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Motivating change in commuters' mobility behaviour: Digital nudging for public transportation use

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ABSTRACT

The urgency of climate change is evident worldwide, but current mobility patterns still cause severe environmental damage. The largest share of these mobility-related problems is caused by everyday private car use, such as commuting. One way to change mobility patterns is through digital nudging in the form of trip recommendations to increase commuters' public transportation use. To examine the effects of the recommendations, we undertake a choice-based conjoint analysis and determine whether participants choose the recommended trip option more frequently and whether the recommendations influence participants' public transportation preferences. Our results show differences based on commuters' travel times and mobility app use. Significant positive effects were observed among commuters with a short travel time who do not usually use mobility apps. This study contributes to the digital nudging and transportation literature, and has practical implications in terms of using recommendations to encourage switching from private cars to public transportation.

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Introduction

In developed countries, mobility behaviour contributes significantly to environmental damage, and air and noise pollution (Hauslbauer et al., 2022; Mulley, 2017). For example, in 2015, 385,000 deaths worldwide could be attributed to greenhouse gas emissions caused by the mobility sector (Anenberg et al., 2019), and in Germany mobility accounts for around 24.5% of greenhouse gas emissions (German Federal Environmental Agency, 2021). Despite its extensive mass transit systems, in 2021 more than 87% of the total distance travelled by individuals in Germany took place in private cars (Keller, 2022) and commuters accounted for more than half of the overall traffic volume in 2017 (Nobis & Kuhnimhof 2018).

One way to reduce the negative effects of those mobility patterns is to increase the use of more sustainable mobility modes. For instance, mobility apps or mobility web applications can make it easier and more convenient to use more sustainable mobility

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modes, such as public transport and bike sharing (van Lierop & Bahamonde Birke, 2021; Willing et al., 2017). Public transportation companies frequently provide their own apps to optimise their transport services, e.g. by providing real-time information on occupancy rates (Zimmermann et al., 2020). As has been shown in other contexts, such as fitness tracking or fostering sustainable behaviour changes in companies, apps can be implemented to motivate behavioural changes (Isensee et al., 2022; Sullivan & Lachman, 2017). In the mobility context, for instance, private car users could receive information about how much their CO₂ emissions could be reduced if they chose among recommended alternative trip options or took public transport instead of driving.

The provision of such information or trip recommendations in a digital choice architecture (e.g. within mobility apps) in order to motivate changes in mobility behaviour is an example of digital nudging. In general, nudging is defined as an alteration of a decision-making environment that aims at a behaviour change without changing economic incentives (Thaler & Sunstein, 2009). Digital nudging transfers this concept to the digital realm via web pages or apps (Weinmann et al., 2016) and is defined as ‘the use of user-interface design elements to guide people’s behaviour in digital choice environments’ (Weinmann et al., 2016, p. 433). The concept of digital nudging has been applied in various research fields, including information systems (IS) (Henkel et al., 2019; Meske & Amojó, 2019; Weinmann et al., 2016), psychology (Demarque et al., 2015; Graham et al., 2011; Taube & Vetter, 2019), business and marketing (Chang et al., 2015; Grinstein & Riefler, 2015; Kronrod et al., 2012), and environmental sustainability (Byerly et al., 2018; Doran et al., 2017; Tiefenbeck et al., 2019).

Although digital nudging is a promising approach to inducing behavioural changes in the mobility context, changing mobility behaviour towards more sustainable options, such as public transportation, is still a complex societal challenge (e.g. Gravert & Collentine, 2021; Hauslbauer et al., 2022; Steg, 2005), and little is known about whether and how digital nudging supports behavioural changes (Henkel & Kranz, 2018). First studies analysed in a randomised controlled trial how digital nudges in a mobility app can support modal changes, e.g. from private car use to public transport use. However, their results were mixed: while their results show that use of the proposed mobility app led to significant changes in their targeted rural area, there were no significant changes during the one-year trial in their targeted city setting, where public transportation use was already high at the beginning of the study (Cellina et al., 2019).

These results exemplify the importance of considering the context of mobility research studies (Hong et al., 2014) and the limits to the transferability of findings across contexts. This study focuses on the mobility decision of private car commuters in Germany. Since such commuters account for a great share of the overall car traffic volume in Germany (Nobis & Kuhnimhof 2018), their decision to adopt more sustainable mobility options like public transportation could significantly influence mobility-related problems such as greenhouse gas emissions and noise and air pollution. Therefore, we pose the following research question:

Can digital nudging in the form of recommendations increase the use of public transportation among private car commuters?

To answer this research question, we conducted a choice-based conjoint (CBC) analysis based on 511 car commuters living in Germany. A CBC analysis is well suited to mimicking people's choice decisions (Backhaus et al., 2015) and provides valuable insights into the mobility preference structure that underlies a commuter's mobility decision to choose a public transportation trip. To assess whether recommendations influence such preferences and increase the use of public transportation, we assigned the sample randomly to a control or the treatment group receiving recommendations. Our results demonstrate that the degree to which digital nudges in the form of trip recommendations influence the mobility choices of private car commuters depends on several contextual characteristics, such as travel time and prior experience using mobility apps. This study contributes to the literature on digital nudging by providing empirical insights into behavioural change. It also contributes to the transportation literature (e.g. Khan et al., 2020) by providing insights into the effects of recommendations on mobility behaviour.

The remainder of this paper is structured as follows: The next section provides an overview of the relevant literature and develops hypotheses for the experimental study. Next CBC analysis and the study design are described. After presenting our results, we discuss how our research contributes to IS theory and practice, the study's limitations, and avenues for future research.

Theoretical background

Digital nudging and recommendations

Empirical studies show that psychological measures, such as monetary and non-monetary incentives, can change people's behaviour to promote public transport use (Hunecke et al., 2010; Möser & Bamberg, 2008). Monetary incentives include subsidies, tax (dis)incentives, or bonus systems. For instance, governments could increase taxes on flights and fossil fuels to promote public transport or subsidise solar panel installation and use. However, in the context of commuting, monetary incentives typically motivate short-term changes for the duration of the incentives, but do not change commuters' long-term mobility behaviour after such incentives end (Zeiske et al., 2021).

Nudging, in contrast, is an example of a non-monetary behaviour change mechanism. The concept of nudging in behavioural economics has been shaped by Thaler and Sunstein (2009). Nudges influence people's behaviour without changing the economic incentives of the options provided. Rather, choice architecture is used to alter people's behaviour in a predictable manner. Choice architecture uses the decision environment, whether physical or digital, to affect behaviour without forbidding or financially bolstering or penalising any of the available options (Thaler et al., 2013). A well-known nudging mechanism is the arrangement of products in a grocery store: By placing certain products, e.g. sustainable products, on the shelves at viewing height, more people will buy these products compared than products placed on other shelves, even though there are no monetary incentives, such as discounted prices, and even though non-sustainable products have not been eliminated from the range (Romaniuk & Sharp, 2016). Such adaptations can influence people consciously or

subconsciously and are well suited to changing habitual choices (Thaler & Sunstein, 2009), such as the everyday decision whether to commute using one's private car or public transportation.

Nudges that aim to induce such pro-environmental behaviour are called green nudges (Beermann et al., 2022; Schubert, 2017). The term pro-environmental behaviour (PEB) refers to behaviour 'that consciously seeks to minimise the negative impact of one's actions on the natural and built world' (Kollmuss & Agyeman, 2002, p. 240). Such green nudges can be used to conserve energy (2019), promote sustainable product purchase (Taube & Vetter, 2019), or to decrease emissions from transportation (Lieberoth et al., 2018). For example, Franssens et al. (2021) show that messages in busses that positively label passengers as sustainable can increase the usage rate of public transportation, and Fyhri et al. (2021) use nudging mechanisms to increase the perceived safety of cycle lanes to promote the use of bicycles. Compared to nudges in other contexts, such as health or education, green nudges aim to benefit societal interests compared to personal interests (Barton & Grüne-Yanoff, 2015).

As more and more choices are being made using digital devices, nudging is also common in the digital realm, such as on web pages, in apps and in online shops. Academic literature defines digital nudging as 'the use of user-interface design elements to guide people's behaviour in digital choice environments' (Weinmann et al., 2016, p. 433). There are many different forms and classifications of digital nudging. Some digital nudges like priming, providing information, or goal-setting are used before an actual action is taken, whereas other nudges like default settings or feedback nudges influence user behaviour during or after a decision is made or an action is taken. Moreover, there are also digital nudges that are mostly combined with other incentives, such as social norms or framing nudges (Zimmermann et al., 2021).

One specific form of digital nudging is the provision of recommendations, for instance, expert recommendations (Dogruel et al., 2017), recommendations based on personal information (e.g. Ghose et al., 2019; Kim et al., 2020), or recommendations based on other people's choices, i.e. social norms (e.g. Kretzer & Maedche, 2018; Wang et al., 2018). These nudges provide information to users before a decision is made or an action is taken, in order to direct users' behaviour in a certain way. Former studies show that recommendations, i.e. concrete suggestions for action, are stronger than digital nudges that provide information objectively to users (2017).

Recommendations have been applied in different research contexts. For instance, Kim et al. (2020) used push-notifications on a smartphone app to make energy-saving recommendations to residents, which led to statistical significant reduction of electricity consumption by the participants in a randomised controlled trial. Kretzer and Maedche (2018) combine recommendations with social norm nudges in a business intelligence system to steer users towards specific reports instead of choosing randomly from all available documents. Their results also show significant effects in steering participants' behaviour in the desired direction. Other studies have tested various types of recommendations (e.g. expert recommendations or recommender systems) for marketing purposes (Adomavicius et al., 2013), to optimise privacy settings (Dogruel et al., 2017), or to induce health-increasing behaviour forms (Hurling et al., 2007).

Promoting pro-environmental mobility decisions

Digital nudging has also been used to promote pro-environmental mobility behaviour (e.g. Kim et al., 2020; Tussyadiah & Miller, 2019). For instance, former studies analysed the effects of digital nudges to encourage PEB in a flight context, specifically to promote CO₂ offset payments by providing defaults and promoting alternative flights with lower emissions (Sanguinetti & Amenta, 2022; Székely et al., 2016). In the recreational travel context, the effects of a digital travel feedback system to successfully enforce sustainable travel choices, including the choice of transportation mode, have been analysed (Jariyasunant et al., 2015). Moreover, real-time information has been used to move people from crowded nature destinations to less crowded areas using occupancy and public transportation information (Pihlajamaa et al., 2019). Bothos et al. (2016) implemented a recommendation system within mobile apps and used route planning applications to reduce the overall CO₂ emissions of the study participants by proposing different routes. Additionally, several studies take a technical approach and make location-based recommendations to steer the participants' mobility behaviour using tailored information (e.g. Gao et al., 2019; Zhu et al., 2017).

Several studies have also analysed the promotion of public transportation. For instance, nudging app users through recommendations such as 'Today it's sunny! Take the opportunity to combine bike with public transportation to save CO₂ emissions' (Anagnostopoulou et al., 2020, p. 171) to actively recommend pro-environmental mobility choices have been analysed. Moreover, digital nudges have been used to promote public transport ticket subscription (Hauslbauer et al., 2022), and Lieberoth et al. (2018) tested different forms of interventions, including gamification elements and digital nudges to promote public transportation instead of private car use in a field experiment. The latter research team's results show that nudging can induce behaviour change, and that the impact of including gamification elements is even larger.

Overall, however, the influence of digital nudges in general and recommendations in particular on pro-environmental mobility choices remain largely unclear, because extant literature shows mixed results regarding their effects. To add clarity in this area, this study analyzes the influence of recommendations as digital nudges on participants' public transportation choices.

Hypotheses development

Building on extant literature, we derive and test three hypotheses to examine the effects of trip recommendations on public transportation trip choices. In our empirical examination, we create a choice environment for public transportation trips similar to the choice environment in mobility apps such as those offered by many German public transportation companies. In addition to providing different trip options, we recommend a 'best trip option' in each choice scenario.

Based on extant findings on digital nudging in general and on the effect of recommendations especially, we hypothesise that this digital nudge serves as an orientation for participants and strengthens their preference for the recommended option (Dogruel et al., 2017). We thus also expect that participants who receive a recommendation are

more likely to choose the recommended option than participants who do not receive a recommendation. We therefore hypothesise:

Hypothesis 1: Recommending a public transport trip option to private car commuters increases the likelihood that they will choose the option.

To gain additional insights into how recommendations increase public transportation use, we draw on extant research. According to Haustein and Hunecke (2013), the differences in mobility choices are based on several criteria that influence the individual's choice situation, and several scholars (e.g. Hinkeldein et al., 2015; Semanjski & Gautama, 2016) have argued that an understanding of these criteria is useful to induce more sustainable mobility behaviour (Hunecke et al., 2010). Numerous studies in the transportation literature have therefore analysed people's mobility choices, i.e. their choice of a transport mode and of a specific trip (e.g. Tang et al., 2022). Building on these findings, our study assumes that the travel time needed for commuting (i.e. short versus long) influences commuters' mobility choices (Chalak et al., 2016; Danaf et al., 2014). Travel time is likely to influence mobility choices because there is more likely a viable public transport option available for shorter commutes than for longer commutes, and because the additional time required for public transportation trips is more likely to be accepted for shorter than for longer commutes (Witchayaphong et al., 2020). We therefore hypothesise:

Hypothesis 2: The effect of recommending a public transport trip option to private car commuters is larger for commuters with a short travel time compared to commuters with a long travel time.

In addition to the effect of travel time, this study also investigates the effect of participants' experience with mobility apps on the effects of app recommendations. Mobility app users consider the apps increasingly important (van Lierop & Bahamonde Birke, 2021) because they provide many different services that improve mobility, often including navigation, departure information, and the in-app option to purchase digital public transportation tickets (Zimmermann et al., 2020). Moreover, research in various fields shows that apps can be used to promote behavioural changes. For example, research indicates that smart metre apps can reduce energy consumption (Abrahamse et al., 2007), and sustainability apps can foster sustainable behaviour in the corporate environment (Isensee et al., 2022).

In contrast, less is known about how different groups of people interact with mobility apps and about the role of mobility app usage experience in determining modal changes, such as from private car to public transportation (van Lierop & Bahamonde Birke, 2021). We expect that people who sometimes or regularly use mobility apps to support their everyday commute to work are more likely to trust mobility app recommendations in planning their trip than people who do not use such apps. To test this, we investigate how mobility app usage experience influences the effectiveness of trip option recommendations. Accordingly, we hypothesise:

Hypothesis 3: The effect of recommending a public transport trip option to private car commuters is larger for mobility app users compared to non-users.

Based on the theoretical background and the deduced hypotheses, we developed the research model depicted in Figure 1, which will be analysed in the following.

Methodology

We developed a between-subject experimental design and conducted a CBC analysis to test these three hypotheses.

Choice-based conjoint analysis

The theoretical foundation of conjoint analysis was developed in the field of psychology by Luce and Tukey (1964). Conjoint analyses have since been applied in many different research fields, including IS (e.g. Berger et al., 2015; Mihale-Wilson et al., 2019; Naous & Legner, 2017). The most popular variant of this analysis is choice-based conjoint analysis (CBC) (Naous & Legner, 2017; Sattler & Hartmann, 2008), which effectively mimics participants' actual choices (Backhaus et al., 2015; Berger et al., 2015). In CBC analysis, participants are presented with different options (i.e. products or services) in several choice sets, from which they can choose one option at a time (Backhaus et al., 2015). CBC analysis is based on the assumption that the value of individual attributes and their attribute levels of a product or service can be determined by evaluating the entire product or service (i.e. the decomposition approach) (Backhaus et al., 2015). For instance, an attribute of a public transport service is its price, and possible attribute levels are € 2.50, € 3.50, and € 4.50. To keep the complexity at a manageable level for participants, Hair et al. (2014) recommend using no more than six attributes.

For each of the attribute levels, a part-worth is calculated, which represents the value of this attribute level for the participants. The overall value of a product or service can be calculated by adding up the part-worths of the attribute levels (Hair et al., 2014). The difference between the attribute level with the highest part-worth and the attribute level with the lowest part-worth indicates how important the attribute is for the overall product or service. By calculating this difference in relation to the sum of the differences of all

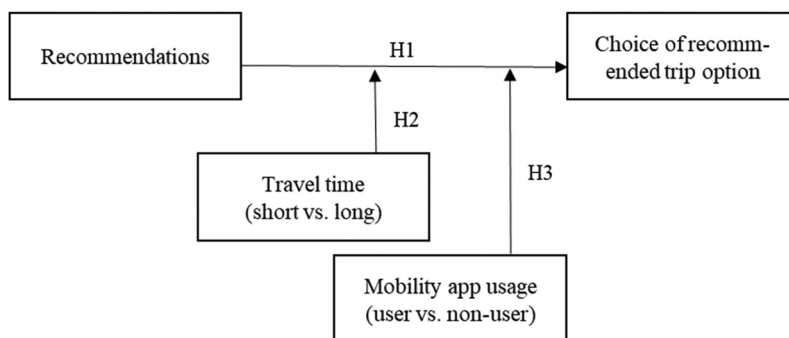


Figure 1. Research model and hypotheses.

attributes, this results in the relative importance of the attribute (Backhaus et al., 2015; Hair et al.,). Therefore, the relative importance indicates to which percentage each attribute determines the overall preference structure.

Survey development

Based on the principles of CBC analyses we designed a survey to analyse the effects of trip recommendations and the preference structures for public transportation trips.

To identify the attributes of a public transport service that are relevant to commuters' mobility choice, this study analyzes relevant scientific research (e.g. Arentze & Molin, 2013; Hensher, 2006; Mahmassani & Chang, 1986; Peer & Börjesson, 2018) and available mobility apps (e.g. DB Navigator). Based on our analysis, we identified all attributes that might be relevant for public transportation trips, such as the price, seat availability, and Wi-Fi availability. In a pre-test, we asked 29 participants to select and rank the attributes by importance in choosing a public transport service for commuting. Participants were permitted to exclude attributes they considered irrelevant and add attributes not yet included in the list. Based on the results of the pre-test, we selected the six most important attributes of a public transportation trip, following the generally recommended maximum number of attributes for a CBC analysis (Backhaus et al., 2015). Further details on the attributes and the pre-test selection process are provided in Table A1 in the Appendix.

In a next step, we defined the attribute levels for the six most important attributes based on two real-world commuting trip examples with different travel times: (1) a short travel time (less than 30 minutes), defined as a commuting trip between two districts in Berlin, and (2) a long travel time (more than 30 minutes), defined as a commuting trip between two different German cities. In a second pre-test, we asked six additional participants to assess the clarity of the attributes and their attribute levels and the supplementary questions concerning the participants' demographic characteristics, mobility behaviour, and mobility app use. Table 1 shows the attributes that were implemented in the CBC analysis and their attribute levels.

Depending on the length of participants' actual daily commute, we sent them either a questionnaire with attribute levels of public transport services with either a short or long travel time. The attribute *time until departure* refers to the waiting time between arriving at the station and the departure of a public transport vehicle (e.g. bus, subway, or train). For example, if participants chose attribute level ≤ 5 , they preferred to wait less than five minutes at the station. The

Table 1. Attributes and attribute levels for CBC analysis (short/long commuting time).

Attributes	Attribute levels		
Time until departure (in mins.)	$\leq 5 / \leq 15$	6–10/16–30	11–15/ ≥ 31
Travel time (in mins.)	$\leq 15 / 31–45$	16–30/46–60	31–45/ ≥ 61
Price (in euros)	2.50/10	3.50/20	4.50/30
Number of transfers	0	1	2/ ≥ 2
Occupation	Low	Medium	High
	(vacant seats)	(vacant seats uncertain)	(no vacant seats)
Greenhouse gas emissions (in grams)	$\leq 150 / \leq 3,500$	151–300/ 3,501–7,000	$\geq 301 / \geq 7,001$

[For the treatment group:]

The first choice is the recommendation of the mobility app.

[All participants:]

Which recommendation would you choose? You have to make twelve choices.

Time until departure	16 – 30 minutes	>= 31 minutes	16 – 30 minutes	Private car
Travel time	31 – 45 minutes	46 – 60 minutes	>= 61 minutes	
Price	30 €	20 €	10 €	
Number of transfers	1	0	>= 2	
Occupation	Medium (vacant seats uncertain)	High (no vacant seats)	Low (vacant seats)	
Greenhouse gas emissions	3,501 – 7,000 grams	>= 3,500 grams	>= 7,001 grams	
	☐	☐	☐	☐

Next

Figure 2. Exemplary choice set for private car commuters with a long travel time (translated).

attribute *travel time* refers to the overall trip time using public transport. The attribute *price* refers to the total cost of a trip, and the attribute *number of transfers* refers to how many times a person has to change between different modes of transport (e.g. from a bus to a train) and/or within a mode of transport (e.g. from train A to train B). The attribute *occupation* refers to how crowded the vehicle currently is. The attribute level low means that there are vacant seats available, medium means that there may or may not be a vacant seat available, and high means that no vacant seats are available. The attribute *greenhouse gas emissions* refers to the grams of greenhouse gas emissions attributable to one person taking the trip in question.

Twelve choice sets were presented to each study participant. We included four identical choice sets for all participants to assess the quality of the data. We also included two other fixed choice sets to perform an intention check (Backhaus et al., 2015; J. Hair et al., 2014). If a participant did not make two identical mobility choices, their dataset was deleted. The other eight choice sets were designed with the software QuestionPro (2021) based on a D-optimal design. Figure 2 illustrates the recommendation nudge for the treatment group and an exemplary choice set for participants with a long travel time.

Each choice set included three different public transport trip options. In addition, participants had the option to continuing to use their private cars. Since our focus group only included people who commute daily using a private car, this choice option was not further detailed. Besides the CBC analysis, the surveys include questions about the participants' demographics, their mobility behaviour regarding their commute (e.g. 'How satisfied are you with the public transport connection between your home and your place of work or educational institution?'), and their use of mobility apps (e.g. 'Which mobility app/s do you use when planning or commuting between your home and your place of work or educational institution?').

Data collection

To test our hypotheses, we collected data from people living in Germany who regularly commute to work by private car. Germany is well-suited for our study because, like most other industrialised countries, Germany is suffering from the negative consequences of mobility behaviour based primarily on private car use, and because the conditions for changing the mobility behaviour of private car commuters is relatively good in Germany because several studies (e.g. German Federal Environmental Agency, 2019; Kuhnimhof et al., 2012) show that, as in some other industrialised countries, the importance of private car ownership and the emotional attachment to one's car is decreasing in Germany.

The surveys were distributed via Facebook between January 2020 and April 2020. We chose Facebook as a medium of data collection based on studies showing that higher response rate and higher data quality can be achieved compared with other sampling strategies (Baltar & Brunet, 2012; Kosinski et al., 2015). A description of the study and links to the questionnaires were posted in different mobility-related Facebook groups, such as groups sharing traffic jam information. To obtain a well-distributed sample, we posted the survey in groups based in specific areas or cities all over Germany. Each post included two links, one for commuters with a short travel time (less than 30 minutes) and one for commuters with a long travel time (more than 30 minutes). As the data collection period was interrupted by the first novel coronavirus 2019 (COVID-19) wave, participants were explicitly asked to answer the questions without considering the COVID-19 outbreak to avoid any disruptive effects on the sample.

To analyse the effects of the public transport service recommendations on participants' mobility choices, we implemented a between-subject experimental design with a control and a treatment condition. For the treatment condition, the first public transport trip option in each choice set was recommended explicitly to participants, whereas there was no such recommendation for the control condition. The recommendation was above each choice set and stated, 'The first choice option is the recommendation of the mobility app' (translation). We chose this manipulation based on former studies showing that text-based recommendations influence people in their behaviour. For example, Adomavicius et al. (2013) show that recommendations can manipulate consumer preferences and rating behaviour, and the study by 2017 uses text-based recommendations to avoid incompatible digital product purchases. Apart from this manipulation, the questionnaires and their respective choice sets were identical. The links for the questionnaires with and without manipulation were randomly assigned to the different Facebook groups.

To attract participants, several Amazon gift coupons were raffled among those who provided an email address. Overall, 1,612 fully completed questionnaires were received. After taking actions to ensure the quality of the data (e.g. removing participants who failed the intention check and deleting questionnaires of participants who did not live in Germany) and removing participants who had commuted via public transport within the last month, 511 questionnaires remained for further analysis, 224 for the control group and 287 for the treatment group.

Data analysis

To examine the effects of the recommendations among participants in the treatment group, we analysed whether there is a statistical significance for the choices of the control and the treatment group for the recommended trip option. As each participant made various choices, we calculated the overall choice rate of the recommended option for participants in the treatment group and the respective option for participants in the control group. For instance, if a participant chose the recommended public transportation trip option in for half of the scenarios, the respective choice rate would be 0.5. Using the choice rate as the dependent variable, we then performed a one-sided t-test to analyse if the public transportation trip option that was recommended to the treatment group was chosen more frequently compared to the control group.

For an additional analysis of the recommendation effects, we analyse the preference structure of the control and treatment group with a CBC analysis using the SPSS Statistics 26 software. As Backhaus et al. (2015) show, although CBC analysis does not provide a specific function for performing this analysis, it can be conducted using a Cox regression analysis instead. When conducting a stratified Cox regression, the likelihood function is maximised (i.e. the maximum-likelihood method). In this research, this function was used to estimate the part-worth of each attribute level, following the lead of Schulz et al. (2021), among others. The first attribute level of the attributes was defined as the basis attribute level.

To assess the quality of each regression model, a likelihood ratio test was used (Backhaus et al., 2015). In addition, to test the predictive validity of the calculated part-worths, the hit rate of each part-worth was determined. The hit rate measures how well participants' choices can be predicted with the estimated part-worths (Backhaus et al., 2015; Berger et al., 2015). For instance, a hit rate of 50% would indicate that participants' choices can be correctly predicted in 50% of all cases using the part-worths. The logit choice model, which is frequently applied in CBC analyses, was used in choice prediction (Backhaus et al., 2015). The random probability was 25%: a choice set included three recommendations for a public transport service and the option to use a private car. Based on the hit rates from previous CBC analysis studies (Kanuri et al., 2014; Wlömert & Eggers, 2016), a hit rate above 50% was considered high.

Results

Sample description

Table 2 provides an overview of the participants' characteristics. The participants were grouped based on whether they were part of the control or the treatment group, i.e. whether or not they received a specific recommendation for one of the public transportation trips. Overall, 46.6% of the participants are female, 52.8% are male, and 0.6% identify as diverse. On average, they are 34 years old and thus younger than the average age in Germany (German Federal Statistical Office, 2020). 41.5% of the participants have a personal average monthly net income of EUR 2,000 or lower, 47.2% have an average income between EUR 2,001–3,600, and 11.3% of all participants have an average income of more than EUR 3,600, compared to a personal average monthly net income in Germany in 2020 of EUR 2,085 (German Federal Statistical Office, 2022). Moreover, 44.2% never used

Table 2. Characteristics of the study participants.

Characteristics of participants	Sample with manipulation (n=287)	Control group (n = 224)	Total (n=511)
<i>Gender</i>			
Female	128 (44.6%)	113 (50.4%)	238 (46.6%)
Male	157 (54.7%)	110 (49.1%)	270 (52.8%)
Diverse	2 (0.7%)	1 (0.5%)	3 (0.6%)
<i>Age</i>			
<25	52 (18.1%)	30 (13.4%)	82 (16.1%)
25–34	123 (42.9%)	78 (34.8%)	201 (39.3%)
35–44	66 (23.0%)	79 (35.3%)	145 (28.4%)
45–54	34 (11.8%)	26 (11.6%)	60 (11.7%)
>= 55	12 (4.2%)	11 (4.9%)	23 (4.5%)
<i>Net income per month (in €)</i>			
<= 1,300	47 (16.4%)	34 (15.2%)	81 (15.9%)
1,301–2,000	67 (23.3%)	64 (28.6%)	131 (25.6%)
2,001–3,600	134 (46.7%)	107 (47.8%)	241 (47.2%)
3,601–5,000	28 (9.8%)	15 (6.7%)	43 (8.4%)
>5,000	11 (3.8%)	4 (1.8%)	15 (2.9%)
<i>Use of Mobility Apps for Commuting</i>			
Never	122 (42.5%)	104 (46.4%)	226 (44.2%)
Rarely	81 (28.2%)	54 (24.1%)	135 (26.4%)
Sometimes	36 (12.5%)	34 (15.2%)	70 (13.7%)
Often	25 (8.7%)	11 (4.9%)	36 (7.0%)
Always	23 (8.0%)	21 (9.4%)	44 (8.6%)

one or more mobility apps for commuting, 40.1% used them sometimes, and only about 15.6% used them often or always.

Manipulation Effects

This section presents the effects of the recommendation manipulation, i.e. whether the digital nudge increased the likelihood that participants in the treatment group chose the public transportation trip option compared with participants in the control group. We therefore calculated what percentage of participants in the treatment group chose the recommended public transportation trip option and compared this to the percentage of participants in the control group that chose the respective option.

To test H1 (*Recommending a public transport trip option to private car commuters increases the likelihood that they will choose the option*), we first analysed the results from all participants in the treatment and the control group. Our results show that the recommendation did not increase the choice probability of the recommended option for the treatment group. In fact, the choice rate of the recommended option was slightly lower for the treatment group with a difference of -0.4% ($p = 0.39$) compared to the control group. To test for significant differences in the choice rates, a one-sided t-test was performed, which revealed no statistically significant differences.

To gain more detailed information about different commuter groups, and analyse whether the recommendations influence certain types of commuter groups we subdivided the treatment group and the control group according to their usual travel time (short vs. long travel time) for commuting. To test H2 (*The effect of recommending a public transport trip option to private car commuters is larger for commuters with a short travel time.*) we again analysed how frequently the recommended public transportation trip (or the respective option for the control group without recommendations) was chosen by the

Table 3. Differences in choice rates (in %) and standard errors for the recommended public transport trip option.

Differences in choice rates for the treatment groups compared to the control groups			
All participants			
Short travel time		Long travel time	
2.7* (0.1927)		-5.1* (0.1760)	
Non-app users	App users	Non-app users	App users
4.3* (0.1982)	1.0 (0.1975)	0.0 (0.1683)	-9.0** (0.1800)

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

participants and compared these choice rates controlling for their usual travel time. Our results show that the choice rates of commuters with a short travel time were statistically higher for the treatment group than for the control group with a difference of 2.7% ($p < 0.10$). Among commuters with a long travel time, however, we observed the opposite effect: the choice rate of the recommended public transport trip was significantly lower for the treatment group by -5.1% ($p < 0.10$) compared to the control group.

In addition to segmenting based on travel times, we also assessed the results mediated by mobility app usage, distinguishing participants who sometimes or regularly use mobility apps to support their everyday commute (app users) from commuters who never use such apps to support their everyday commute (Non-app users). To test H3 (*The effect of recommending a public transport trip option to private car commuters is larger for mobility app users compared to non-users.*) we analysed how often participants chose the recommended public transportation trip (or the respective option for the control group without recommendations) and compared these choice rates controlling for their mobility app use. Our results show that, among non-app users, the choice rate was significantly higher among participants in the treatment group than among participants in the control group with a difference of 4.3% ($p < 0.10$), but only among participants with a short travel time. Our results show no difference with a value of 0.0% ($p = 0.49$) among non-app users with a long travel time between members of the control group and the treatment group. Among app users, our results show either no significant effect on the choice rates for participants with a short travel time with a difference of 1.0% ($p = 0.35$) between the treatment and the control group or a significant adverse effect for long travel times with a difference of -9.0% ($p < 0.05$).

Table 3 summarises our results of the effect of the recommendations on the choice rate of the recommended public transport trips. More details for the choice rates of each group are included in Table A2 in the Appendix.

Preference structures for public transportation trip choices

In addition to the immediate effects on the choice rate of the recommendation, we also analysed whether the recommendations for the treatment group caused any changes in the overall public transportation preferences compared to the control group. We undertook a CBC analysis to analyse the choices of the participants in more depth, starting with the control groups (control group categorised by travel time and mobility app usage).

Likelihood ratio tests for the groups resulted in a p-value of 0.000, which indicates that the regression models for all four groups were highly statistically significant and distinguishing according to mobility app usage and length of commute yields meaningful subgroups with similar public transportation trip preferences. To evaluate the prediction quality of the estimated part-worths (resulting from the Cox regression), we calculated the hit rate for each group. Our results show that the hit rates ranged from 49% to 82%, which means that participants' mobility choices were predicted with a sufficiently high degree of predictive validity, according to hit rates in extant research implementing CBC analysis (Kanuri et al., 2014; Wlömert & Eggers, 2016).

To analyse the preference structure for public transportation trips, the relative importance for each attribute (e.g. price or occupancy) was calculated based on the part-worths. The relative importance in our study indicates the extent to which an attribute of a public transportation trip determines the choice of the participants. Our results reveal differences among all groups studied, indicating the influence of mobility app usage and travel time on public transportation trip choices.

Our results show that travel time was the most important attribute among non-app users and app users in the control group with a short travel time (32.7% and 39.6%, respectively), followed by price (18.6% and 14.2%, respectively) and number of transfers (18.1% and 24.9%, respectively). The lowest relative importance is assigned to the greenhouse gas emissions by both short travel time groups (7.1% and 5.7%, respectively). In contrast, the group of commuters with a long travel time pay much more attention to the greenhouse gas emissions when choosing a public transportation trip, especially non-app users (31.1% and 15.1%, respectively). For the app user groups, the least important attribute is time until departure (5.4% and 9.5%, respectively). Table 4 below summarises the relative importance values for the public transportation attributes for the control groups.

Similar to the procedure for the control group, we analysed the public transportation preference structure of the treatment group to derive whether the recommendation indirectly affects public transportation preferences other than an increase in the choice rate of the recommended option. Here again, likelihood ratio tests performed for each group resulted in a p-value of 0.000, which shows that the regression models were highly statistically significant. The calculated hit rates ranged from 46% to 92%, which is evidence that participants' mobility choices were predicted with a sufficiently high degree of predictive validity.

The resulting values for relative importance of the attributes indicate the following effects. Among participants in the control group, the attribute *travel time* was most

Table 4. Relative importance of the attributes (in %) for the control groups.

Attribute	Short travel time		Long travel time	
	Non-app users	App users	Non-app users	App users
Time until departure	10.7	5.4	14.9	9.5
Travel time	32.7	39.6	13.6	15.9
Price	18.6	14.2	7.4	29.1
Number of transfers	18.1	24.9	18.0	12.9
Occupation	12.7	10.2	15.0	17.5
Greenhouse gas emissions	7.1	5.7	31.1	15.1

Table 5. Relative importance of the attributes (in %) for the treatment groups.

Attribute	Short travel time		Long travel time	
	Non-app users	App users	Non-app users	App users
Time until departure	5.4	7.0	6.5	6.5
Travel time	35.3	36.3	13.5	23.8
Price	11.6	12.0	20.0	13.9
Number of transfers	21.2	17.9	13.4	19.4
Occupation	11.9	13.0	28.0	27.1
Greenhouse gas emissions	14.5	13.8	18.7	9.4

important among participants with a short travel time (35.3% for non-app users and 36.3% for app user). For the participants in the treatment group with a long travel time, the attribute *occupation* has the highest relative importance (28.0% and 27.1%, respectively), which is higher than the values for the control group. With regard to the attribute *greenhouse gas emissions*, the recommendations had the reverse effect on participants in the treatment group with short and long travel times: While the results show higher values for the participants with a short travel time in the treatment group (14.5% and 13.8%, respectively) compared to the control group (7.1% and 5.7%, respectively), the relative importance values among participants with long travel times in the treatment group are considerably lower (18.7% and 9.4%, respectively) compared to the control group (31.1% and 15.1%, respectively). Across all four groups, the attribute *time until departure* is the least important (5.4% and 7.0%, respectively), which is comparable to the control group for the app users, however the results for the non-app users in the control group show higher values for this attribute. Table 5 summarises the results for the public transportation preference structure for the treatment groups.

Discussion

This paper examines how digital nudging, specifically recommendations, influence private car commuters' choices of public transportation trips. To analyse the effects of such trip recommendations, we formulate three hypotheses and test them empirically by calculating and comparing the effects recommendations have on a treatment and a control group. To gain deeper insights, we also tested the effects of the recommendations based on whether participants have a short (less than 30 minutes) or long (more than 30 minutes) daily commute to work and whether or not they sometimes/regularly use mobility apps to support their daily commute (non-app users vs. app users). Finally, we undertook a CBC analysis to examine the effects of the recommendations on public transportation trip option preferences.

As summarised in Table 6 below, our results show that Hypothesis 1 is not supported, i.e. recommending a public transportation trip option does not significantly increase the likelihood that private car commuters will choose that option. Hypothesis 2 is supported, i.e. the effect of recommending a public transport trip option to private car commuters is larger for commuters with a short travel time. Lastly, Hypothesis 3 is not supported, i.e. the effect of recommending a public transport trip option to private car commuters is not larger for mobility app users compared to non-users when comparing the control group to the treatment group.

Table 6. Overview of hypotheses and study results.

Hypotheses	Findings
Hypothesis 1: Recommending a public transport trip option to private car commuters increases the likelihood that they will choose the option.	Not supported
Hypothesis 2: The effect of recommending a public transport trip option to private car commuters is larger for commuters with a short travel time.	Supported
Hypothesis 3: The effect of recommending a public transport trip option to private car commuters is larger for mobility app users compared to non-users.	Not supported

Theoretical contributions

This study contributes to theory in several ways. First, this paper sheds light on the effects of recommendations as digital nudges in the mobility context on an individual level. It is well established that digital nudging is, in general, a promising approach to changing individual behaviour (Henkel et al., 2019; Meske & Amojó, 2019; Weinmann et al., 2016), and extant research shows that recommendations, as one form of digital nudging, can have positive effects on behaviour change (Adomavicius et al., 2013; Anagnostopoulou et al., 2020; Bothos et al., 2016). Our study contributes granularity to these general findings, showing that the positive effects are greater among car commuters with a relatively short commute than among private car commuters with a relatively long commute, i.e. the increase in the likelihood of choosing the recommended public transportation option is higher for the former than for the latter group. These results demonstrate that recommendations have the potential to affect individual behaviour but are also sensitive to specific individual mobility context characteristics (Hong et al., 2014).

Such mobility context sensitivity underscores findings in extant literature. For instance, in the smartphone app context, Cellina et al. (2019) analyse the effects different nudging and gamification elements to induce modal changes to more sustainable transportation options. Their results show that behaviour change effects are evident in a car-dependent urban area, but no significant effects are evident in a city where public transportation is frequently used. Other studies also identify context sensitivity in the public transportation choice context (e.g. Grison et al., 2016, 2017), pointing to the need for in-depth analysis of the mobility context in the mobility choice context. Our findings further underscore the need for objective criteria to control for context and assess the transferability of empirical results in digital nudging research.

Second, we contribute to the literature by undertaking a CBC analysis to provide detailed insights into the motivational drivers of public transportation trip choice, i.e. the relative importance of trip attributes. Conjoint analyses have been used in many different research fields (e.g. Mihale-Wilson et al., 2019; Naous & Legner, 2017), including the mobility context (e.g. Schulz et al., 2021) because the methodology mimics actual choices to a high degree (Backhaus et al., 2015; Berger et al., 2015). This is highly relevant because the knowledge of the factors that determine actual choices can be used to promote sustainable behaviour (Hinkeldein et al., 2015; Semanjski & Gautama, 2016). Haustein and Hunecke (2013) show identify several criteria that determine such motivational drivers (e.g. mobility behaviour, socio-demographic, spatial, or attitudinal criteria), showing how they can be used to form mobility target groups.

For instance, our results for the control group show that travel time is the most important attribute for private car commuters with a short travel time (32.7% for non-

app users and 39.6% for app users in the control group), followed by price (18.6% and 14.2%, respectively). These results underscore the importance of minimising cost and time for short trips, whereas other factors like emissions are less relevant. For longer trips, in contrast, other attributes relevant to ride comfort, such as occupation (15.0% and 17.5%, respectively), are more relevant. These examples demonstrate how our results help to understand which context-dependent factors are relevant for private car commuters when motivating them to choose public transportation trips, which has relevance for future study designs.

Third, our results underscore the importance of tailoring interventions like digital nudges to specific target groups (Semanjski & Gautama, 2016). For instance, our results show that the greenhouse gas emissions of a trip are relevant to private car commuters with long commutes (31.1% and 15.1%, respectively). Therefore, these users could be motivated to switch to commuting by public transportation by including personalised information on the greenhouse gas emission reduction of choosing a recommended public transportation trip option rather than driving a private car. Former studies show that including such tailored information can increase the effects of digital nudging. For instance, Ghose et al. (2019) based their recommendations on the current location of an app user, and Hurling et al. (2007) tailored advice to optimise a physical activity program. In the mobility context, Cellina et al. (2019) and Bucher et al. (2019) use personalised eco-feedback to decrease CO₂ emissions and to provide suggestions for more sustainable modal choices.

Overall, these theoretical implications show how our results can contribute to different research streams, including information systems, transportation research and digital nudging.

Practical implications

The results of our study have important implications for practice, e.g. for public transportation companies, city managers and mobility app developers.

First, our results show how recommendations as digital nudges can be used to make the mobility choices of private car commuters more environmental friendly. The findings can be used to integrate recommendations into mobility apps (e.g. Google Maps or apps offered by public transportation companies) to increase the use of more sustainable modes of transportation, such as public transport. For instance, mobility apps that offer different transportation modes (such as Google Maps) could label the most environmentally friendly option as the best trip option when users compare different alternatives. Also, push-notifications could be sent to users when they are not currently using the app to recommend more environmental friendly trip options for upcoming commuting trips based on former behaviour or settings (e.g. the place of residence and work can be saved in most mobility apps).

However, as our results show, there are no immediate effects of the trip recommendations for the overall sample of participants. This indicates, that although digital nudging is a promising approach to induce behaviour change in peoples' mobility behaviour (e.g. Franssens et al., 2021; Fyhri et al., 2021), such interventions must be tailored carefully to the targeted users. To tailor interventions, two different types of user data could be used within mobility apps. On the one hand, users could actively provide data when creating

an account (e.g. demographic data or data about mobility preferences). On the other hand, mobility apps could use data based on former trip choices. For instance, if users always prefer to commute by car, mobility apps could recommend trip options that combine a car ride and a public transportation option optimally to promote behaviour changes with lower-thresholds for users.

Second, on a more detailed level, our results provide information on specific user groups, for whom trip recommendations could significantly affect public transportation trip choices based on how long their commute is and whether they sometimes/regularly use mobility app to support their daily commute by private car. Our results thus emphasise the need to personalise digital nudges in general (Meske & Amojó, 2019) and trip recommendations in particular. For instance, our results indicate that recommendations can increase the likelihood that private car commuters with a short commute will choose a recommended public transportation option but can decrease the likelihood that private car commuters with a relatively long commute will choose the same option. One explanation for this is that there are most likely more reasonable trip options available for shorter trips (e.g. from one district in Berlin to another) compared to longer trips (e.g. between two cities in Germany). In general, using public transportation often takes longer than driving a private car, but this increase is likely smaller and therefore less critical for shorter commutes, such as within a city with an extensive public transportation network and potentially limited parking availability. Therefore, recommendations for mode changes should especially be deployed for shorter trips rather than for all trip selections.

Our results also indicate that, on one hand, recommendations can increase the likelihood that private car commuters who never use a mobility app to support their everyday commute choice will choose a recommended trip option and are therefore a promising potential user group. To realise this potential public transportation companies could point out the benefits of mobility apps in offline environments, such as train stations or in other public buildings to further encourage mobility app usage. Moreover, they could also increase their cooperation with other service offers, such as smart city apps or booking platforms for hotels. This way, more potential users could test or use mobility app services without having to download an additional app of public transportation providers. On the other hand, recommendations can decrease the likelihood that commuters who sometimes/regularly use a mobility app will choose the same recommended trip option. A few explanations could be that private car commuters who regularly use mobility apps are more experienced at using objective trip option information effectively or have become immune to or suspicious of digital nudging interventions, perhaps to the point of rejecting them on principal. Therefore, practitioners should be aware of the risk of overusing trip recommendations to the point that users ignore or intentionally reject them.

Third, our results show that recommendations might not only lead to direct effects (i.e. an increase in the choice of the recommended option) but also influence the overall preference structure for public transportation trips. For instance, our results show that the relative importance of greenhouse gas emissions is much higher to private car commuters who receive a recommendation and who have a short travel time compared to private car commuters with a short travel time who do not receive a recommendation. This effect matches the effect for the increased choice rate of the recommended option for this group, as the recommendation focuses on a more sustainable trip option (public

transport) compared to the participants' usual mode of transportation (private car). However, for the group of participants with long travel times, the relative importance of greenhouse gas emissions is lower for participants who receive a recommendation than for those who do not. Based on these findings, practitioners should always control for possible undesired context-relevant results when implementing recommendations as digital nudges and carefully consider which attributes, such as greenhouse gas emissions or price, are most relevant for which types of commuters choosing a mode of transportation or a specific trip option.

Limitations and future research

This study was subject to several limitations that should be addressed in future research. First, we only collected data from car commuters living in Germany. Since the importance of private car ownership and the emotional attachment to one's car is decreasing among the younger generation (e.g. German Federal Environmental Agency, 2019; Kuhnimhof et al., 2012) in Germany, the conditions are conducive to changing the currently still predominant private-car-based mobility behaviour in Germany with the help of apps. However, as attitudes towards public transport, the quality and availability of public transport, and the prevalence of public transport use varies significantly across countries and cultures (Kuhnimhof et al., 2012), future studies should examine how these logistical, attitudinal and infrastructural differences influence people's mobility choices when using a mobility app. For example, while it is common for members of all levels of society to ride the train or subway in Western European countries (German Federal Environmental Agency, 2019), this may not be the case in countries where most people view a private car as a status symbol (e.g. Pojani et al., 2018; Steg, 2005). Furthermore, the public transport infrastructure in countries such as the United States, China and India is less homogenous and in many ways significantly different to that in Germany, which will likely lead to different results and should be addressed by future research located in other national settings.

Another limitation of our study relates to the data collection methodology we used. Since we collected data through an online survey, we did not observe the study participants' actual mobility behaviour, but rather only the choices they made in response to the survey questions. Even though CBC analysis is widely considered the best method to mimic people's behavioural choices (Backhaus et al., 2015; Berger et al., 2015), there may be deviations from real-world behaviour, such as if participants had to actually pay a high price for a recommended public transport service. Future studies should track commuters' actual mobility choices and behaviour through a mobility app in a field study setting comparable to Cellina et al. (2019) and Lieberoth et al. (2018).

Finally, we collected data during the first COVID-19 outbreak in Germany in 2020. Although we told our participants to respond as if there were no lockdown and no heightened danger associated with public transport use, we cannot rule out subconscious effects, such as an increased focus on the occupation attribute of public transportation trips or a general decrease in the use of public transport. Similarly, many employees significantly increased the share of work they performed in a home office setting during the lockdown, which reduced their overall commuting time. This may have subconsciously lowered the subjective relative importance of their daily commute time. Several studies have analysed the impact of

Covid on public transportation use behaviour (e.g. De Vos, 2020; Gramsch et al., 2022) and future research should examine the long time effects to better understand evolving and new mobility patterns.

Conclusion

In this paper we analyse how digital nudges in the form of trip recommendations affect public transportation trip choices of private car commuters in Germany. To examine the effects of the recommendations, we analysed if the trip recommended public transportation trip option is chosen more frequently by participants who received them than by participants who did not receive them. We also undertook a CBC analysis to understand the relative importance of various factors and the effect of the recommendations on participants' preferences for public transportation options.

Our results show that the effects of trip recommendations vary according the length of private car commuters' commute and whether or not they use mobility apps sometimes/regularly to support their everyday commute. Our results also show that significant positive effects of trip recommendations in mobility apps can only be attained for private car commuters with a short travel time who do not regularly use mobility apps to support their daily commute by car. Moreover, our results underscore the importance of tailoring recommendations as digital nudges specifically to the mobility context of the various target groups to maximise behaviour change effects. Overall, our results provide valuable insights to practitioners desiring to motivate a modal shift for car commuters to public transportation, which can contribute to lessening the environmental damage caused by current mobility patterns.

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Appendix

Table A1. Public transportation trip attributes and number of selection as relevant attribute in the pre-test.

Public transport trip attribute	Number of selection as relevant attribute
Price	21
Travel time	20
Means of transportation (e.g. bus or train)	3
Transfer time	4
Occupation	10
Reliability/Possibility of delay	8
Time until departure	11
Time until arrival	9
Seat reservation available	5
Number of transfers	23
Bonus points available	1
Wi-Fi available	9
Greenhouse gas emissions	13
Connection ticket included	5
More	2

Table A2. Differences in choice rates (in %) and standard errors for the recommended public transport trip option.

Differences and choice rates of the treatment group and the control group			
All participants			
-0.4 (14.5/14.1) (0.1878)			
Short travel time		Long travel time	
2.7* (14.8/17.5) (0.1927)		-5.1* (13.1/8.0) (0.1760)	
Non-app users	App users	Non-app users	App users
4.3* (10.8/15.1) (0.1982)	1.0 (18.4/19.4) (0.1975)	0.0 (8.1/8.1) (0.1683)	-9.0** (17.0/8.0) (0.1800)

Note: (*p< 0.10, **p< 0.05, ***p< 0.01).