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The potential impact of Google Maps on mode choices: Evidence from a stated preference experiment☆

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ABSTRACT

This paper analyzes the potential influence of digital mapping tools (with Google Maps as the primary example) on mode choice behavior. For the purpose of this study, we use survey data gathered in Vienna (Austria) during 2022. Almost 80% of respondents state that they regularly use Google Maps, and a large majority evaluate Google Maps positively concerning ease of use, trust, or general usefulness. Our analyses reveal that, on average, respondents perceive real-life travel times as somewhat longer than the corresponding Google-Maps-based travel times (by 2%–11%). However, a large degree of heterogeneity is present, which seems to be at least partially driven by respondents' speed choices. Based on a stated preference experiment, in which respondents were asked to choose between transport modes, assuming that the travel times stated in the experiment either originate from Google Maps (*GoogleMaps* treatment) or correspond to accurately measured average travel times (*Baseline* treatment), we can show that the perceived differences between real-life travel times and Google-Maps-based travel times are only considered to a limited extent in the mode choices. More specifically, such deviations are mainly acted upon when individuals expect to be faster than the Google Maps estimate.

1. Introduction

Digital mapping tools such as Google Maps are increasingly used by individuals to support mobility-related decision-making. These tools typically aim to provide easily accessible travel information (Lin and Batty, 2009; Ramadan et al., 2025), and in doing so, they influence the travel behavior of their users (Montello, 2018; Cornacchia et al., 2024). As even the best maps have flaws and no human perception of geographic space is without distortions, it becomes particularly important to study how maps influence human behavior (Montello, 1997; Quattrone et al., 2015; Wagner et al., 2021; Gentzel and Wimmer, 2023). Despite the ubiquitous presence of digital mapping tools, their role in shaping user decision making remains understudied.

In this paper, we investigate the influence of digital mapping tools on users' mode choice decisions. More specifically, we aim at understanding (1) whether individuals believe that the travel times generated by digital mapping tools (such as Google Maps) correspond to their real-life travel times, and (2) to which extent individuals take any perceived deviations between actual and estimated travel times into account when deciding on a transport mode. For these research purposes, we conducted a survey among 1321 citizens of Vienna (Austria). Respondents were asked about their use of digital mapping tools (in particular in the context of travel-related decisions). They were randomly assigned to one of two treatments: *Google Maps* and *Baseline*. In the former, they were asked if and to what extent they perceive Google Maps (the most widely used mobility app) as over- or underestimating travel times (for each transport mode separately); possibly due to the

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underlying algorithms employed by Google Maps (which, for instance, ignore the time required to find a parking space and other types of 'time overhead' Miotti and Hellweg, 2025) or their own speed choices (i.e., walking/cycling/driving relatively slow or fast, respectively). In the *Baseline* treatment, they were asked if they thought their own (mode-specific) travel times were faster or slower than objectively measured average travel times (here focusing on the role of their own speed choices).

Our survey also included a stated preference (SP) experiment in which we collected hypothetical travel mode choice data from all respondents. Such SP experiments are frequently used in transport studies to measure the preferences of individuals for specific trip attributes, with travel time and cost usually being the central ones. The trade-off between the time and money attribute can be expressed as monetary valuation of travel time savings, often abbreviated by "value of time" (see, for instance, the review by Wardman et al., 2016). The time valuations are a central element in transport economics, as time savings are generally a large component of the benefits associated with infrastructure improvements (Mackie et al., 2001). In the SP experiment conducted here, respondents assigned to the *GoogleMaps* treatment were told that the information on the (mode-specific) travel times originates from Google Maps, while respondents assigned to the *Baseline* treatment were told that the (mode-specific) travel times correspond to objectively measured average travel times. Using state-of-the-art discrete choice modeling approaches, we can determine whether respondents take the stated travel times "at face value", or whether they actually take into account any perceived deviation between real-life travel times and Google Maps'/average travel times in their mode choices.

This paper adds to the literature on the impact of information on travel behavior by expanding our understanding of how digital mapping tools influence travel behavior. Although a large number of such studies have been conducted (Mokhtarian and Tal, 2013), studies focusing on the impact of digital mapping tools, in particular on mode choices, are scarce (Sun et al., 2021). Even more specifically, our paper has an explicit focus on the potential role of perceived discrepancies between digital map-based and real-life travel times, and therefore also contributes to the earlier literature that focuses on how discrepancies between different sources of travel time estimates may affect travel behavior, and in turn the implied time valuations (e.g. Peer et al., 2013, 2014). Our study also adds to the existing literature on human–computer interaction in the context of digital maps (mostly in the form of apps), by offering insights into how users perceive them, use them, and mentally process the provided information. This research therefore aims at deepening our understanding of the interplay between digital mapping tools, user cognition, and travel mode decisions. (e.g. Verplanken et al., 1997; Peer et al., 2014; Angelaki et al., 2020; Wagner et al., 2021; Aoustin and Levinson, 2021). The earlier literature is summarized in more detail in Section 2.

The potential implications of this research extend beyond academia. When discrepancies between actual door-to-door travel times and those estimated by digital mapping tools are perceived to be present but are not taken into account when deciding between transport modes, suboptimal transport mode choices will result. The same is true if such discrepancies objectively exist (as some recent evidence by Link et al. 2023 (for public transport) and Wagner et al. 2021 (for car travel) suggests) but travelers are not aware of them. Subsequently, this research may also inform further improvements in digital mapping tools, for instance with respect to their accuracy and usability.

The remainder of this paper is structured as follows. Section 2 gives an overview of the related literature. Section 3 discusses the design of the study, in particular the survey and the empirical specifications used for analyzing the stated preference choices made by the respondents. Section 4 presents the descriptive results derived from the survey, and Section 5 presents the results of the choice models. Finally, Section 6 discusses the results obtained in this paper and concludes.

2. Literature

There is a large body of literature focused on the extent to which travelers take into account external information sources in their travel decisions. They generally find that travelers do take into account external information sources in their choices; however, especially in the context of mode choices, the impact of information is substantially limited by travel habits (Verplanken et al., 1997; Chorus et al., 2006; Havlíčková et al., 2020). Moreover, there seems to be a large extent of heterogeneity in the information needs of travelers, with demand for information often being relatively high for public transport usage and real-time information (Tang et al., 2022).

In spite of the high usage rates of digital mapping tools, in particular, since the advent of smartphones, studies focusing on how the information provided by such tools affects decisions are relatively rare (Sun et al., 2021).

This is particularly true for its impact on mode choices, while the context of route choices (e.g. Chen, 2013; Cornacchia et al., 2024) and travel patterns in general (e.g. Casquero et al., 2022) seems to be covered more thoroughly in the literature. Exceptions are the studies by Gan (2015) and Meng et al. (2018), who have an explicit focus on mode choices. Similar to our study, they mostly rely on stated preference data (in the case of Meng et al. (2018) also revealed preference data are used) to estimate the impact of travel information on mode choices (with both studies emphasizing the role of information on the use of multimodal alternatives). However, in contrast to our study, the provided information is not associated with a specific tool (such as Google Maps) but instead is generic. Even more importantly, unlike our study, they do not investigate the role of potential disparities between real-life travel times and those provided by the information source.

Among the few studies that do focus on such disparities, is Wagner et al. (2021) who study how predictions made by Google Maps influence users' perceptions and travel choices. To analyze this influence, a pre-study in a classroom setting (n = 36) as well as an online survey (n = 521) were conducted. They study users' intuitive perception of travel time, before using the Google Maps Mobile App as a 'treatment' to see how it influences their perceptions of travel time and choice of transport type. Then, they contrast this original Google Maps treatment to a mock-up 'warning label version' of Google which informs users about biases in Google Maps, and an 'unbiased version' of Google Maps based on ground truth data. They also indicate that Google Maps systematically underestimates travel times by car: car travel time estimates do not take into account the walk to the nearest street (unlike for the public transport alternative, that does consider access and egress walk times). In addition, the time needed to find a parking space is not included in the calculation of the travel time. Wagner et al. (2021) suggest that these underestimates have an impact on users' mode choices. While they go some way in teasing apart the complex ways in which human beings interpret geographic space, the study and its generalizability are quite limited, not at least because its sample consists only of students and university alumni (whereas our study relies on a large representative sample).

Also Aoustin and Levinson (2021) look at Google Maps and resulting travel time perceptions. They show that individuals estimate real-life travel times to be longer compared to those stated by Google Maps, especially for travel times by car.[1] Similar to our study, Aoustin and Levinson (2021) shed light on the divergence between real-life travel times and those provided by Google Maps; however, in contrast to our study, they do not attempt to link these to user behavior. A limitation (which the study of Aoustin and Levinson (2021) has in

[1] Interestingly, they also find that, with the exception of the car, the journey times for transport modes that respondents rarely use were reported as longer than the corresponding Google-Maps-based journey times. This is in line with earlier studies like Van Exel and Rietveld (2010) who find a similar pattern.

common with our study) is that it only accounts for reported travel times rather than observed travel times. Studies like Peer et al. (2014) have systematically documented that reported travel times may deviate substantially from actual (realized) travel times. More specifically, they detect a clear tendency for travelers to exaggerate their actual travel times when reporting them.

A recently published working paper (Link et al., 2023) avoids the drawback of relying on reported travel times by comparing travel time estimates produced by Google Maps (for public transport) and a local OpenRouteService (ORS) installation based on OpenStreetMaps (for car, walking, and cycling trips) with GPS traces, based on which actual travel times can be derived. This analysis is a 'byproduct' of their mode choice analysis in the context of the 9-Euro ticket introduction in Germany. They discuss the generation of choice sets consisting of the chosen and several unchosen transport mode alternatives, such that discrete choice models can be estimated. Link et al. (2023) find a major underestimation of travel time for car routes (by almost one-third when comparing mean durations) and a slight overestimation (around 4%) for public transport; in both cases the differences between estimated and observed travel times were higher for shorter trips. The authors attribute the bias in car travel times to the ORS not taking into account congestion, but are not sure how the overestimation in the case of public transport can be explained. Finally, they acknowledge that their research is not able to draw conclusions regarding the "extent to which travelers base their mode choice decision on such under- or overestimations" (Link et al., 2023, p.23) – a question that is at the center of our research presented in this paper.

Quattrone et al. (2015) connect the topic of travel behavior with the emergence of biases in crowd-sourced spatial datasets by investigating the differences between how power users and occasional users contribute to such datasets. However, the authors themselves acknowledge that they are not able to look more closely at how these biases influence user behavior. More broadly, there are several valuable contributions that focus on the relationship between travel behavior and the use of digital mapping tools (Qiao et al., 2016; Dastjerdi et al., 2019; Gupta and Sinha, 2022). For instance, Gupta and Sinha (2022) find that younger users with higher education, more smartphone experience, medium-to-high household income, and lower vehicle ownership had a very high probability of being classified as a multimodal traveler. Another strand of the literature examines the role of digital mapping tools in measuring travel behavior (Sun and Wandelt, 2021; Svaboe et al., 2023).

Finally, several papers focus on the comparison between various digital mapping tools. Trapsilawati et al. (2019) investigate users' trust and reliance on navigation systems, comparing Google Maps and Waze. The results of this study show that users have higher trust in Waze than in Google Maps, and Google Maps users changed their reliance on Google Maps to Waze upon experiencing Waze features. Wu (2019) conducted a comparative analysis of travel time data for Sydney, Australia, drawing from both Google Maps and Uber Movement, in order to assess their consistency. The findings reveal that travel times from Uber Movement on average tend to be lower than those provided by Google Maps. Ciepłuch et al. (2010) describe a comparison of the accuracy of OpenStreetMap for Ireland with Google Maps and Bing Maps. The authors find that while there is no clear "winner" amongst the three mapping platforms each shows individual differences and similarities for each of the case study locations.

Our study complements and expands the existing knowledge by placing itself at the intersection of the literature regarding the impact of information on mode choices, the literature that focuses on discrepancies between different travel time estimates (e.g., perceived vs. actual travel times) and their impact on time valuation (see for instance the review by Wardman et al., 2016), and the literature that concerns human–computer interaction, here in particular in the context of digital maps and even more precisely Google Maps. To our best knowledge it is the first paper that touches upon these three thematic areas at the same time. Our approach of using stated preference experiments and discrete choice modeling techniques is probably the most widely used method to analyze travel-related decision-making, including the potential role of discrepancies between different sources of travel times estimates (e.g., between actual and perceived travel times Peer et al. 2014 or between actual and approximated travel times Peer et al. 2013).

3. Data collection, experimental design, and modeling framework

3.1. Overview

The empirical analysis presented in this paper is based on survey data collected in Vienna (Austria) in November and December 2022.[2] The survey was conducted online and the data were collected by a panel provider, resulting in 1321 complete responses.[3] The main question blocks included in the survey concerned:

1. Socioeconomic characteristics
2. Travel behavior
3. Usage of digital mapping tools (in the context of travel)
4. Travel time perceptions
5. A stated preference (SP) mode choice experiment
6. Perceived quality and user-friendliness of Google Maps

Each respondent was (randomly) assigned to one of two different treatments. Question blocks (4) and (5) of the questionnaire differed depending on the treatment a respondent was assigned to, while all other parts were identical across treatments. The two treatments are defined as follows:

- **GoogleMaps**: In the *GoogleMaps* treatment, respondents are asked about the extent to which the travel times provided by Google Maps match their travel time expectations (question block 4). In the stated preference experiment (question block 5), they are informed that the stated travel times are based on Google Maps. We focus on Google Maps as an example of a digital mapping tool that already exists and is widely used in many regions world-wide.[4]
- **Baseline**: The *Baseline* treatment serves as a reference scenario. Here, in question block 4, respondents are asked to which extent their travel time expectations deviate from an accurately measured average travel time. Correspondingly, in the stated choice experiment (question block 5), respondents are told to imagine that the stated travel times are based on accurately measured door-to-door travel times. The *Baseline* treatment has been introduced for two main reasons: (1) to determine to what extent the findings derived in the *GoogleMaps* framing are specific to Google Maps, or whether they are also applicable to other mobility apps (even those unknown to respondents, such as the, in reality, nonexistent RoutePlanner app, which is mentioned to respondents as an information source in the mode choice experiment); and (2) whether any deviations between app-generated and reported real-life travel times are due to app-generated travel times being perceived as incorrect versus own travel speed choices being the primary cause for the deviations.

[2] The design of this study and the underlying survey have been informed by a pre-test conducted among 165 students of the Vienna University of Economics and Business Administration in summer 2022.

[3] Due to the use of a panel provider, we have no information on the response rate.

[4] For instance, in the United States, Google Maps is the most popular map application by a considerable margin (measured by the number of downloads) (Statista, 2023).

3.2. Deviations between real-life and Google Maps/average travel times

For each main mode of transport *m* (walking, cycling, public transport, car), participants were asked to report what – based their experience – their expected (door-to-door) travel time would be if the travel time either resulting from Google Maps (in the *GoogleMaps* treatment) or the (correctly measured) average travel time (in the *Baseline* treatment) was equal to **30 min** (which is a fairly usual trip duration in Vienna; in fact, the average trip length for Vienna is 28 min BMVIT, 2016). Specifically, they were asked the following questions (and were able to provide reasons behind their answers in open text fields):

GoogleMaps treatment: *Suppose you are shown travel times for different modes of transport from Google Maps for a route in Vienna. In your experience, how long do you actually take for this route?*

Baseline treatment: *Suppose you are shown average travel times for different means of transport for a route in Vienna. In your experience, how long do you actually need for this route?*

In further analyses, these reported (mode-specific) travel time expectations are denoted by TT_m^{EXP}. Throughout the manuscript, we usually refer to them as reported real-life travel times (sometimes abbreviated to reported travel times or real-life travel times). It is important to recognize that these expectations are not trip-specific but reflect a general (transport-mode-specific) expectation that real life travel times differ from those provided by Google Maps or from the average travel time. While for the latter, the main source of any perceived discrepancy is likely to result from own speed choices (that is, individuals perceiving themselves as walking/cycling/driving slower or faster than the average), for the former it is likely a mix of own speed choices as well as Google-Maps-specific biases (e.g., induced by the underlying algorithms).

3.3. Stated preference experiment

3.3.1. Design

We set up a simple (labeled) stated preference (SP) experiment in which respondents were asked to decide between four different transport modes *m*: walking, cycling, public transport, and car (see Fig. 3 in the Appendix for a screenshot of the experiment). The transport modes differ in terms of travel times and costs. Respondents were shown eight of these hypothetical choice situations. The setup of the choice experiment was deliberately chosen to be simple, in order to focus on the role of travel times and corresponding perceptions rather than on other potentially relevant attributes like scheduling or crowding. The cost attribute was included in order to be able to derive monetary valuations of travel time. Besides travel habits, costs and travel time tend to be the main variables that explain mode choices (Wardman et al., 2016). We do not personalize the design of the survey (by varying the cost and time attribute around some reference trips); instead, we choose attribute values that are realistic for a large number of trips within the city of Vienna (according to the most recent mobility survey available for Austria BMVIT, 2016, 87.2% of trips within Vienna last less or equal to 45 min)[5]:

Travel time attribute (TT_m^{SP}): The travel time attribute is described as resulting from Google Maps (in the *GoogleMaps* treatment) or to represent accurate average travel estimates based on the (hypothetical) Routeplanner app (in the *Baseline* treatment). It can assume the following values: 10, 15, 20, 30, or 45 min. We have chosen 45 min as the maximum, as the active travel mode options (cycling, walking) tend to have fairly low relevance above that threshold (an average walking trip in Vienna lasts around 17 min and an average cycling trip 19 min BMVIT, 2016). Finally, to avoid unreasonable attribute combinations, we constrain the walk alternative to always be slower than the bike alternative (while we do allow for active modes to be faster than public transport or car, which can be the case in dense urban settings).

Cost attribute ($Cost_m^{SP}$): The cost attribute (only relevant for the public transport and car alternatives) can amount to 1, 2, 3, or 4 Euro[6]. Again, to ensure a realistic presentation, the cost attribute is set to 0 for the walking and cycling alternatives, respectively. The stated prices represent fairly realistic values for a car trip within Vienna (especially when including parking costs or when having to rent a car). The prices also cover a realistic range for public transport trips, which in reality amount to 2.40 Euros for trips within Vienna.

The experimental design was derived using the software NGENE.[7] The design consists of 12 blocks including 8 choice situations each. It is identical across the two treatments, with each respondent being randomly assigned one of the 12 blocks. The design was optimized using the widely employed D-error efficiency criterion (Rose and Bliemer, 2007), which minimizes the determinant of the asymptotic variance–covariance matrix resulting from estimating a model using prior information on parameter estimates. In our case, we use prior information on the parameters from a recent time valuation study conducted in Austria (Schmid et al., 2019), specifying a simple multinominal logit (MNL) model with alternative-specific constants (capturing intrinsic preferences/habits regarding specific modes), (mode-specific) travel time coefficients, and a cost coefficient.

3.3.2. Framing

Participants were told to imagine that they were about to leave home at 11 AM on a weekday to conduct a trip within the city of Vienna and that they check their smartphone app shortly before departure to find out the travel times (and costs) associated with the four main transport modes (the trip hence corresponds to a non-urgent trip during a weekday). In the *GoogleMaps* treatment, the app corresponds to Google Maps, and in the *Baseline* treatment, it corresponds to the so-called RoutePlanner app.

This is explained to be a hypothetical application developed by Viennese scientists that indicates objective door-to-door travel times, which are based on accurate measurements made by Viennese scientists. In the *Baseline* treatment, respondents might perceive the travel times stated in the SP as biased mainly because of their own speed choices, while in the *GoogleMaps* treatment both own speed choices as well as the perception that Google Maps provides biased travel time estimates (for a specific transport mode) may play a role.

[5] While personalized SP designs (e.g., by pivoting the attribute levels around a reference trip) have the advantage that they are more realistic to respondents, they may have substantial downsides in the context of our study: First, our focus was not on trips that respondents are already fairly familiar with, as in these cases mobility apps are probably less relevant and moreover, for such trips mode choices are often to a large extent determined by habits. This would have rendered the definition of an appropriate reference trip difficult. Second, even if we had tried to gather information on a trip that a respondent is only vaguely familiar with, we might have obtained considerable heterogeneity in terms of past mode choice and app usage habits on that trip that we would have to control for. Finally, there is little evidence that personalized SP designs reduce hypothetical biases (Hultkrantz and Savsin, 2018).

[6] A one-way ticket for public transport in Vienna costs €2.40, based on the City of Vienna's pricing. The cost of car usage for a 10 min trip is derived from calculations by ADAC (2024) in Germany, adjusted for the distribution of cars by model to estimate a fleet-representative average of €0.5017 per kilometer. A study by Kalinowska and Steininger (2009) includes data from Austria and Germany, drawing on surveys of Austrian, German, and broader European research. This study evaluates road infrastructure costs and incorporates external average and marginal social cost calculations, applying consistent cost estimates for both countries.

[7] NGENE: https://choice-metrics.com/.

3.4. Discrete choice model

3.4.1. Model specifications

For the analysis of the choice data generated from the stated preference experiment, we estimate four different multiple discrete choice models, which are described in more detail below. While Model 1 simply represents the trade-off between travel time and costs, Models 2, 3, and 4 additionally test whether respondents take into account their reported deviations between real-life and Google-Maps-based/average travel times when making their mode choices. In all models, we adopt additive utility functions. Moreover, we estimate all models in willingness-to-pay (WTP) space, with the WTP corresponding to the ratio of the travel time and the cost coefficient (Train and Weeks, 2005). Compared to a separate estimation of the time and cost coefficients, this approach has the advantage that the WTP for travel time savings (i.e. the value of (travel) time) can be estimated directly, hence avoiding the ex-post division of the coefficients, which can – especially in the context of random coefficients (as in the mixed logit case) – lead to implausible time valuation estimates (Daly et al., 2012). Three of the four models (1,2,4) are estimated as standard multinomial logit (MNL) models, whereas Model 3 is estimated as a mixed logit model (with random coefficients).

Model 1: Standard MNL model

The first model that we estimate is a standard MNL model with alternative-specific constants (α_m), cost coefficient (β^{cost}), and the mode-specific travel time valuations (VOT_m). The alternative (mode-)specific utility function can thus be written as follows (omitting subscripts for individuals $n \in \{1,\dots,N\}$ and choice situations $t \in \{1,\dots,8\}$ for simplicity):

$$U_m = \alpha_m + \beta^{cost} * (Cost_m^{SP} + VOT_m * TT_m^{SP}) \tag{1}$$

Model 2: MNL model accounting for misperceptions

The second model extends the first model by adding a term that captures whether respondents react to the deviations they reported between a Google-Maps-based/average travel time (of 30 min) and the travel time they would expect based on their own experience (TT^{EXP}). The additional term contains the travel time attribute TT_m^{SP} multiplied by (TT^{EXP}/30-1), implying that the term becomes 0 if TT^{EXP} equals 30 min (and hence no perceived deviation is present). The VOT_m^{dev} captures the time valuations attached to deviations: if VOT_m^{dev} is not significantly different from 0, we can conclude that perceived deviations between real-life travel times and Google Maps/average travel times are not taken into account when deciding between transport modes; on the contrary, if the VOT_m^{dev} is similar in size to the VOT_m, we can conclude that the perceived travel time deviation are fully considered when choosing between transport modes. Similar specifications have been used in earlier studies by Peer et al. (2013,?), who study the impact of deviations between actual and approximated, and actual and reported, respectively, on travel-related choices.

Further, we also define $\mathbf{1}^{Google}$, which equals 1 if an individual is in the *GoogleMaps* treatment, and 0 otherwise. β_m^{Google} then captures any potential difference in the VOT_m^{dev} between the two treatments.

$$U_m = \alpha_m + \beta^{cost} * (Cost_m^{SP} + VOT_m * TT_m^{SP} + VOT_m^{dev} * (1 + \mathbf{1}^{Google} * \beta_m^{Google}) * (\frac{TT^{EXP}}{30} - 1) * TT_m^{SP}) \tag{2}$$

Model 3: MXL model accounting for mis-perceptions

Next, we re-estimate Model 2 as a mixed logit (MXL) model. The mixed logit model is specified such that we estimate the cost and the time coefficients as random coefficients (indicated by $\tilde{\beta}^{cost}, V\tilde{O}T_m$, $V\tilde{O}T^{dev}$ in Eq. (3)). Besides that, the only difference between Models 2 and 3 is that the latter does not any longer contain the term that captures differences between the two treatments $(1 + \mathbf{1}^{Google} * \beta_m^{Google})$ as the estimation results of Model 2 suggest that no such differences exist:

$$U_m = \alpha_m + \tilde{\beta}^{cost} * (Cost_m^{SP} + V\tilde{O}T_m * TT_m^{SP} + V\tilde{O}T_m^{dev} * (\frac{TT^{EXP}}{30} - 1) * TT_m^{SP}) \tag{3}$$

More specifically, as positive values of β^{cost} and negative values of the VOT (and VOT^{dev}) would be unreasonable, we assume a log-normal distribution[8] of the random coefficients for both:

$$\tilde{\beta}_n^{cost} = -\exp(\beta^{cost} + \sigma_{cost} \cdot \eta_n^{cost}), \quad \text{with } \eta_n^{cost} \sim N(0,1) \tag{4}$$

$$V\tilde{O}T_{m,n} = \exp(VOT_m + \sigma_{VOT,m} \cdot \eta_{m,n}^{vot}), \quad \text{with } \eta_{m,n}^{vot} \sim N(0,1) \tag{5}$$

$$V\tilde{O}T_{m,n}^{dev} = \exp(VOT_m^{dev} + \sigma_{VOT,m}^{dev} \cdot \eta_{m,n}^{dev}), \quad \text{with } \eta_{m,n}^{dev} \sim N(0,1) \tag{6}$$

Model 3 (as all other 3 models) does not account for interactions with socio-economic variables. Several variables (income, age, gender, education) have been interacted with the cost and the time coefficients (including (VOT_m^{dev}) both in the MNL and MXL specifications, but mostly turned out to be insignificant. We have therefore decided to not include them in the final specification. Instead, we conduct an analysis of the posterior distribution of the $V\tilde{O}T_m^{dev+}$ to determine to which extent they are related to person-specific characteristics (see Section 5.1).

Model 4: MNL accounting for mis-perceptions separately for under- and over-estimations

Finally, we estimate an MNL model in which separate VOT_m^{dev} coefficients are estimated for when one expects the real-life travel time to last *longer* than the 30 min associated with Google Maps or average travel times (VOT_m^{dev+}) and when one expects them to last *shorter* than 30 min (VOT_m^{dev-}). This model can hence shed light on whether differences in valuations exist depending on whether one expects the travel time to be longer or shorter than the 30 min threshold.

$$U_m = \alpha_m + \beta^{cost} * (Cost_m^{SP} + VOT_m * TT_m^{SP} + (VOT_m^{dev+} * \max[\frac{TT^{EXP}}{30} - 1, 1] + VOT_m^{dev-} * \min[\frac{TT^{EXP}}{30} - 1, 1]) * TT_m^{SP}) \tag{7}$$

We have also tried to estimate this specification using a mixed logit model setup resembling that of Model 3, however, the coefficients were not entirely stable even with a large number of draws (>2000), most likely due to the high number of random coefficients (13 instead of 9) and several of them VOT_m^{dev} coefficients being close to 0. We, therefore, do not present the corresponding model results here.

3.4.2. Model estimation

All models were estimated using the R-package Apollo.[9] For the Mixed Logit Model, we use Modified Latin Hypercube Sampling (MLHS) as proposed by Hess et al. (2006) to generate the draws. We present here the results for R = 2500; however, the coefficients were already stable at a substantially lower number of draws (around R = 500). The Eicker-Huber-White sandwich estimator is used to calculate the standard errors, thereby also accounting for the panel structure of the dataset.

4. Descriptive results

4.1. Sample characteristics

The sample characteristics are summarized in Table 1, which shows descriptive statistics for the entire sample, as well as separately for the two treatment options (*GoogleMaps* and *Baseline*). As expected (due to the random assignment to the two treatments), we do not observe any statistically significant differences in the socio-economic and mobility-related characteristics of the two sub-groups.

[8] Also normal distributions were tested but the resulting models performed worse in terms of coefficient stability and model fit.

[9] Apollo: http://www.apollochoicemodelling.com/.

Table 1
Descriptive statistics of selected variables included in the survey.

Characteristic	Unit	Overall	Google	Science	p-value	*Pop.*
		N = 1321	*N = 644*	*N = 677*		
Socioeconomic variables						
Age	years	44.33	44.12	44.53	0.7	41
Gender: male	%	47.39%	47.20%	47.56%	>0.9	49%
Household net income (per month)					0.8	
0–1999 Euro	%	25.89%	25.47%	26.29%		
≥2000 Euro	%	58.14%	59.01%	57.31%		
unknown	%	15.97%	15.53%	16.40%		
Education: high school or higher	%	70.02%	72.20%	67.95%	0.10	79%
Children: ≥1	%	17.03%	19.10%	15.07%	0.061	
People in household: ≥4	%	15.75%	16.61%	14.92%	0.4	14%
Reside in outer districts of Vienna	%	78.35%	78.11%	78.58%	0.9	74%
Reside in Vienna since less than 6 years	%	5.83%	4.66%	6.94%	0.10	
Regularly used transport modes (>once/week)						
Walking	%	74.94%	75.16%	74.74%	>0.9	
Cycling	%	13.10%	14.29%	11.96%	0.2	
Public transport	%	70.02%	71.43%	68.69%	0.3	
Car	%	43.07%	41.77%	44.31%	0.4	
App usage						
Regular use of Google Maps	%	78.58%	78.42%	78.73%	>0.9	
Regular use of Wien Mobil	%	46.63%	47.36%	45.94%	0.6	
Regular use of Wiener Linien website	%	30.43%	30.43%	30.43%	>0.9	
Regular use of Apple Maps	%	20.59%	20.34%	20.83%	0.9	
Never uses Google Maps	%	10.83%	9.94%	11.67%	0.4	
Travel decisions with app usage	%	40.06	40.04	40.08	>0.9	
Expected travel time for 30-min.-baseline (TT_m^{EXP})						
Walking	min.	31.82	30.57	33.00	<0.001	
Cycling	min.	31.43	31.17	31.68	0.2	
Public transport	min.	33.86	33.20	34.49	0.003	
Car	min.	32.16	32.23	32.10	0.8	
Variables related to SP experiment						
SP decisions were based on:					0.2	
Comparing attributes	%	67.30%	69.72%	64.99%		
Predetermined preferences	%	16.20%	15.68%	16.69%		
Randomly	%	6.13%	4.81%	7.39%		
Other	%	10.37%	9.78%	10.93%		
Treatment was taken into account	%	68.89%	68.94%	68.83%	>0.9	

Mean; %
Welch Two Sample t-test; Pearson's Chi-squared test
The final column ('Pop.') includes corresponding values for the entire population of Vienna (all for 2022) based on official Viennese population statistics: https://www.wien.gv.at/statistik/bevoelkerung/.

Our sample is largely representative of the Viennese population, as indicated by the corresponding population statistics in Table 1 (however, it should be noted that our survey only focuses on adults, whereas the population statistics comprise the entire population). One exception is that older people seem to be under-represented in the survey: while 24.2% of the adult Viennese population is older than 65 years (Statistics Austria, 2023b), only 12.2% of our respondents are above 65 years. A likely reason is the lower digitization rate among the older population[10]: older persons might be less inclined to fill in online surveys, and also might be less familiar with (and interested in) digital mapping tools (i.e. the central theme of the survey).

Also in terms of the regularly chosen travel modes, our sample seems to be fairly representative of the Viennese population. A majority of respondents (75%) regularly walk and use public transport (70%). 43% of respondents regularly drive a car, whereas only 13% cycle regularly. The latter result is in line with official modal split statistics for Vienna (e.g., in 2022, cycling had a modal split of 9% Wiener Linien, 2023), which however are measured at the trip level and are hence not entirely comparable.

4.2. Usage of mobility apps and evaluation of google maps

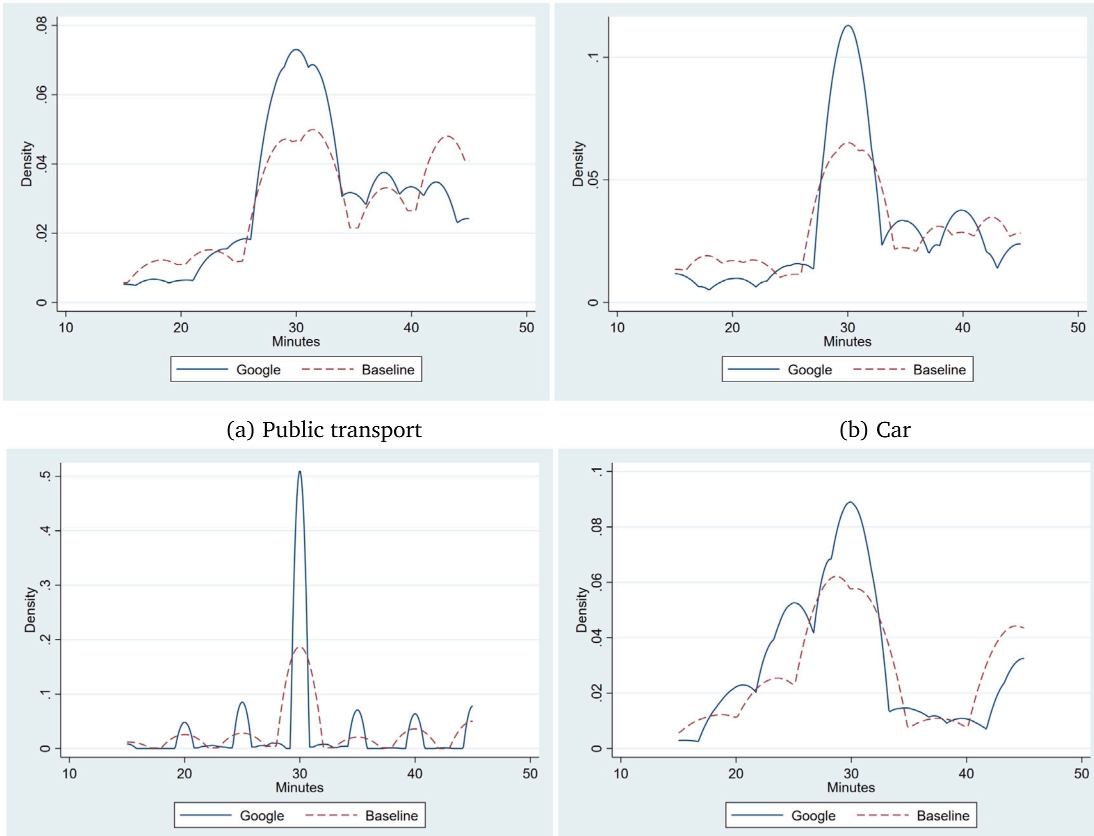
A large share of respondents indicates that they regularly use digital mapping tools (mobility apps). Only 4.6% of respondents report that they never use one for any of their travel decisions. Fig. 2 in the appendix shows the distribution of the share of travel decisions for which respondents state to use a digital mapping tool.

The digital mapping tool most commonly used in the context of travel-related decision-making in Vienna is *Google Maps* (regularly used by almost 80% of respondents, and never used by only 10%), followed with some margin by the local app *Wien Mobil* (regularly used by 47%), and the website of the local public transport provider *Wiener Linien*, which 30% of respondents use regularly. *Apple Maps* is used regularly by about 20% of respondents, whereas only a very small share of respondents make regular use of alternative software options such as *Wegfinder, Transportr, OpenStreetMaps*.

Our study design is in line with the widespread usage of Google Maps,[11] as we also emphasize Google Maps; not only does one of the two treatments focus on Google Maps; additionally, we also included a question block in the survey, in which participants were asked to

[10] A representative survey by Statistics Austria shows that only 70 percent of Austrians aged 65–74 have used the internet in the three months leading up to the survey in 2022 (Statistics Austria, 2023a).

[11] An exploratory pre-study among students of the Vienna University of Economics and Business (Austria) showed that Google Maps was by far the most widely used mobility information service. Based on that, we felt confident to focus on Google Maps also in the main (representative) survey.



(a) Public transport

(b) Car

(c) Bike

(d) Walk

Fig. 1. Kernel density distributions of the reported travel times (TT_m^{EXP}) for all four transport modes and the *Google* and *Baseline* treatments.

rate Google Maps on various aspects using a Likert scale ranging from "totally disagree" (1) to "completely agree" (7). In line with the relevant literature (Quattrone et al., 2015; Ohm et al., 2016; Schöning et al., 2014; Link et al., 2023; Wagner et al., 2021), the statements cover various aspects, including (1) trust in the accuracy and reliability of Google Maps, (2) the perceived risk associated with relying on Google Maps for navigation, (3) the perceived usefulness of Google Maps in assisting with their travel and navigation needs, (4) the perceived ease and user-friendliness of Google Maps, and finally (5) the inclination to use Google Maps in the future. All of these aspects were covered by multiple question items (see Table 4 in the Appendix).

As indicated by the results presented in Table 4, Google Maps is overall evaluated quite positively in terms of perceived usefulness and perceived ease of use, with most question items having a mean value of 5 to 6 on the 1–7 scale, with the upper endpoint indicating higher agreement with the provided statements. We find that generally, the behavioral intention to use Google Maps in the future is high with averages between 5.3 and 5.5. Trust in Google Maps (as well as in Google overall) is ranked somewhat lower with averages between 4 and 5.1. A result also relevant for the next subsection (regarding deviations between app-provided and real-life travel times) concerns the perceived risk of arriving too early or too late at the destination when using Google Maps. Both risks are evaluated as relatively low, with the agreement of the underlying statements amounting to 3.08 for arriving too early, and 2.93 for arriving too late. Finally, we conduct an exploratory factor analysis and extract the resulting composite score for each variable category. These will be used as explanatory variables in some of the analyses presented below.

4.3. Deviations between real-life and google maps/average travel times

Here, we discuss the findings related to the questions discussed in Section 3.2, i.e. the perceived deviation of reported real-life travel times (TT_m^{EXP}) from the information provided by Google Maps (in the *GoogleMaps* treatment) and from average travel times (in the *Baseline* treatment). Respondents were not obliged to answer this question (the main reason being that not all respondents can be expected to be familiar with all types of modes); nevertheless, the overall response rate for this question amounted to 85% (out of 5284 ($= 1321 * 4$) possible answers, 4488 were provided).[12]

In order not to lose any observations in further analyses, we make two adjustments to the data. First, we assume that in the case of respondents who did not provide an answer, the expected real-life travel time equals 30 min (i.e. the reference travel time mentioned in both treatments and for all transport modes). Second, we also observed that some respondents stated unrealistically long or short travel times. In order to avoid excluding these observations, we introduce bounds

[12] For the two treatments separately, we find similar response rates of 83% for the *GoogleMaps* treatment and 86% for the *Baseline* treatment.

at 15 and 45 min: everyone reporting a real-life travel time less than 15 min (above 45 min) is assigned the value of 15 (45) min.

The resulting distributions of real-life travel times reported by the respondents are presented in Fig. 1 (separately for each of the four transport modes and the two treatments).

All distributions are fairly symmetric around the mean, with public transport being the most clearly left-skewed distribution (for both treatments). The means of the distributions (which are also reported in Table 1), are somewhat higher than 30 min (ranging from 30.6 to 34.5 min) for all transport modes and both treatments. On average, respondents thus believe that real-life travel times tend to be longer compared to those foreseen by Google Maps (in the *GoogleMaps* treatment) as well as compared to average travel times (in the *Baseline* treatment). The differences in the averages between the two treatments are small (only for walking and public transport, TT_m^{EXP} is significantly smaller for the *Baseline* treatment). However, we can observe from Fig. 1 that there are substantially more observations with an exact travel time of 30 min for respondents in the *GoogleMaps* treatment compared to those in the *Baseline* treatment for all transport modes. This is quite surprising given that the *Baseline* treatment was meant to represent unbiased travel times. Moreover, all distributions exhibit a pattern commonly observed for reported time distributions: respondents have a tendency to provide travel times that are rounded to the nearest 0 or 5 min value. Overall, the fact that the two treatment yield very similar distributions seems to suggest that travelers mainly think about their own speed choices as reason for any deviations of the TT_m^{EXP} from the 30 min baseline. The limited differences between the treatments are inconsistent with a substantial role of biases induced by the algorithms employed by Google Maps.

Finally, also heterogeneity in the answers is quite high for both treatments and all transport modes. The deviations reported by respondents, as documented in open-text fields, encompass a wide spectrum of reasons. These include individual variances in waiting times and transfer durations due to personal physical conditions, unforeseen operational disruptions within public transport systems, and broader external factors such as traffic congestion, roadworks affecting car travel, encountering red traffic lights while cycling, individual physical limitations, and deliberate preference for a leisurely walking pace.

To get a more systematic picture of what drives these stated deviations from the Google Maps/average travel times, we estimate separate Ordinary Least Square (OLS) models for all four transport modes as well as the two treatments. In these models, the dependent variable equals the real-life travel time reported by respondents (TT_m^{EXP}),[13] with socio-economic and mobility-related variables as well as the variables representing evaluations of Google Maps (see Table 4) serving as explanatory variables. The results of these eight regression models are shown in Table 5. Their explanatory power is, however, fairly modest, with the R-squared adjusted ranging from 0.005 to 0.09. Especially for walking, cycling (*GoogleMaps* treatment only), and car, we find that participants tend to state longer travel times for the transport modes that they regularly use. Also, older respondents tend to state longer travel times, especially for walking and public transport. Conversely, male respondents tend to state shorter travel times for all transport modes. Having a higher education tends to be associated with longer reported real-life travel times. The same is true for respondents living in more peripheral districts of Vienna. Those, who frequently use mobility apps report on average report shorter travel times. Finally, the evaluations of Google Maps can only explain a small share of the variation in the dependent variable: the perceived ease of using Google Maps is associated with lower reported (real-life) travel times for most modes (except car), while the behavioral intention of using Google Maps in the future is associated with longer reported (real-life) travel times (especially in the *Baseline* treatment).

5. Choice modeling results

In this section, we present the choice modeling results of the models outlined in Section 3.4. To estimate the coefficients more precisely, we exclude those respondents who have indicated that they had made their choices in the stated preference experiment randomly (6.1%) or based on pre-determined preferences for specific modes (without considering the attributes) (16.2%) (see bottom of Table 1).[14] The resulting sub-sample consists of 1026 individuals (and 1026*8=8202 choice situations). Their distribution of choices over the 4 mode choice alternatives is fairly balanced: 29.9% choose walking, 15.4% cycling, 31.4% public transport, and 23.3% choose the car.

Table 2 shows the estimation results for the four models. Across all models, we obtain realistic estimates of the time valuations. In the three MNL models, we find values of 23–24 Euro/h for walking, 16–19 Euro/h for cycling, 11–12 Euro/h for public transport, and 10 Euro/h for car.[15] Similar to that study, in our case, the valuations derived from the mixed logit model (Model 3) are significantly higher. The much higher Rho-square (adj.) of Model 3 shows there is substantial unobserved heterogeneity present across respondents (the corresponding model without random coefficient yields a Rho-square (adj.) of 0.21 as compared to 0.37 for Model 3) . Moreover, by comparing the results of Model 2 and 4 to those of Model 1 (which does not account for any deviations between reported real-life and Google-Maps-based/average travel times), we can observe that the time valuations are not much affected by whether we add the additional term capturing a possible deviation between real-life and Google-Maps/average travel times.

Regarding the VOT^{dev} coefficients, we find that they are significantly different from 0 ($p \leq 0.05$) for public transport and car in Model 2 and for bike and car in Model 3 (the MXL specification) (note that the term capturing the VOT^{dev} is missing in Model 1, whereas Model 4 contains VOT^{dev+} and VOT^{dev-}, the results of which will be discussed below). These findings provide some (albeit not fully consistent) evidence that for these modes, respondents react to the travel times shown in the stated preference (SP) experiment (TT_m^{SP}) by adjusting them by their own travel time expectations (captured by TT_m^{EXP}). However, the extent to which they do so is limited, as all VOT_m^{dev} estimates that are significantly different from 0 are much smaller in size than the corresponding time valuations (VOT_m), implying that – on average – these deviations are not accounted for to the same extent as the travel times stated in the SP experiment. Finally, Model 2 also shows that

13 We have also run the OLS models with the dependent variable being equal to the absolute deviation from the 30 min baseline, as it can be expected that especially the psychometric variables like trust/risk/etc. are more closely associated with the deviation rather than the absolute times stated by respondents; however, the signs and sizes of those psychometric variables that are statistically significant were not different from the results presented here.

14 While excluding those who choose randomly is fairly undisputed and common, there can be reasons to keep non-trading respondents in the sample (as their behavior is can still be considered to be the result of utility maximization; see for instance Hess et al. 2010). In our case, however, the main aim was to estimate the VOT_m and VOT_m^{dev} as accurately as possible; including respondents who say they have not considered the attributes would run counter to this aim. Re-running the model with the entire set of observations, shows that the Rho-square (adj.) drops substantially for Models 1, 2, and 4, while it remains roughly constant for Model 3.

15 These values are somewhat different from the results of a recent time valuation study conducted in Austria, which finds (population-weighted) time valuations for walking of 10 Euro/h, for cycling of 12 Euro/h, for public transport of 8 Euro/h, and for car of 12 Euro/h (Schmid et al., 2019), even though they are of a similar magnitude. Given that the study of Schmid et al. (2019) includes also revealed preference data, makes use a fairly different SP design, and has been conducted in Austria as a whole (as opposed to Vienna only) it is unsurprising to find differences in the resulting time valuations.

Table 2
Choice modeling results (t-statistics in brackets)

	Model 1		Model 2		Model 3		Model 4	
	Coef.	*t-stat.*	*Coef.*	*t-stat.*	*Coef.*	*t-stat.*	*Coef.*	*t-stat.*
α_{walk}	1.54***	(12.25)	1.54***	(12.22)	2.61***	(8.83)	1.54***	(12.25)
α_{bike}	−0.69***	(−5.7)	−0.69***	(−5.66)	0.54**	(2.23)	−0.66***	(−5.33)
α_{public}	0.54***	(6.63)	0.54***	(6.62)	0.61***	(4.12)	0.54***	(6.59)
VOT_{walk}	23.13***	(16.68)	23.14***	(16.55)	31.65***	(12.51)	23.79***	(16.22)
VOT_{bike}	16.49***	(15.59)	16.36***	(15.53)	53.09***	(11.87)	18.68***	(14.06)
VOT_{public}	11.77***	(18.53)	11.31***	(17.96)	16.27***	(13.58)	11.84***	(16.48)
VOT_{car}	10.47***	(18.25)	10.25***	(17.95)	18.98***	(15.01)	10.33***	(15.87)
β^{cost}	−0.34***	(−18.8)	−0.34***	(−18.78)	−0.56***	(−14.49)	−0.34***	(−18.78)
VOT^{dev}_{walk}			0.32	(0.21)	0.76	(1.01)	−1.64	(−0.87)
VOT^{dev}_{bike}			5.35	(1.62)	8.08*	(2.75)	−5.53**	(−2.07)
VOT^{dev}_{public}			3.24**	(2.34)	1.15	(0.99)	1.66	(1.03)
VOT^{dev}_{car}			3.43**	(2.29)	2.48***	(2.92)	2.97	(1.57)
VOT^{dev+}_{walk}							−1.64	(−0.87)
VOT^{dev+}_{bike}							−5.53**	(−2.07)
VOT^{dev+}_{public}							1.66	(1.03)
VOT^{dev+}_{car}							2.97	(1.57)
VOT^{dev-}_{walk}							6.44***	(2.33)
VOT^{dev-}_{bike}							20.71***	(5.18)
VOT^{dev-}_{public}							8.25***	(3.09)
VOT^{dev-}_{car}							4.71**	(2.02)
β^{Google}_{walk}			3.29	(1.13)				
β^{Google}_{bike}			−0.17	(−0.04)				
β^{Google}_{public}			1.45	(0.67)				
β^{Google}_{car}			−0.18	(−0.08)				
$\sigma_{VOT,walk}$					0.26***	(11.72)		
$\sigma_{VOT,bike}$					0.93***	(20.08)		
$\sigma_{VOT,public}$					−0.64**	(−17.46)		
$\sigma_{VOT,car}$					1.1**	(24.89)		
σ_{cost}					0.63***	(12.91)		
$\sigma^{dev}_{VOT,walk}$					2.22***	(4.71)		
$\sigma^{dev}_{VOT,walk}$					0.05	(0.11)		
$\sigma^{dev}_{VOT,walk}$					−1.89***	(−2.83)		
$\sigma^{dev}_{VOT,walk}$					1.28***	(12.5)		
Nr. of Indiv.	1026		1026		1026		1026	
Nr. of choices	8202		8202		8202		8202	
Model type	MNL		MNL		MXL		MNL	
Nr. of coef.	8		16		21		16	
LL(final)	−8991.82		−8956.23		−6986.53		−8920.4	
Adj.Rho-square	0.189		0.192		0.367		0.195	

$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$
Note 1: Standard errors in brackets
Note 2: The adj. Rho-square is calculated for the observed modal split (rather than equal shares). The LL of a model accounting only for the alternative-specific constants (α) is equal to -11096.79.

these findings do not significantly differ between the *GoogleMaps* and the *Baseline* framing.

Model 4 shows that a potential reason for the differences across modes VOT^{dev}_{m} coefficients might be due to the extent of over- vs. underestimation inherent in the modes (see Fig. 1). All the VOT^{dev-}_{m} estimates are significantly different from 0 at the 5% level, whereas among the VOT^{dev+}_{m} estimates, only the VOT^{dev+}_{walk} has a t-statistic larger than 1.96 (2.07). This provides an indication that respondents predominantly consider those travel times and modes in their choices, for which they expect the real-life travel to be *shorter* than the Google-Maps-based/average travel time.

5.1. Analysis of the heterogeneity in VOT^{dev}_{m}

Model 3 shows that a substantial amount of heterogeneity exists in the estimated VOT^{dev}_{m}, which we intend to explore further in this section. For this purpose, we derive individual-specific estimates for the VOT^{dev}_{m} and the VOT_{m} by estimating their most likely value, given the choices observed for that individual (conditionals): for each individual, posterior model parameter distributions are simulated (again using R = 2500 draws), with their mean corresponding to the most likely (individual-specific) value for the VOT^{dev}_{m} and the VOT_{m} (see Train 2009; Chapter 11).

We then use the individual-specific values for the VOT^{dev}_{m} as the dependent variable in 8 regressions (one for each combination of treatment type and transport mode). For consistency reasons, we only include those respondents who report a deviation from the 30 min baseline in the regressions,[16] as for those who do not report such a deviation the VOT^{dev}_{m} carries little meaning. In terms of explanatory variables, we include the person-specific posterior estimates of the VOT_{m}, as well as various other socio-economic, mobility-related, and Google-Maps-related variables (see Table 3).

As shown in Table 3, we find in almost all models that – not surprisingly – there is a positive correlation between the individual-specific conditionals of the VOT^{dev}_{m} and the VOT_{m}. Reporting a higher real-life travel time ($TT^{EXP}_{m}/30$), however, is only associated with a higher VOT^{dev}_{m} for the case of walking. Socio-economic variables seem to matter little; we dropped most of them from the final specification as none of the corresponding coefficients was significantly different from 0. In contrast, various indicators for how Google Maps is perceived (see Table 4 for the variable definitions; here we use the scores from the exploratory factor analysis as explanatory variables) seem to be

[16] Moreover, we exclude overall 12 outliers with a VOT^{dev}_{m} amounting to more than 100 Euro/hour.

Table 3
OLS regression results: explaining variation in the VOT_m^{dev} coefficients (based on conditionals)

	Dependent variable: VOT_m^{dev}							
	Walking		Cycling		Public transport		Car	
	Google	Baseline	Google	Baseline	Google	Baseline	Google	Baseline
VOT_m	0.56***	0.76***	0.0000	0.0001**	0.36***	0.23***	0.02***	0.01***
	(0.11)	(0.11)	(0.0001)	(0.0001)	(0.05)	(0.04)	(0.01)	(0.005)
$TT_m^{EXP}/30$	6.56***	3.14**	0.004	−0.003	−0.07	−0.83	−0.19	0.03
	(1.67)	(1.24)	(0.01)	(0.01)	(1.65)	(1.20)	(0.43)	(0.33)
Socio-economic variables								
Age (in years)	0.01	0.04	0.0001	0.0003*	0.06**	0.03	−0.02**	−0.01
	(0.03)	(0.03)	(0.0002)	(0.0002)	(0.03)	(0.02)	(0.01)	(0.01)
Gender: male	−2.16**	0.72	−0.01	−0.0001	−1.63**	−0.15	0.37	−0.35
	(0.95)	(0.88)	(0.005)	(0.005)	(0.83)	(0.72)	(0.24)	(0.23)
Perceptions of Google Maps								
Perceived risk	0.01	0.13	−0.003	0.003	−1.27**	1.75***	0.32**	−0.11
	(0.67)	(0.57)	(0.003)	(0.003)	(0.58)	(0.46)	(0.16)	(0.15)
Perceived easy of use	−1.48	1.15	−0.01**	−0.0003	−0.14	0.53	−0.75***	0.10
	(1.01)	(0.92)	(0.01)	(0.005)	(0.90)	(0.74)	(0.25)	(0.24)
Perceived usefulness	2.30**	−0.34	0.01***	0.003	0.27	0.80	0.78***	−0.29
	(1.04)	(1.00)	(0.01)	(0.01)	(0.90)	(0.80)	(0.25)	(0.25)
Regularly used modes (>1/week)								
Walking	0.33	−4.75***						
	(1.30)	(1.15)						
Cycling			0.0003	0.02**				
			(0.01)	(0.01)				
Public transport					−3.42***	−1.55*		
					(1.02)	(0.88)		
Car							0.06	−0.18
							(0.26)	(0.25)
Constant	−18.02***	−20.11***	8.08***	8.07***	0.63	2.79	5.78***	5.51***
Observations	331	340	238	267	336	376	305	357
R^2	0.16	0.22	0.06	0.05	0.26	0.15	0.13	0.06
Adjusted R^2	0.14	0.20	0.03	0.02	0.24	0.14	0.11	0.04

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

related to VOT_m^{dev} (as expected, especially for respondents assigned to the *GoogleMaps* treatment): for instance, we find that higher perceived ease of using Google Maps is associated with a lower VOT_m^{dev} in the *GoogleMaps* treatment, possibly because those who perceive Google Maps as being easy to use exhibit a more "naive way" of interacting with it, taking the travel times at face value.

6. Discussion and conclusions

Digital mapping tools, particularly Google Maps, play a central role in travel-related decision-making. Our survey – broadly representative of the Viennese population – shows that the majority of respondents regularly use such tools within Vienna, with Google Maps being the most widely used (80% report regular use), followed by locally developed alternatives. Only 4.6% of participants reported never using digital mapping tools for travel decisions. Given Google Maps' broad user base in Austria and internationally, it was used as the primary example throughout the survey.

Consistent with the findings of Aoustin and Levinson (2021), respondents generally perceive real-life travel times to be slightly longer than the estimates provided by Google Maps. On average, reported travel times range from 30.6 min for walking to 33.2 min for public transport, compared to a standardized Google Maps estimate of 30 min. However, the reported travel times exhibit considerable variability, with a notable share of respondents expecting to reach their destination faster than suggested by the app, indicating that some users perceive Google Maps to overestimate travel durations in certain contexts.

Overall, respondents express predominantly positive evaluations of Google Maps. In particular, most perceive the risk of arriving either too early or too late when relying on its travel time estimates as relatively low. These descriptive findings suggest that Google Maps' travel time estimates are not widely perceived as systematically biased. Instead,

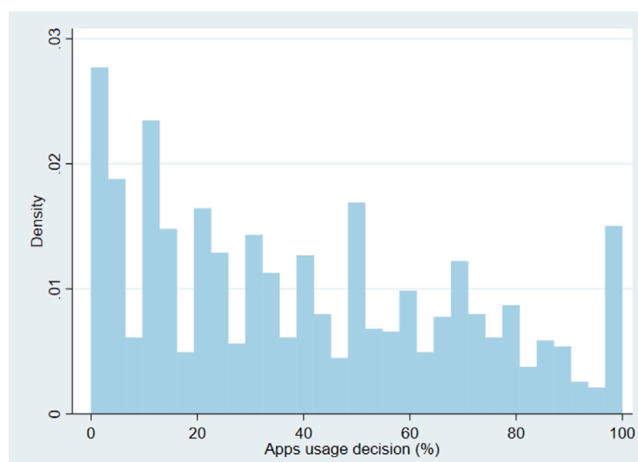


Fig. 2. Density plot of travel decision for which digital mapping tools are used.

discrepancies between reported real-life travel times and Google Maps estimates appear to stem largely from individual- and mode-specific speed choices, especially for cycling and car travel. This interpretation is supported by observed patterns in the data: older respondents tend to report longer travel times, particularly for walking and public transport, while male respondents report shorter travel times across all modes. Notably, for all four transport modes, more respondents believe that Google Maps estimates align with their actual travel times than believe that average travel times derived from objective measurements do. This further suggests that respondents place considerable weight on

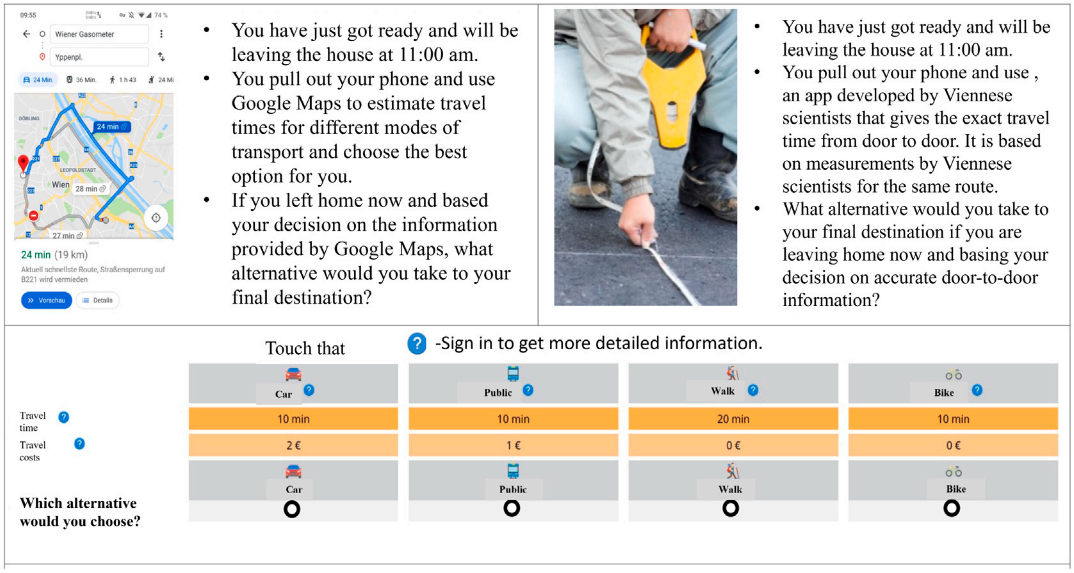


Fig. 3. Screenshot Stated Preference Experiment.

Table 4
Google Maps perceptions.

Compound variable	*"With respect to using Google Maps, to which extent would you agree with the following statements?"*	Mean	sd.	Cronbach's α
Trust	Google Maps is trustworthy.	4.91	1.53	0.78
	Google Maps keeps promises and commitments.	5.14	1.38	
	I trust Google Maps because the company has my best interests in mind.	4.04	1.63	
Perceived risk	If I use Google Maps, I risk arriving too early at my destination.	3.08	1.49	0.71
	If I use Google Map, I risk arriving too late at my destination.	2.93	1.45	
	If I use Google Map, I risk choosing the wrong means of transport.	2.91	1.50	
Perceived usefulness	Overall, I find Google Maps useful.	5.68	1.40	0.92
	I think Google Maps is valuable to me.	5.21	1.55	
	The content of Google Maps is useful to me.	5.46	1.41	
	Google Maps is functional.	5.51	1.36	
Perceived ease of use	My interaction with Google Maps is clear and understandable.	5.32	1.44	0.91
	Interacting with Google Maps does not require much mental effort.	5.44	1.51	
	I find Google Maps easy to use.	5.49	1.48	
	I find it easy to find the information I need with Google Maps.	5.36	1.44	
Behavioral intention	If I have the opportunity, I will use Google Maps.	5.28	1.57	0.92
	If I have the opportunity, I predict that I will use Google Maps in the future.	5.50	1.51	
	It is likely that I will use Google Maps in the near future.	5.52	1.55	
Observations	1321			

Note: The answers to the question items were recorded along a Likert scale with 7 levels ranging from *"completely disagree"* (1) to *"completely agree"* (7).

their personal speed choices when evaluating the accuracy of app-based estimates.

Importantly, our findings indicate that mode choice behavior – and in turn, time valuations – are only marginally influenced by the inclusion of a variable capturing perceived deviations between reported real-life and Google Maps or average travel times. In other words, even if these deviations are reported to exist, they appear to have limited impact on actual decision-making. This aligns with previous research, such as Peer et al. (2014), which suggests that discrepancies between reported and actual travel times tend to play a minor role in influencing behavioral choices. Interestingly, respondents seem more likely to account for these deviations when they believe real-life travel will be shorter than the app-based or average travel time estimate, revealing a behavioral asymmetry in how travel information is processed. A plausible explanation is that individuals are typically more familiar with the modes in which they perceive themselves as faster, and are therefore more inclined to choose those modes in stated preference scenarios.

The broader implications of our research become evident when situated within the context of recent studies by Link et al. (2023) and Wagner et al. (2021). Link et al. (2023) report that Google Maps tends to overestimate public transport travel times in Germany, while Wagner et al. (2021), focusing on Vienna, find some evidence that door-to-door travel times involving car use are underestimated. They argue that such biases are particularly relevant in cities like Vienna, where public transport networks are highly developed: Google Maps includes access and egress times for public transport but typically omits equivalent components, such as walking to and from parking, in car travel time estimates. Miotti and Hellweg (2025) refers to these additional components as "time overhead" and shows that they are longest for car trips in dense urban areas, adding an average of seven minutes compared to walking trips. Our findings suggest that most Viennese respondents are not fully aware that Google Maps car travel time estimates exclude such "time overheads". However, we cannot entirely rule out the possibility that respondents deliberately omitted these considerations from their survey responses, possibly viewing them as beyond the intended scope of digital mapping tools, while still accounting for them in real-world decision-making.

Taken together, our results highlight several important insights for transport planners and policymakers. The widespread reliance on digital mapping tools, coupled with generally positive user perceptions, suggests that platforms like Google Maps now serve as central reference systems for everyday travel decisions. Although many users recognize deviations between app-based and real-life travel times, these are rarely accounted for in mode choices, indicating a high degree of trust in the platform's estimates. But even though these perceived discrepancies do not substantially influence mode choice, their salience suggests they may still inform how users perceive different travel modes. To better align perceived travel conditions with actual experiences and to support more informed and sustainable mobility decisions, digital mapping tools should incorporate additional behaviorally relevant information, such as parking search time or expected crowding. Since widely used platforms like Google Maps are proprietary and offer limited transparency, there is a clear need for greater public oversight. Promoting open-source or co-developed alternatives that integrate these additional dimensions could ensure that digital travel tools support broader goals related to sustainability, equity, and multi-modal accessibility.

Given the exploratory nature of this study, further research is necessary to develop a more comprehensive understanding of how digital mapping tools affect decision-making. Various improvements and extensions of the research design employed in this study seem worthwhile:

- It would be insightful to conduct studies similar to ours but using revealed preference (real-life) data rather than stated preference data on mode choice behavior. Studies such as Krčál et al. (2019) suggest that respondents tend to simplify their choice behavior in hypothetical settings and may not account for biases to the same extent as they would in real-life settings.
- The research design would likely benefit from more concreteness as opposed to the rather generic framing adopted in its current version. Both the elicitation of perceived discrepancies between Google-Maps-based/average travel times and experienced travel times as well as the framing of the SP experiment could be personalized (e.g., by basing them on real-life revealed preference (RP) data). This would render the setting more realistic and specific for respondents, and allow us to study differences between routes, time-of-the-day, or the extent of pre-existing routines. In the current version, we have refrained from doing so; as this is the first paper with this particular research focus, we wanted to avoid introducing too much heterogeneity, which might later on be challenging to control for (e.g., due to confounding variables and selection effects). Instead, we have opted for a design that is likely to be realistic to a large number of respondents. For similar reasons, future SP-based studies should expand the attribute space to include aspects such as comfort, reliability, safety, and environmental considerations.
- Related to the previous point, a main limitation of the current design is that due to the generic way of asking about discrepancies between real-life and Google-Maps-based/average travel times and the fact that each respondent was subject only to one treatment, it turned out to be difficult to explain the respondents' answers by person-specific variables. It would have been preferable if this question was accompanied by a more specific explanation, also regarding the type of trip (e.g., the amount of walking included to go from origin to destination), and if we had asked subjected the respondents to both treatments. This would probably have allowed us to better disentangle the different sources for the perceived discrepancies (in particular own speed choices vs. algorithm-induced biases), and then test which of them actually affects mode choice behavior.
- A considerable degree of heterogeneity exists in the information requirements of travelers, which has not been accounted for in this study. For instance, demand for information tends to be particularly high when it comes to public transport usage and real-time information (Tang et al., 2022). Also, specific user groups and user contexts (for example tourists, students, etc.) might exhibit a higher demand for information.
- The observed effects may be context-dependent. For instance, given Vienna's strong public transport network, perceived travel time deviations may have a more limited influence than they would in more car-dependent cities. Future studies should compare different urban and user contexts to assess the generalizability of our findings.
- Lastly, it would be quite straightforward to extend the scope of this research to other digital mapping tools, other geographical areas, as well as other choice dimensions including for instance the departure time preferences and participation in car-sharing or park-and-ride programs.

Finally, to underpin the relevance of the research conducted in this paper, an important avenue for future research would be to conduct other studies similar to that of Link et al. (2023) in order to gather more knowledge on how closely travel times estimates by Google Maps correspond to actual door-to-door travel times.

CRediT authorship contribution statement

Stefanie Peer: Writing – review & editing, Writing – original draft, Visualization, Supervision, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Françeska Tomori:** Writing – original draft, Visualization, Investigation, Formal analysis, Data curation. **Ben Wagner:** Writing – review & editing, Methodology, Investigation, Funding acquisition, Data curation, Conceptualization. **Till Winkler:** Writing – review & editing, Software, Methodology, Investigation, Data curation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. App usage

See Fig. 2.

Appendix B. Screenshot stated preference experiment

See Fig. 3.

Appendix C. Perception of Google Maps

Table 4 shows for each of the five variable categories Cronbach's α, which can range from 0 to 1, with a high value signaling a high internal consistency of the question items included in that category. For all variable categories, Cronbach's α is above the often cited validity threshold of 0.7, with three of the variable categories even exhibiting a value above 0.9.

Appendix D. Perceived deviations from Google Maps/average travel times

Table 5 presents OLS regression results with the reported real-life travel times (as opposed to the 30 min travel times communicated by Google Maps (*Google Maps* treatment) and average travel times (*Baseline* treatment)) serving as dependent variable.

Table 5
OLS regression results with reported real-life travel times (TT^{EXP} as dependent variable)

	Dependent variable: reported real-life travel times							
	Walking		Cycling		Public transport		Car	
	Google	Baseline	Google	Baseline	Google	Baseline	Google	Baseline
Socio-economic variables								
Age (in years)	0.08**	0.11***	−0.07*	−0.0003	0.07**	0.07**	0.03	0.03
	(0.03)	(0.04)	(0.04)	(0.04)	(0.03)	(0.03)	(0.04)	(0.04)
Gender: male	−3.70***	1.47	−1.20	−0.03	−3.42***	−2.10**	−1.43	−2.31**
	(1.03)	(1.13)	(1.19)	(1.18)	(0.91)	(0.92)	(1.08)	(1.08)
Education: high school or higher	1.29	0.48	2.50*	1.60	2.53**	1.50	2.54**	2.35**
	(1.16)	(1.21)	(1.31)	(1.26)	(1.02)	(1.00)	(1.20)	(1.16)
District: outer	1.58	0.72	3.12**	1.77	2.37**	3.67***	2.75**	−0.19
	(1.25)	(1.37)	(1.42)	(1.42)	(1.10)	(1.12)	(1.31)	(1.31)
Google Maps perceptions								
Trust	1.27	−1.03	1.28	−0.27	−0.03	−0.29	0.10	−0.04
	(0.83)	(0.88)	(0.95)	(0.92)	(0.73)	(0.72)	(0.86)	(0.84)
Perceived risk	−0.75	0.08	−0.58	−0.11	−0.41	−1.46***	−0.12	0.49
	(0.65)	(0.67)	(0.74)	(0.70)	(0.58)	(0.55)	(0.68)	(0.64)
Perceived usefulness	1.04	−0.24	1.06	1.41	1.55	0.47	3.85**	0.37
	(1.44)	(1.56)	(1.64)	(1.61)	(1.27)	(1.27)	(1.50)	(1.48)
Perceived ease of use	0.07	−2.10*	−0.27	−2.61**	1.18	−2.80***	0.10	0.15
	(1.11)	(1.25)	(1.27)	(1.30)	(0.98)	(1.02)	(1.16)	(1.19)
Behavioral intention	−0.13	3.93***	1.44	2.70**	−1.20	3.29***	−1.33	2.21*
	(1.15)	(1.26)	(1.31)	(1.31)	(1.02)	(1.03)	(1.20)	(1.20)
% travel decisions with app usage (%)	−0.01	−0.005	−0.06***	−0.01	−0.02	0.01	−0.06***	−0.03*
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Regularly used transport modes (>1/week)								
Walking	1.39	2.66**						
	(1.22)	(1.32)						
Cycling			6.31***	−0.10				
			(1.71)	(1.80)				
Public transport					0.91	−0.91		
					(1.02)	(1.01)		
Car							3.48***	2.58**
							(1.11)	(1.09)
Constant	21.97***	20.71***	24.39***	23.57***	25.75***	27.03***	23.44***	26.58***
	(2.48)	(2.71)	(2.71)	(2.73)	(2.22)	(2.29)	(2.50)	(2.50)
Observations	644	677	644	677	644	677	644	677
R^2	0.07	0.05	0.09	0.02	0.08	0.07	0.11	0.05
Adjusted R^2	0.05	0.03	0.08	0.005	0.06	0.05	0.09	0.04

Note: standard errors in brackets $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Data availability

Data will be made available on request.

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