavior; behavior change; behavior change techniques; attitudinal segmentation; time pressure; mobility as a service; MaaS; randomized controlled trial; factorial study

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1. Introduction

Over the past decade, greenhouse gas concentrations have surged to unprecedented levels, prompting the Intergovernmental Panel on Climate Change (IPCC) to call for urgent global action to limit warming to 1.5 °C [1]. Transport emissions are a sizable part of the problem: in 2019, transport contributed approximately 23% of global CO_2 emissions related to energy use [2], positioning it as a critical focus for emission reduction efforts. There is a growing awareness among behavioral scientists and climate experts that achieving necessary reductions will depend heavily on meaningful shifts in human behavior [3]. Recognizing this challenge, the IPCC, for the first time, devoted an entire chapter to behavior change in its most recent report on "demand-side mitigation" [4].

Transforming travel behavior and reducing emissions will require substantial shifts in mobility patterns. Travel choices and behavior are influenced by a wide range of interlinked factors. Analysis of aggregated findings from 75 studies from several relevant disciplines suggest that infrastructure factors account for many observed differences in mode choice, while personal norms (feelings of moral obligation, [5]) that favor low-carbon modes and a sense of personal control over transport decisions are influential in encouraging mode shifts [6]. Changes to infrastructure and the built environment are generally slow and costly to achieve, and the impacts bear out in the longer term when supported by shifting social norms [6]. It is, therefore, valuable to explore options that can be used alongside infrastructure changes and adjustments to influence transport choices. Efforts to change travel behavior can be placed along a spectrum, ranging from restrictive to facilitative [7]. At the restrictive extreme, measures may eliminate choices altogether (e.g., legal bans or physical barriers) or policies may reduce access or availability without full prohibition. Fiscal measures like taxes, subsidies, and other financial measures create financial incentives or disincentives to guide behavior but can produce unequal impacts, particularly affecting those on lower incomes. Meanwhile, at the facilitative end of the spectrum, choice architecture involves structuring information or contexts to nudge individuals toward desired actions without removing their freedom of choice. Approaches closer to the facilitative end of the spectrum preserve choice and, therefore, are more likely to play a role in maintaining perceived behavioral control—a key factor in encouraging shifts in mode choice. Digital channels, such as journey-planning apps, are typically toward this end of the spectrum, enabling subtle shifts in preferences while emphasizing user empowerment and informed choice. This is reflected in the growth of Mobility as a Service (MaaS) apps, which reorient transportation planning around user needs rather than industry-centric models [8]. Definitions of MaaS are evolving, but MaaS apps generally offer users the ability to plan, book, and pay for journeys or routes that integrate two or more modes of transport, which may be offered by different providers [9].

As such, MaaS is proposed as a viable alternative to single-occupancy vehicle use, promoting sustainable behavioral shifts [10]. Smartphone access is not universal, and not all smartphone owners will use travel planning apps. Those who do may reserve their use for unfamiliar or complex trips rather than routine, habitual travel. Nevertheless, with the growing adoption of digital platforms, such apps show promise for influencing travel choices, especially as they become ever-more integrated into everyday use. Journey-planning apps also offer a holistic approach, potentially including several different transport modes and an ongoing channel of communication with users. Journey-planning MaaS apps therefore provide a valuable method to reach and influence travelers. This raises the following question: How can they be most usefully designed and deployed to increase the likelihood of successfully influencing journey choices?

Despite the growing consensus about the potential of MaaS apps as tools for influencing sustainable travel choices and behaviors, there is limited research on how such apps incorporate evidence-based behavior change techniques or how they could be optimized to do so. Most existing studies on persuasive mobility apps focus on behavior change tools explicitly designed to appeal to users already motivated to make eco-conscious choices [11–18]. These apps cater to a self-selecting audience seeking behavioral change, but they are less likely to engage the broader population. By contrast, MaaS apps, primarily intended for journey planning, have the unique ability to reach a wider, more diverse audience—including passive users who may not actively seek sustainable travel options. This highlights the importance of investigating how behavioral insights can be embedded in MaaS apps to influence decision-making among a broader user base.

Much of the prior research on travel behavior change has emphasized extrinsic motivators, such as gamified rewards and point systems [11]. While effective in some contexts, findings from health and well-being apps suggest that curated combinations of diverse behavior change techniques, applied according to theoretical frameworks, achieve greater impact than reliance on individual strategies [19–24]. This underscores the need to explore the application of a broader set of behavior change techniques in MaaS apps, moving beyond extrinsic motivators to include approaches that foster intrinsic motivation and sustained behavior change.

Additionally, while segmentation has been widely used to understand mobility behaviors [25–29], and there is growing research exploring the impact of segmentation and personality in persuasive mobility apps [15,30,31], its application within MaaS apps remains largely unexplored. This represents a missed opportunity, as segmentation could provide valuable insights into how different user groups respond to various behavioral interventions. Moreover, time pressure—a critical factor influencing travel decisions—is often overlooked in studies of digital interventions, leaving a gap in understanding its interaction with segmentation and app design. Addressing these gaps is crucial to maximizing the effectiveness of MaaS apps in driving sustainable travel behaviors.

This study seeks to fill these research gaps by examining the combined effects of behavior change techniques, psychographic segmentation, and time pressure on sustainable route selection within a simulated MaaS environment. Section 2 provides the theoretical framework, detailing the behavioral insights and segmentation framework underpinning this study, and justifies the hypotheses. Section 3 details the experimental design, participant recruitment, and analytical methods. Section 4 presents the results of descriptive and inferential analyses, while Section 5 discusses the findings in the context of the existing literature and practical applications, and Section 6 outlines future research opportunities. Finally, Section 7 concludes by summarizing key contributions and implications for sustainable travel interventions.

2. Theoretical Background and Hypothesis Justification

2.1. Embedding Behavioral Insights

Insights from behavioral science have been successfully deployed to influence a range of pro-environmental and health-supportive behaviors [32–36]. Evidence suggests that apps that draw from behavior change theory and apply a range of behavior change strategies and techniques are more successful than those that do not in changing users' health-related behaviors [21,37–39]. A recent evidence review of studies into behavioral theory-informed apps found that the use of theory is likely to result in significant effects [40]. Approaches informed by behavioral science have been successfully employed in gamified or habit-changing apps to influence mobility behaviors [12,14,15], but these apps are used by a self-selecting group of users who are setting out to change their behavior. There is currently a lack of evidence on the application of such theories and techniques in journey-planning or MaaS apps used by a wider cross-section of travelers for the primary purpose of planning a trip. This suggests that there is the potential to apply techniques used successfully in other domains within journey-planning apps. There is also a paucity of studies comparing apps that use behaviorally informed techniques with those that do not. This study, therefore, sought to compare journey choices made by users of a theory-informed journey-planning app (intervention app) with those of users of an active control app that provided journey options without applying behavioral techniques.

The application of behavioral theory and techniques can take many forms, reflecting the wide range of theories and frameworks available. Two of the most common approaches used for designing and evaluating behavioral apps are the Persuasive Systems Design framework [41] and the Behavior Change Technique (BCT) taxonomy [42], each of which provides clusters of techniques drawn from psychological theory and evidence. Several studies evaluate the presence of these approaches in apps in a range of fields [24,43,44]. A review of 31 studies of behaviorally informed apps found that most (45%) used BCTs [40] drawn from the BCT taxonomy [42]. The taxonomy provides a detailed definition of 93 theory-informed techniques, which are conceptualized as the smallest units of "active ingredients" that have the potential to change behavior. The taxonomy provides the most comprehensive set of techniques, and the uniquely clear and unambiguous definitions aid with fidelity and linking back to mechanisms of action and theory for future analysis. Therefore, this study deployed a control condition app without BCTs and a selected set of BCTs within the intervention app designed to encourage and facilitate the selection of green routes and discourage the selection of grey routes.

Hypothesis 1 (H1). *Participants using the intervention app with BCTs will be more likely to select green routes compared to those using the control app without BCTs.*

2.2. Targeted Approaches

In the past, some behavior change interventions have sought to use a single approach or set of approaches to influence individuals across a population. Recent critiques and concerns about small effect sizes, particularly for nudge-type interventions, point out limitations in one-size-fits-all approaches and the importance of having sufficient regard for context, including population [45–49]. Increasingly, research indicates that broad application may dilute impact and that targeted interventions—accounting for the needs, characteristics, and circumstances of specific groups—could enhance effectiveness. This has led to calls for a more targeted approach to reflect individual heterogeneity in behavioral responses [50]. Work to target nudge interventions includes targeting according to personality [51] and other traits [52,53]. In behavioral science more broadly, there is growing interest in the use of segmentation to facilitate more tailored interventions. In transport-related behaviors, this has included calls for the use of segmentation to understand differing behavioral drivers and target messaging and interventions [54].

However, there is a lack of evidence available on the impact of segmentation within journey-planning apps. Therefore, this study aims to explore whether participants drawn from different segments respond differently in their mode choices in control and intervention conditions. Reflecting the finding that personal norms are influential in supporting mode choice shifts [6], this study draws from a proprietary, attitude-based segmentation developed in previous work. The segmentation is based on established methods originally developed and applied to the UK's digital TV switchover, where insights informed communication strategies and the design of user-friendly TV equipment and inclusive solutions for millions of viewers [55]. It involved conducting principal component analysis on a quantitative dataset to identify key underlying themes, followed by hierarchical and k-means cluster analysis to develop clusters around these factors. While a full description of the segmentation used here is beyond the scope of this paper, it categorizes participants based on their attitudes to public transport, the environment, technology, and their travel needs. For this study, three segments with the highest mean scores for attitude to technology were chosen for inclusion to reflect the likely usage of real-world apps, while differing on other dimensions, as described in Table 1. For ease of reference, the three segments selected were named Maximizers (high environmental attitude, high attitude to public transport, and low travel needs), Advocates (low environmental attitude, high attitude to public transport, and high travel needs), and Solo Explorers (high environmental attitude, low attitude to public transport, and high travel needs).

Table 1. Key characteristics of segments.

Segment Name	Environmental Attitude	Attitude to Public Transport	Need to Travel
Maximizers	High	High	Low
Advocates	Low	High	High
Solo Explorers	High	Low	High

Hypothesis 2 (H2). *Participants in the Maximizer group will have the highest likelihood of selecting green routes, while those in the Solo Explorer group will have the lowest likelihood.*

Hypothesis 3 (H3). *Exposure to BCTs (intervention condition) will have a greater positive effect on the selection of green routes for segments with high environmental attitudes (Maximizers and Solo Explorers) compared with those with low environmental attitudes (Advocates). However, since Maximizers are hypothesized to have a higher baseline likelihood of choosing green routes, the magnitude of change due to the intervention may be more pronounced for Solo Explorers.*

2.3. Time Pressure

In addition to individual differences, travel choices are shaped and influenced by a range of other contextual factors, including the built environment; infrastructure; the availability, cost, and reliability of services; weather conditions; and situational elements such as time pressure. While factors like built environment, weather conditions, or service quality vary between locations, time pressure is a universal condition that can affect travel choices. Time pressure also stands out in that it has been shown to influence cognitive processes [56] and emotional responses [57,58], altering stress levels and executive functioning [59]. Studies through a number of theoretical lenses [60] find that objective and perceived [59] time pressures appear to affect both decision processes and outcomes [61]. Impacts on cognitive performance can include reduced attention, reduced acquisition of information, selective information processing, accelerated decision processing, difficulty generating alternatives, reduced capacity to evaluate options, increased reliance on past behaviors, and reduced ability to adapt to new situations [56,60,62,63]. Heightened time pressure has been found to influence consumer behaviors, including focusing on higher-quality brands and increased likelihood of making impulsive, hedonistic purchases [64,65], with effects noted in online environments as well as traditional shops [66]. Impacts on altruistic [67], pro-social [68], and pro-environmental [69,70] behaviors have also been noted. Since journey choices are a purchasing decision and, for some travelers, are likely to incorporate social and environmental considerations, it seems likely that time pressure may influence travel choices. In fact, in transport planning, Utility Expectation Models often assume that travel duration is among the primary determinants of travel decisions, and studies suggest that under high time pressure, travelers may rate trip time as more important than when under lower levels of time pressure [71]. In addition, there is some evidence to suggest that under time pressure, individuals may be less sensitive to rewards and may make less value-directed decisions [62]. As such, this study sought to explore whether time pressure altered users' baseline (control) journey choices and whether it appeared to influence their receptiveness to behavioral change techniques.

Past studies also suggest that reactions to time pressure may not be universal. Individual differences in internal time urgency, abstract thinking and problem-solving abilities [72], personality traits [73], underlying pro-social biases [67], and underlying attitudes to risk [60] appear to moderate the effects of time pressure. This study therefore sought to explore whether the impact of time pressure differed between user segments.

Despite the wealth of literature exploring high time pressure, the impact of low time pressure is less studied. However, there are indications that the relationship between time pressure and decision processes and outcomes does not appear to be linear [63]. Studies suggest that there may be an optimum level of time pressure: under moderate time pressure individuals appear to process information more quickly without switching to less beneficial processing patterns [56]. A non-linear relationship is also noted between time pressure and behaviors in areas including innovation performance [74] and work engagement [75]. There is also some indication that under low time pressure, consumers are more likely to make utilitarian impulse purchases [65]. This study therefore explored the impact of low, moderate, and high time pressure on journey choices.

Research suggests that decision-making under time pressure is influenced by the interaction of cognitive load and information-processing efficiency. Moderate time pressure may represent a cognitive "sweet spot", where individuals process information more efficiently without resorting to heuristics or risk-averse behaviors, which are more common under extreme time constraints. By contrast, low time pressure can result in over-analysis or procrastination, delaying decisions and reducing engagement with goal-directed behavior. High time pressure, on the other hand, often overwhelms cognitive resources, forcing users to rely on habitual or default choices, such as car travel. These findings align with evidence from consumer behavior studies, which demonstrate that moderate pressure enhances goal-directed actions while extreme time constraints hinder effective decision-making.

From a practical perspective, journey-planning apps could leverage this insight by simplifying decisions under high-pressure scenarios through, for example, pre-loaded preferences or prominently displayed green route defaults. By reducing cognitive demands in these situations, apps may maintain higher rates of green route selection even when users face significant time constraints.

Hypothesis 4 (H4). *Participants will be most likely to select green route choices under moderate time pressure and less likely to book green routes under high time pressure and low time pressure.*

Individual responses to time pressure are shaped by differences in intrinsic motivation, perceived behavioral control, and cognitive processing. Value–Belief–Norm Theory suggests that strong pro-environmental norms and intrinsic motivations can buffer against situational pressures [76–78]. Therefore, segments with high environmental attitudes, such as Maximizers and Solo Explorers, are likely to exhibit greater resilience under varying time pressure due to their alignment with pro-environmental values and intrinsic motivation. These individuals may view sustainable travel choices as consistent with their core beliefs, enabling them to maintain green route selection even under stressful conditions. By contrast, Advocates—who are characterized by lower environmental attitudes despite strong preferences for public transport—may be more susceptible to the negative effects of time pressure. Without strong intrinsic motivation to guide their decisions, they may rely more on situational cues or habitual behaviors. Additionally, lower perceived behavioral control in stressful scenarios, such as high time pressure, may exacerbate this group's difficulty in making green choices. This highlights the potential of designing interventions that address segment-specific barriers, such as providing reassurance or simplifying choices for segments with weaker intrinsic motivations.

Hypothesis 5 (H5). *Participants in segments with high environmental attitudes (Maximizers, Solo Explorers) will show a smaller decline in green route selection under both high and low time pressure compared to Advocates, who have lower environmental attitudes.*

Moderate time pressure appears to provide an optimal balance of urgency and cognitive capacity, allowing individuals to remain engaged and process information effectively without being overwhelmed by stress or disengaged due to a lack of urgency.

Under these conditions, BCTs are likely to exert their strongest influence. For instance, techniques such as goal setting may feel more relevant and achievable, while feedback and rewards can reinforce decision-making in favor of green route selection. This balance enhances the likelihood that users will internalize and act on the behavioral cues embedded in the app. Compared to high time pressure, which can induce stress responses and reduce cognitive flexibility, and low time pressure, where a lack of urgency may lead to procrastination or reduced focus on goal-directed behavior, moderate time pressure enables individuals to process information more effectively. Environmentally focused messaging and goals applied through BCTs are more likely to resonate with those with high environmental attitudes, such as Maximizers and Solo Explorers. This may make them particularly receptive to behavioral cues when cognitive resources are not overtaxed. Moderate time pressure allows these individuals to fully engage with features like personalized feedback, goal setting, and progress tracking, which align with their existing values and motivations. This alignment between personal attitudes and app interventions can amplify the effect of BCTs, making sustainable choices both appealing and actionable.

Hypothesis 6 (H6). *Exposure to BCTs will increase the likelihood of selecting green routes under moderate time pressure across all segments. This effect will be particularly pronounced for those with high environmental attitudes (Maximizers, Solo Explorers).*

3. Materials and Methods

3.1. Study Design

This study investigated the effects of exposure to BCTs, attitudinal segment membership, and time pressure on the likelihood of choosing a green route (more environmentally friendly; focused on public, shared, and active transport with no car use) or a grey route (less environmentally friendly; including car travel) in a journey-planning app. It employed a mixed-effects, blinded, randomized, controlled, 2 × 3 × 3 factorial design (Table 2). The independent variables included two between-subjects factors: (1) condition (control app without BCTs vs. intervention app with BCTs) and (2) segment (Maximizers, Advocates, Solo Explorers), as well as one within-subjects factor: (3) time pressure (low, moderate, high). The dependent variable was route choice (green vs. grey).

Table 2. Summary of factorial design.

Condition	**Low Time Pressure (n = 600)**	**Moderate Time Pressure (n = 600)**	**High Time Pressure (n = 600)**
Control: No BCTs (n = 300)	Maximizers; Advocates; Solo Explorers	Maximizers; Advocates; Solo Explorers	Maximizers; Advocates; Solo Explorers
Intervention: With BCTs (n = 300)	Maximizers; Advocates; Solo Explorers	Maximizers; Advocates; Solo Explorers	Maximizers; Advocates; Solo Explorers

To manipulate the independent variables and control for other factors, two simulated travel planning apps were created: a control version without BCTs and an intervention version with BCTs. The simulated apps presented an interactive image of a smartphone screen on a computer. Live participants navigated the app using their mouse, mimicking the interaction of a finger on a touchscreen. Simulated environments allow for the collection of digital trace data to track behavior without needing to rely on self-report measures, reducing the risk of social desirability and other biases [79] and producing experiments with greater ecological validity. As such, researchers have begun to use simulations to study decision-making and behavior in controlled environments, allowing for the manipulation of specific variables while minimizing confounding influences. Simulated online supermarket stores have been successfully used to study purchasing decisions [80,81] and simulated social media apps have been developed to facilitate the study of online behaviors [82,83]. In this study, the use of simulated journey-planning apps ensured a consistent user experience across participants and enhanced internal validity by isolating the effects of the experimental conditions. The experiment design facilitated the analysis of the main effects and interactions among condition, segment, and time pressure, allowing for a detailed examination of the factors influencing travel choices. This study received ethical approval from Goldsmiths, University of London, ensuring compliance with guidelines for informed consent, data protection, and participant welfare throughout the research process.

3.2. Participants

The sample size was calculated based on a confidence interval of 95% and power of 80% for the $3 \times 3 \times 2$ factorial design. Given the inclusion of three repeated measures (low, moderate, and high time pressure), an intra-class correlation (ICC) of 0.25 was assumed to account for the expected consistency of participants' responses across these measures. This adjustment reflected moderate within-participant correlation across repeated measures and ensured that the analysis accounted for dependencies in the data. Based on these parameters, a minimum of approximately 607 participants were required.

A total of 4265 participants were recruited for pre-screening in several waves from a nationally representative UK sample via the online recruitment platform Prolific [84]. They were compensated for their time according to the platform's standard guidelines governing fair rates, and initial consent was obtained before participants completed a screening survey presented in the online questionnaire package SurveyMonkey. The results were used to filter participants, with those showing above-average attitudes toward technology screened in and those below-average screened out. Participants who answered an attention check question incorrectly were also screened out. The remaining participants were further categorized by environmental attitudes, attitudes toward public transport, and travel needs to create three segments (Maximizers, Advocates, and Solo Explorers, see Table 1). Those within the target segments were invited to follow a link to the online experiment builder platform Gorilla to participate, resulting in a final sample of 600 participants (200 per segment). Further recruitment was limited by the maximum representative sample size provided by the recruitment platform and the substantial number of pre-screened participants needed to identify eligible study participants. Informed consent was obtained again before the main study began. Remuneration was provided upon completion of the screening survey and, for those screened in, also at the end of the experimental study, ensuring ethical treatment and fair payment for participation.

3.3. Procedure

Upon entering the Gorilla platform and completing the consent form, participants were required to use a computer or laptop with a keyboard, and the platform was configured to accept only these devices. They began by watching a scene-setting video to familiarize themselves with the fictional town where the tasks took place. The video also controlled for variables such as weather and public transport reliability. Participants then answered a short quiz to confirm their understanding, receiving feedback congratulating or correcting them as needed.

Using Gorilla's randomizer functionality, participants were assigned to either the control or intervention condition. They completed three travel booking tasks that asked them to book a trip between two locations based on the scenario provided. The scenarios were designed to simulate varying levels of time pressure, introduced through instructions presented at the start of each task. In the low-pressure scenario, participants were given a relaxed context with no specific deadline (a picnic in the park with no specific start time). The moderate-pressure scenario introduced a flexible but limited timeframe to create a moderate sense of urgency, as might often be experienced in day-to-day life. In the high-pressure scenario, participants were told that they were running late for a scheduled event, emphasizing urgency (a friend was already waiting for them at the theatre and the doors would close soon). Participants had no time limit for completing the tasks themselves. Within each scenario, participants were presented with six route options. Unbeknown to participants, half had been classified as green and half as grey. Instructions were standardized across conditions. Participants were directed to behave as they normally would, given the parameters of the fictional town, and no explicit mention was made of sustainable travel or selecting green routes at any point during the study or recruitment. Distraction tasks were included between the main journey-booking tasks to reduce carryover effects.

After completing the final task, participants reflected on their choices, answered demographic questions, and were debriefed.

3.4. Materials

This study utilized a variety of materials to recruit participants, provide a consistent experimental environment, and manipulate the independent variables. These included a scene-setting video, simulated journey-planning apps, distraction tasks, and surveys integrated into the Gorilla platform. The following subsections describe these in detail.

3.4.1. Scene-Setting Video

A scene-setting video was created using the online animation creation package Animoto and embedded within the Gorilla platform. The video introduced participants to the fictional town of Pineville, providing a consistent context for the travel booking tasks. Captions within the video were used to control for potential confounding factors, including the following:

- Built and social environment: “Pineville is safe, well-lit, and not hilly.”
- Transport options: “It has good signage and great cycle paths. Public transport is reliable.”
- Weather conditions: “The weather today is fine: 22 °C, a light breeze, and no rain forecast.”
- Initial time pressure level: “You have a few errands, but your day is relaxed.”
- Cost of transport options: “All you need to do is book your travel. There’s an app for that: Tix2Ride. Your travel card includes ALL travel modes.”
- Participant role: “You are in Pineville, but be yourself. Act as you would in your day-to-day life.”

3.4.2. Simulated Journey-Planning Apps

A simulated journey-planning app was developed using Gorilla's task-builder functionality. Screen and button images were layered and reaction hotspots were applied to allow participants to interact with the interface and enable the recording of their action responses. This setup replicated a realistic app experience while ensuring precise data capture.

A control app was designed to mimic the functionality of a real smartphone app, allowing participants to navigate via clickable buttons and menus to search for and select a chosen route (Figure 1). The simulation started with a phone home screen featuring the Tix2Ride app icon. Within the app, the home screen featured the journey booking page with input boxes for start and destination, along with a clickable profile icon. The profile page provided a summary of trips and top-up timing; the search results page listed six available routes, with options to view details for each. Route options were listed with green and grey routes alternating, and trip duration was emphasized above arrival time (Figure 1c). The journey option pages provided detailed information about the selected route, with options to book or return to the results page. Finally, the booking page confirmed the selection and concluded the task.

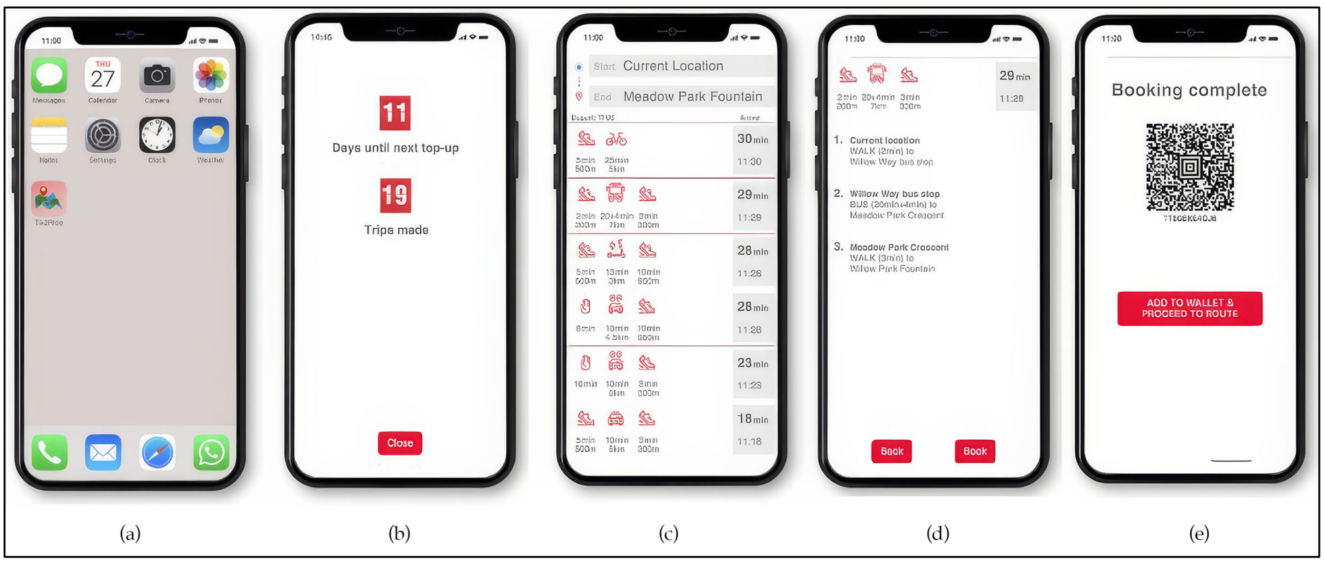

Figure 1. Screen images from control condition app (no BCTs): (**a**) phone home screen with app button showing app logo; (**b**) pop-up showing basic account information (limited feedback on behaviors/outcomes); (**c**) search results page; (**d**) route detail page; (**e**) booking confirmation.

Additional functions incorporating a variety of BCTs (Table 3) were then added to the baseline to create the intervention app (Figure 2). The same route options were provided, but information was presented differently and additional features and functionality incorporating BCTs were added. The intervention app utilized a home screen widget (a "button" that was larger than in a standard app, which included a points total to imply previous engagement with the app), phone home screen notification providing reassuring and congratulatory messaging, a goal-setting pop-up that allowed users to select their key motivation (getting fit, saving carbon, avoiding busy services, or none of the above), a profile page monitoring and providing feedback of past behavior performance data, and rewards in the form of badges. The results page (Figure 2e) was ordered with green route options at the top of the page, followed by grey routes. Routes featured icons indicating alignment with goals (fitness, carbon-saving, staying calm) or pollution levels and the points available to be claimed or deducted upon choosing a route. Arrival time was emphasized over trip duration. The journey option pages (Figure 2f) contained additional information about routes including wait times and the availability of micro-modes such as e-bikes or docking spaces. In the moderate time pressure scenario, a pop-up was displayed upon opening the app providing a badge award relevant to the goal that the participant selected. In the high time pressure scenario, participants saw a message acknowledging their time pressure and were offered the option to see all six routes or only the top two. Upon selecting a grey route, participants were informed that others sharing their goals usually booked a different route and were given the option to proceed or review their choice. When a green route was selected, the participant received a congratulatory message on the booking confirmation screen.

Table 3. BCTs included in the intervention app's features and content.

BCT Code and Label	Description	App Feature(s)
1.3 Goal-setting (outcome)	Set or agree on a goal defined in terms of a positive outcome of wanted behavior	"Set a goal" pop-up
1.6 Discrepancy between current behavior and goal	Draw attention to discrepancies between a person's current behavior and the person's previously set outcome or behavioral goals	Dialogue box referencing choices of others with a shared goal
2.1 Monitoring of behavior by others without evidence of feedback	Observe or record behavior with the person's knowledge as part of a behavior change strategy	App data tracking
2.2 Feedback on behavior	Monitor and provide informative or evaluative feedback on performance of the behavior (e.g., form, frequency, duration, intensity)	Profile page: behavioral data (e.g., trips made) available for user to reference
2.3 Self-monitoring of behavior	Establish a method for the person to monitor and record their behavior(s) as part of a behavior change strategy	Profile page: behavioral data (e.g., trips made) available for user to reference
2.4 Self-monitoring of outcome(s) of behavior	Establish a method for the person to monitor and record the outcome(s) of their behavior as part of a behavior change strategy	Profile page: outcome data (e.g., carbon saved) available for user to reference
2.7 Feedback on outcome(s) of behavior	Monitor and provide feedback on the outcome of performance of the behavior	Profile page: outcome data (e.g., carbon saved) available for user to reference
5.1 Information about health consequences	Provide information about health consequences of performing the behavior	Icons indicating fitness benefits of a given route
5.3 Information about social and environmental consequences	Provide information about social and environmental consequences of performing the behavior	Icons indicating environmental benefits of a given route
6.2 Social comparison	Draw attention to others' performance to allow comparison with the person's own performance	Dialogue box referencing choices of relevant others
9.2 Pros and cons	Advise the person to identify and compare reasons for wanting (pros) and not wanting (cons) to change the behavior	Search results/icons: highlighting benefits and disadvantages of route options
10.4 Social reward	Arrange verbal or non-verbal reward if and only if there has been effort and/or progress in performing the behavior (includes "Positive reinforcement")	Dialogue box: congratulatory message on progress
10.8 Incentive (outcome)	Inform that a reward will be delivered if and only if there has been effort and/or progress in achieving the behavioral outcome (includes "Positive reinforcement")	On-screen messaging: reward points offered upon selection of specific choices

10.9 Self-reward	Prompt self-praise or self-reward if and only if there has been effort and/or progress in performing the behavior	Home screen notification: prompting self-congratulation for progress toward goals
10.11 Future punishment	Inform that future punishment or removal of reward will be a consequence of performance of an unwanted behavior (may include fear arousal) (includes "Threat")	On-screen messaging: information about removal of reward points upon selection of specific choices
11.3 Conservation of mental resources	Advise on ways of minimizing demands on mental resources to facilitate behavior change	Dialogue box: offering reduction in number of search results
13.2 Framing/reframing	Suggest the deliberate adoption of a perspective or new perspective on behavior (e.g., its purpose) in order to change cognitions or emotions about performing the behavior (includes "Cognitive structuring")	On-screen messaging/icons: introduction of alternative framing (i.e., fitness or environmental gains)
14.3 Removal of reward	Arrange for discontinuation of contingent reward following performance of the unwanted behavior (includes "Extinction")	Removal of reward points upon selection of specific choices
15.3 Focusing on past success	Advise to think about or list previous successes in performing the behavior (or parts of it)	Dialogue box: message encouraging users to remember past success

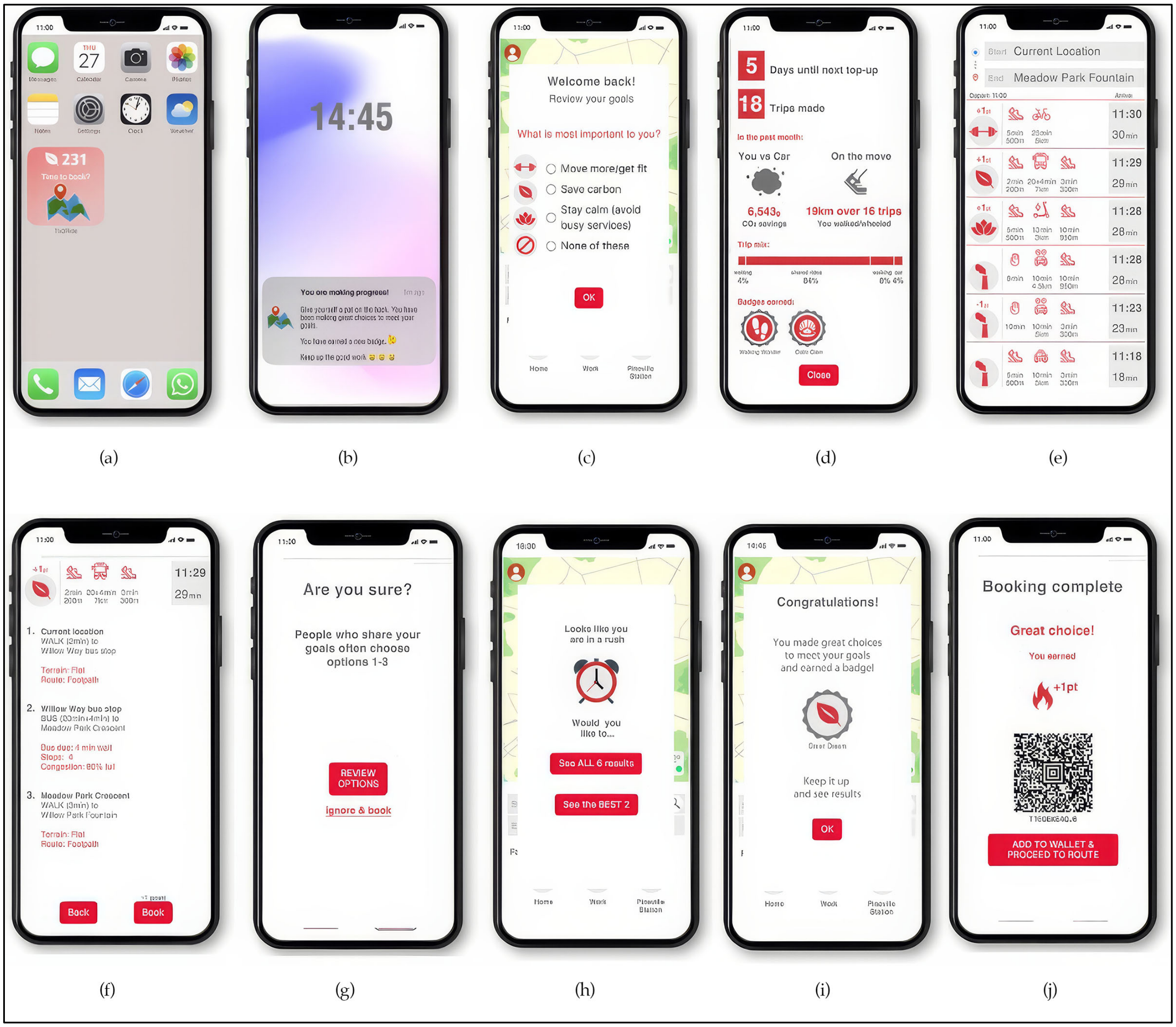

Figure 2. Screen images from intervention condition app (including BCTs): (**a**) phone home screen with "widget" button emphasizing points from past engagement; (**b**) notification showing congratulatory messaging and prompting self-praise; (**c**) goal-setting/review pop-up; (**d**) pop-up/profile page providing feedback on behavior and outcomes; (**e**) results page showing goal- and outcome-relevant icons; (**f**) route detail page providing information to remove uncertainty (e.g., bike dock availability, walking route incline, etc.); (**g**) prompt to review choice in line with goals and behaviors of relevant others; (**h**) option to reduce route options to conserve mental resources; (**i**) congratulatory messaging and reward (badge); (**j**) booking confirmation reinforcing choice and awarding a point.

The above feature and content additions to the intervention app incorporated several BCTs to encourage green route selection. Table 3 summarizes the BCTs used, the app features in which they were implemented, and the specific scenarios where they were applied. This table highlights how the intervention operationalized BCTs to influence participant decision-making. The BCTs incorporated into the intervention app were selected based on established principles of behavior change theory, with a particular emphasis on goal-setting, feedback, verbal encouragement, praise, and rewards. These principles align with theories including Self-Regulation Theory [85] and Control Theory [86], which highlight the importance of clear goal-setting, actionable feedback, and reinforcement to motivate and sustain behavior change. The app was designed to balance extrinsic motivation, such as rewards and praise, with intrinsic motivation by fostering autonomy and connecting personal goals with broader social and environmental benefits, such as reducing carbon emissions. These BCTs were operationalized to guide user choices while preserving autonomy, a critical factor for voluntary behavior change, and manage cognitive loads by simplifying complex decisions through framing and structured feedback. By combining these elements, the app aimed to guide users through reflective and iterative cycles of goal selection, progress monitoring, and positive reinforcement, ultimately encouraging sustainable travel choices and fostering long-term behavior change.

3.4.3. Distraction Tasks

Distraction tasks were selected from Gorilla's pre-designed psychological tasks library to serve as cognitive resets between booking tasks. These tasks were brief, standardized, and ensured that participants were not unduly influenced by previous scenarios. After the first (low time pressure) task, participants were presented with the Simon Task [87], a spatial inference task that asked them to press a key to indicate whether a stimulus was presented on the right or left of the screen. After the second (moderate time pressure) task, participants completed a categorization task [88] requiring them to select whether a stimulus word, such as "dolphin", was a "mammal" or "fish". The Simon Task and categorization task are available to be sampled freely on the Gorilla website.

3.4.4. Survey Elements

The questionnaire builder module on the Gorilla platform was used to create and present several surveys and tasks during the experiment flow:

- Quiz Questions: Three quick questions to check attention and understanding following the scene-setting video. Skip logic functionality was used to provide immediate congratulatory or corrective feedback.
- Reflection Questions: Free text questions were used to collect qualitative data on participants' decision-making processes at the end of the study.
- Demographic Survey: A radio button and drop-down questions were used to capture information on participants' characteristics at the end of the study.

3.5. Data Analysis

First, descriptive analyses were performed to summarize the proportion of participants selecting green routes across segments, time pressure levels, and conditions (control vs. intervention). Percentages and trends were visualized using summary tables and graphs to provide an initial understanding of the data distribution and patterns.

Next, to analyze the likelihood of participants selecting green transport modes, a multilevel logistic regression approach was employed. This method was chosen over standard logistic regression because of the nested structure of the data, with repeated measures (travel booking tasks) nested within participants. In addition, because all independent variables (condition, segment, and time pressure) were categorical, other methods such as linear mixed-effects models were not appropriate. Multilevel logistic regression allows for the analysis of categorical predictors while accounting for the hierarchical nature of the data, ensuring robust and accurate parameter estimation [89].

The analysis followed the three-step procedure outlined by Sommet and Morselli [89]. First, an empty model (intercept-only) was fitted to calculate the ICC, which revealed that 26.4% of the variance in mode choice was attributable to between-participant differences. This result justified the use of a multilevel approach. In the second step, time pressure (low, moderate, high) was added as a fixed effect to capture the influence of time constraints on transport mode choice. In the final model, condition (control vs. intervention) and segment (Maximizers, Advocates, Solo Explorers) were included as between-subject factors, along with all two-way and three-way interactions between time pressure, condition, and segment. This comprehensive model tested the main hypotheses regarding the effects of exposure to behavioral techniques, segmentation membership, and time pressure and their potential interactions.

The dependent variable was mode choice, dichotomized as green (more environmentally friendly, without car travel) or grey (less environmentally friendly, including car travel). The independent variables included time pressure, a within-subject factor with three levels (low, moderate, high), and condition and segment, which were between-subject factors. Medium time pressure, the control condition, and Advocates were set as the reference categories for interpretation. Random intercepts were included to account for individual differences in the baseline likelihood of choosing green.

Model fit was assessed using Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC), with lower values indicating improved model fit. Statistical significance was evaluated at a threshold of $p < 0.05$. All analyses were conducted using SPSS Version 27 with the Generalized Linear Mixed Models (GLMM) procedure.

4. Results

This section presents the findings of the descriptive and multilevel logistic regression analyses, examining the effects of condition, segment, and time pressure on the likelihood of selecting green transport modes.

4.1. Descriptive Statistics

Descriptive analyses revealed that participants in the intervention condition consistently selected green routes more frequently than those in the control condition across all segments and time pressure levels. Maximizers were the most likely to choose green routes under all time pressures and conditions, except in the control condition at moderate time pressure, where marginally more Advocates selected a green route. Solo Explorers were the least likely to choose green routes under all time pressures and conditions, except in the intervention condition at moderate time pressure, where they were marginally more likely than Advocates to select a green route. Across all segments and conditions, green bookings were highest at moderate time pressure, except for Maximizers in the control condition, who showed greater levels of green bookings at low time pressure. These patterns are summarized in Table 4 and visualized in Figure 3.

Table 4. Proportion of participants selecting a green route by segment, condition, and time pressure level.

Segment	Condition	Low Time Pressure	Moderate Time Pressure	High Time Pressure	All Time Pressures
Maximizers	Intervention	94.74%	97.89%	92.63%	95.09%
	Control	79.05%	76.19%	66.67%	73.97%
	All	86.50%	86.50%	79.00%	84.00%
Advocates	Intervention	90.10%	95.05%	85.15%	90.10%
	Control	75.76%	77.78%	54.55%	69.36%
	All	83.00%	86.50%	70.00%	79.83%
Solo Explorers	Intervention	88.89%	95.96%	79.80%	88.22%
	Control	60.40%	66.34%	44.55%	57.10%
	All	74.50%	81.00%	62.00%	72.50%
All	Intervention	91.19%	96.27%	85.76%	91.07%
	Control	71.80%	73.44%	55.41%	66.89%
	All	81.33%	84.67%	70.33%	78.78%

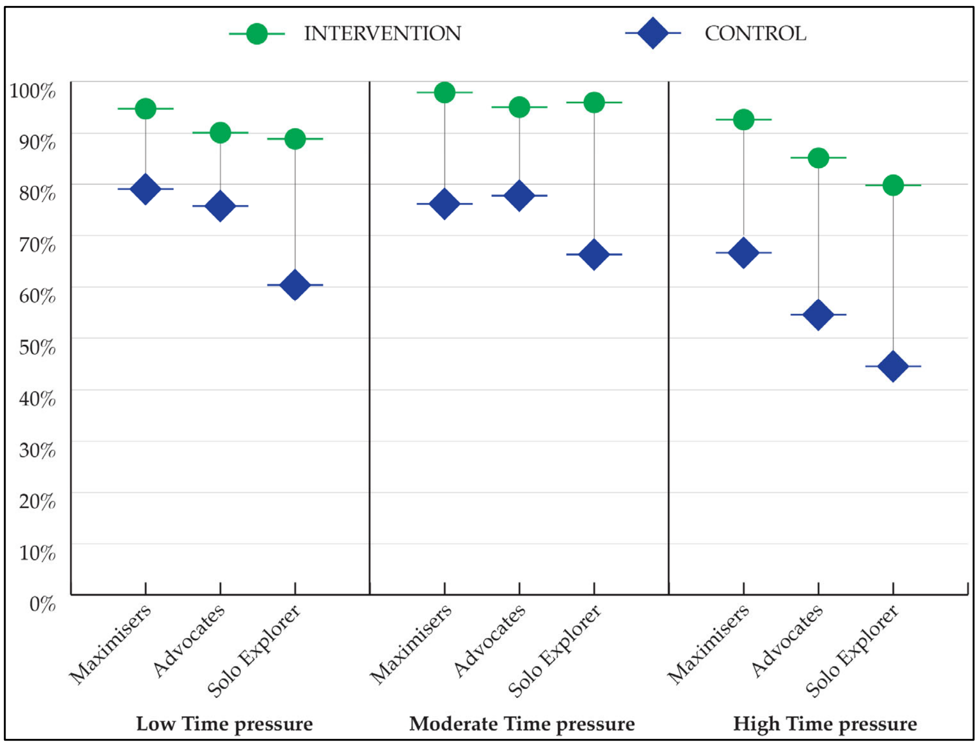

Figure 3. Proportion of participants making green route selection (%) by attitudinal segment, time pressure level, and condition.

4.2. Inferential Statistics

The multilevel logistic regression model was used to analyze the effects of condition, segment, and time pressure on the likelihood of selecting green transport routes. The final model demonstrated improved fit compared to simpler models, with an AIC of 8302.56 and a BIC of 8313.54 (compared with AIC = 8347.84 and BIC = 8353.33). The difference in the AIC between the final and intermediate models of approximately 45 points indicated a considerably better fit while accounting for model complexity, as differences greater than 10 are generally regarded as strong evidence favoring the model with the lower AIC [90]. Random intercepts accounted for 26.4% of the variance in mode choice, indicating that a significant proportion of the variability in green route selection was attributable to differences between participants.

Significant main effects were observed for condition, segment, and time pressure (Table 5). Participants in the intervention condition were significantly more likely to select green routes compared to those in the control condition (*OR* = 5.39, 95% CI = [4.32, 6.72], $p < 0.001$). Segment also had a significant effect, with Solo Explorers being less likely to select green routes than Advocates (*OR* = 0.31, 95% CI = [0.12, 0.83], $p = 0.020$). Differences between Maximizers and Advocates were not statistically significant ($p = 0.353$).

Time pressure influenced the likelihood of green route selection, with lower odds observed under low (*OR* = 0.16, 95% CI = [0.09, 0.24], $p < 0.001$) and high (*OR* = 0.48, 95% CI = [0.27, 0.85], $p < 0.001$) time pressure compared to moderate. These results suggest that moderate time pressure was optimal for encouraging green route selection across all segments and conditions.

These findings are summarized in Table 5, which presents the fixed effects of the multilevel logistic regression model.

Table 5. Fixed effects of multilevel logistic regression model predicting green route selection.

Variable	Coefficient	Std. Error	Odds Ratio	95% CI	*p*-Value
Intervention (vs. Control)	1.685	0.212	5.39	[4.32, 6.72]	<0.001
Solo Explorers (vs. Advocates)	−1.161	0.502	0.31	[0.12, 0.83]	0.02
Maximizers (vs. Advocates)	−0.382	0.405	0.68	[0.31, 1.52]	0.353
Low Time Pressure (vs. Moderate)	−1.863	0.31	0.16	[0.09, 0.24]	<0.001
High Time Pressure (vs. Moderate)	−0.741	0.315	0.48	[0.27, 0.85]	<0.001

Interaction terms for condition, segment, and time pressure were included in the multilevel logistic regression model to explore potential interdependencies. As summarized in Table 6, no interaction terms reached statistical significance (all $p > 0.05$). This lack of significance may reflect the study's sample size, which was well-powered for main effects but may have been underpowered for interaction effects. Interaction terms typically involve smaller effect sizes and additional variability, requiring larger or more targeted samples to detect reliably. While non-significant, the odds ratios for some interactions suggest possible trends worth exploring in future research. For example, the interaction between condition and segment indicated that Solo Explorers in the intervention condition may have been slightly more likely to select green routes than Advocates, though this effect was not statistically significant (*OR* = 1.23, 95% CI = [0.45, 3.38], $p = 0.69$). Similarly, the interaction between time pressure and condition suggested a potentially greater influence of the intervention under moderate time pressure (*OR* = 1.45, 95% CI = [0.61, 3.46], $p = 0.41$). These trends should be interpreted cautiously and require further investigation with larger, more targeted samples.

Table 6. Interaction effects of multilevel logistic regression model predicting green route selection.

Variable	Coefficient	Std. Error	Odds Ratio	95% CI	*p*-Value
Condition × Segment (Solo Explorers)	0.206	0.543	1.23	[0.45, 3.38]	0.69
Condition × Segment (Maximizers)	−0.145	0.472	0.86	[0.33, 2.27]	0.765
Condition × Time Pressure (Low)	−0.317	0.614	0.73	[0.23, 2.32]	0.675
Condition × Time Pressure (High)	0.123	0.548	1.13	[0.38, 3.37]	0.807
Segment × Time Pressure (Low)	0.452	0.612	1.57	[0.52, 4.69]	0.337
Segment × Time Pressure (High)	−0.295	0.612	0.75	[0.25, 2.29]	0.649
Condition × Segment × Time Pressure	−0.325	0.789	0.72	[0.18, 2.86]	0.614

In summary, the multilevel logistic regression model revealed significant main effects of condition, segment, and time pressure on green route selection, highlighting the independent contributions of these predictors. While no significant interactions were detected, trends observed in the interaction terms warrant further exploration in future studies with larger samples. These results provide a foundation for discussing the implications of behavioral interventions, psychographic segmentation, and decision-making under varying time pressures.

5. Discussion

This study aimed to investigate how exposure to BCTs, psychographic segmentation, and time pressure influenced green route selection in a simulated journey-planning app. The results supported the hypothesis that behaviorally informed app features increase the likelihood of sustainable travel choices, with participants in the intervention condition being significantly more likely to select green routes compared to the control condition. Differences between psychographic segments and the non-linear effects of time pressure on decision-making further emphasize the importance of tailoring interventions to user characteristics and contextual factors.

The strong main effect of exposure to BCTs (H1) aligns with previous research on behaviorally informed apps, which demonstrates their ability to influence pro-environmental and health-supportive behaviors. This study extends these findings to journey-planning apps, addressing a critical gap in the literature. Notably, Solo Explorers were the least likely to select green routes across conditions, suggesting that interventions must carefully consider segment-specific attitudes and needs (H2). While Advocates demonstrated higher green selection rates under the control condition, exposure to BCTs appeared to close this gap, underscoring the potential for targeted design to shift behavior (H3).

Time pressure significantly influenced green route selection, with moderate time pressure facilitating the highest rates of green bookings, supporting H4. This finding highlights the potential for interventions to be more effective under optimal cognitive and situational conditions. However, the lack of significant interactions between condition, segment, and time pressure (H5, H6) suggests that further research is needed with larger samples in order to explore whether there are potential interactions or if these factors operate independently.

Segment-specific differences (H2) revealed important nuances. Advocates and Maximizers, characterized by positive attitudes toward public transport, demonstrated higher baseline green route selection rates. In contrast, Solo Explorers—despite high environmental attitudes—consistently selected green routes less often, reflecting the potential role of perceived inconvenience, autonomy preferences, or habitual behaviors. This suggests that transport-specific attitudes may outweigh broader environmental concerns in influencing travel decisions. These findings highlight the attitude–behavior gap often observed by researchers studying sustainable consumption and pro-environmental behaviors, where contextual or practical barriers inhibit action despite positive intentions in areas such as sustainable consumption [91–94]. The absence of a significant difference between Advocates and Maximizers is likely attributable to the similarity in their segment profiles. Although Maximizers exhibited higher environmental attitudes, Advocates' strong preferences for public transport appeared to compensate for their lower environmental concern. This overlap in segment characteristics likely explains their comparable baseline likelihoods of selecting green routes. These findings underscore that attitudes toward public transport appears to be a stronger behavioral driver than environmental attitudes. They also highlight the importance of considering multiple dimensions when designing and evaluating targeted interventions.

Meanwhile, it is notable that at moderate and low time pressure, exposure to BCTs closed the gap between Solo Explorers and Advocates, suggesting that BCTs may be an effective tool to reach those otherwise less likely to make sustainable transport decisions. This gap-closing effect may reflect the ability of BCTs to simplify decision-making processes under moderate time pressure, allowing Solo Explorers to overcome perceived barriers such as inconvenience or lack of confidence in public transport options. By reducing cognitive load and enhancing perceived behavioral control, these techniques may help align intentions with actions. At high time pressure, there was less of a gap-closing effect. This could indicate differences in responses or decision-making processes between the segments at high time pressure, reflecting previous studies that have surfaced individual differences in areas such as risk perception and aversion. As such, segment-specific traits may play a role: Solo Explorers, for instance, may prioritize autonomy or familiarity, while Advocates rely on habitual preferences for public transport. This suggests that the effectiveness of BCTs may be moderated by cognitive and emotional responses unique to each segment under high-pressure conditions.

From a practical perspective, these results suggest that journey-planning apps should seek to embed BCTs in their features and content to encourage sustainable travel decisions. Techniques such as personalized feedback, goal-setting, and social comparison proved effective in increasing green route selection across all segments. To maximize their impact, apps should not only focus on the environmental impact of route choices but also enable users to set and track personal goals, creating a personally relevant sense of achievement and reinforcing long-term behavioral change. Visual tools like progress trackers or comparison charts can emphasize the relative benefits of green routes over less sustainable options. These features address universal, cognitive mechanisms, making them broadly applicable across diverse user profiles. Their inclusion can help journey-planning apps transform individual travel decisions into meaningful contributions to reducing transport emissions.

Tailoring app features to address segment-specific barriers is another critical design consideration. For Solo Explorers, who may be resistant to public transport use despite high environmental concerns, apps could incorporate customized recommendations that prioritize convenience or autonomy, such as demand-responsive or micro-mobility transport options. Where public transport service performance supports it, tools such as real-time updates on reliability or guarantees of service quality could also alleviate concerns about inconvenience or unreliability and build trust. For Advocates and Maximizers, who demonstrate higher baseline green route selection rates, app design should focus on reinforcing positive habits and maintaining engagement. Features such as loyalty rewards for consistent green travel or gamified elements like "streaks" for consecutive green route selections could further motivate these segments and strengthen habitual behaviors.

Finally, the results underscore the importance of addressing the cognitive and emotional challenges posed by time pressure. Moderate time pressure fosters green decision-making, suggesting that apps can optimize this cognitive "sweet spot" by simplifying choices. Features such as default green options or pre-saved user preferences can make sustainable decisions easier and faster. Under high time pressure, where cognitive load and heuristic decision-making dominate, stress-responsive messaging and real-time adaptive tools may help maintain sustainable behaviors. Innovations such as predictive analytics to detect time pressure scenarios could enable apps to adjust their functionality dynamically, improving their responsiveness to users' situational needs.

By integrating these principles, journey-planning apps can become powerful tools for influencing sustainable transport choices. As digital platforms increasingly shape travel decisions, leveraging behavioral insights and psychographic segmentation can maximize their impact on reducing transport-related emissions while delivering a seamless user experience.

6. Limitations and Future Research Opportunities

While this study provides robust evidence for the effects of BCTs, psychographic segmentation, and time pressure on sustainable travel choices within the context of a simulated journey-planning app, some limitations should be noted. Conducting this study in a simulated environment rather than real-world conditions was crucial to allow for the controlling of key factors such as service reliability, cost, and journey length, ensuring a robust comparison of control and intervention conditions; however, it did not fully reflect the complexities of real-world travel decisions. Moving to a real-world trial would provide an opportunity to test the ecological validity of these findings and assess the impact of uncontrolled external factors, which may moderate the effectiveness of BCTs. This study focused on participants who were likely to engage with journey-planning apps, excluding those with low attitudes toward technology. This was a deliberate choice to reflect the likely app-using population. However, future research should explore low-tech-user groups to understand whether they can be encouraged to adopt journey-planning apps or whether alternative methods of influencing their travel decisions may be more effective.

Time pressure was manipulated at three discrete levels, which may not have captured the full range of time pressure experiences in real-world travel scenarios. However, the experimental approach allowed for the clear, consistent testing of its effects and revealed important non-linear relationships. Further research could explore how continuous or situationally defined time pressure influences decision-making in naturalistic settings.

As is common in early-stage behavioral research, this study measured behavioral intent rather than actual travel behavior. This limitation was partially mitigated by the immersive and realistic presentation of the simulated app, which went beyond self-reported intent in providing ecological validity. Nevertheless, the lack of follow-through on decisions remains a limitation. Similarly, this study did not track behavior longitudinally, meaning it could not assess whether the observed effects of BCTs persisted over time or translated into lasting habits or whether habitual behavior would be affected in the same way as in the one-off trips featured in this study. Given the importance of habit formation for sustainable behavior change, future studies should incorporate longitudinal designs to evaluate the durability of these effects and explore whether repeated or continued exposure reduces the effects of BCTs.

The intervention app contained a large number of BCTs. While this is consistent with findings that combining groups of complimentary BCTs can be more effective than using isolated BCTs [23], it is not possible from this study to assess the relative efficacy of individual techniques or how specific techniques performed with different segments. A longitudinal real-world trial may open up the opportunity to explore these avenues. One promising option would be to present the staged introduction and removal of techniques or groups of techniques to allow for a fuller assessment. This approach would be best suited to a live app setting.

Finally, the sample size, while sufficient to detect larger, main effects, may have been underpowered to reliably detect interaction effects, limiting the ability to explore more complex relationships. Larger sample sizes in future research would address this issue and potentially reveal additional nuanced interactions.

Despite these limitations, this study has several strengths. The use of a simulated environment provided a controlled setting to rigorously test the impact of BCTs while minimizing confounding variables. This study's factorial design and multilevel logistic regression approach enabled a detailed analysis of multiple factors, offering robust insights into decision-making. Moreover, the results provide practical guidance for designing behaviorally informed apps and open new directions for real-world and longitudinal research.

In addition, there is the potential to expand the approach beyond public and shared transport to other contexts. There are a growing number of driver advisory apps and in-car systems designed to enable the energy-efficient use of electric vehicles, influence driving behaviors to reduce fuel and energy consumption, reduce energy use through route planning, and encourage patterns of usage and behavior that support energy-efficient charging. It would be valuable to explore the existing and potential future use of BCTs and segmentation in such apps to reduce transport emissions as EV use grows.

7. Conclusions

This study highlights the potential of BCTs embedded in journey-planning apps to promote sustainable travel choices. By tailoring interventions to user psychographic profiles and accounting for contextual factors like time pressure, these apps can effectively influence decision-making and contribute to reducing transport emissions. The findings underscore the importance of segment-specific design and user-centered approaches and highlight the importance of attitudes to public transport and environmental motivations. The results provide a strong foundation for future research, including real-world trials and longitudinal studies to explore the durability and scalability of these interventions. These insights offer practical guidance for developers and researchers aiming to harness digital tools for meaningful environmental impact.

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Conflicts of Interest: The author Andrew Broadbent was employed by the company Hitachi Europe Limited. The remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Abbreviations

The following abbreviations are used in this manuscript:

AIC	Akaike Information Criterion
BIC	Bayesian Information Criterion
BCT	Behavior Change Technique
GLMM	Generalized Linear Mixed Models
IPCC	Intergovernmental Panel on Climate Change
ICC	Intra-Class Correlation Coefficient
MaaS	Mobility as a Service
OR	Odds Ratio

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