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Achieving social routing via navigation apps: User acceptance of travel time sacrifice

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ABSTRACT

Trip information and navigation systems are expected to become key components of future traffic management strategies, which, if properly exploited, may contribute to the mitigation of car usage externalities. In this study, we investigate social routing recommendations, which could be associated with nudges, and delivered via a navigation app, aiming at promoting sustainable routing behavior, where some drivers are asked to take longer routes and make travel time sacrifices (TTS). In particular, we propose a framework including data collection and behavioral modeling to identify the impacts of various types of information delivered to drivers, goals of the detour, and personal characteristics on drivers' TTS behavior. The methodology includes stated choice and revealed choice experiments in two European cities, Amsterdam and Helsinki, and a mixed ordered-response logit model to provide insights into TTS behavior. Our analyses show that delivering different information and nudges results in different levels of TTS. However, regardless of the goal of the detour, offering incentives to drivers enables achieving a higher level of TTS. Comparing the stated and revealed data, regarding TTS and compliance rate, also clarifies significant differences between these two types of data.

1. Introduction

1.1. Motivation

Navigation tools, especially those in smartphone apps and in-car systems, have become increasingly popular and users' route choice behavior can be easily affected by providing pre-trip information and route advice. Providing drivers with sensible route advice through navigation apps is generally known as a successful traffic management tool with the potential to reduce traffic externalities such as congestion, air pollution, and accidents (Cheng et al., 2020; Fontes et al., 2014). Hence, understanding drivers' responses to such information has a strong potential for devising and implementing novel policies and strategic management approaches affecting traffic on a network level.

In some cases, although following the advice of the navigation app improves road network efficiency, it may increase personal travel time (distance).[1] In other words, some drivers may need to travel along longer routes for the sake of benefiting other travelers, translating to a so-called *sacrifice*. In this paper, this behavior is denoted as social routing behavior, the recommended longer route is called the socially responsible route (SRR), and the time difference between the suggested SRR and the fastest route is referred to as travel time sacrifice (TTS).

When it comes to making a sacrifice and taking a detour, not all drivers are keen to behave socially, and a stimulus may be needed to encourage a change in their behavior. Traditionally, road pricing has been considered a prescriptive tool to stop some drivers from traveling along specific routes, aiming at achieving improved network performance (Bergendorff et al., 1997; Yang and Huang, 2004). However, implementing road pricing schemes in practice was often unsuccessful due to public dissatisfaction (May et al., 2010) and discrimination and inequitable welfare distribution across the population (Levinson, 2010; Vosough et al., 2022). As a result, many studies (Ettema et al., 2010; Leblanc and Walker, 2013; Sun et al., 2020; Cohen-Blankshtain et al., 2023), gave attention to encouragement (e.g., an incentive for voluntary participation), instead of punishment (e.g., mandatory road toll). Social routing advice, therefore, needs to be accompanied by *nudging* and *incentivizing* drivers, pushes them to take a route that is usually longer than their preferred, e.g., faster[2] route while contributing to a social goal.

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[1] Not all social routing schemes rely on sacrifice. A social routing scheme has the potential to reduce travel time not only for participating drivers but also for the whole network. For instance, Szep et al. (2023), in addition to the sacrificed-based scheme, introduced a collective good-perspective social routing scheme called collective good which is framed to benefit both participating drivers and the system.

[2] Note that we use the term "faster" within the paper to denote the route that brings maximum expected benefit for a driver; however, different criteria can be considered as well (e.g., shorter, more economical, etc.).

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Several studies (Kerkman et al., 2012; Djavadian et al., 2014; Ardeshiri et al., 2015; Ringhand and Vollrath, 2018; van Essen et al., 2019, 2020; Mariotte et al., 2021; Szep et al., 2023) demonstrate that the amount of TTS negatively impacts the share of drivers who comply with social routing advice, meaning that the greater the TTS, the fewer drivers take the SRR. Thus, a critical aspect of a successful routing advice system is to propose TTS levels that align with users' preferences. Having said that, identifying the factors that shape drivers' receptiveness to various levels of TTS, such as sociodemographics, drivers' attitudes, trip-related attributes, driving-related behavior, and the way that social routing is framed and presented, is of interest. By understanding these factors, one can design and offer the most appropriate SRR tailored to individual preferences, promoting greater acceptance and compliance among drivers, in order to achieve the desired social goal.

1.2. Objectives and contributions

To the best of the authors' knowledge, no study has investigated the factors affecting TTS, especially, the types of information and social goals of the detour, therefore, a comprehensive framework to address this gap in the field of social routing behavior is absent. To bridge this gap, we present a TTS choice framework consisting of collecting proper data and employing a discrete choice modeling approach to determine factors affecting TTS. We hypothesize and then confirm that drivers are inclined to make bigger sacrifices when they are offered monetary incentives. Another hypothesis, subsequently verified, posits that SP and RP data result in finding different influential factors on drivers' acceptance of TTS. To this end, two types of data are collected: stated preference (SP) and revealed preference (RP), while a discrete choice model that accounts for both ordinal and mixed effects of TTS is applied. Therefore, this study contributes to the existing literature in two ways: (1) developing a framework consisting of data collection and choice theory to generate more knowledge on drivers' preferences on the acceptance of various levels of TTS, and (2) comparing the outputs of SP data with RP data concerning the impacts of different variables on TTS.

The findings of this study, derived from the implementation of nudge and incentive policies in two European cities, Helsinki and Amsterdam, contribute to identify the key factors that frame the drivers' willingness to adopt different levels of TTS. Understanding these factors, by considering various scenarios and stimuli, is the basis for devising and implementing enhanced nudge and/or incentive policies and successfully embedding social routing advice in navigation systems in the future, in order to achieve the desired policies, expressed in terms of social goals, e.g., less congested, safer, and more livable cities.

The rest of this paper is organized as follows. Section 2 reviews the literature on social routing advice, its concept, data, factors, and existing modeling approaches. Section 3 describes the methodology of the study which is a framework including data collection and modeling for investigating influential factors on TTS. Section 4 presents the statistical analysis of the collected data. Model outputs are presented in Section 5. Section 6 concludes and identifies possible extensions.

2. Literature review

Routing advice is not a new tool in the field of transportation management. In fact, during the 90 s, after the advent of variable message signs and highway advisory radio, several studies focused on analyzing route choice behavior while developing dynamic traffic equilibrium traffic management strategies under the Advanced Traveler Information System (Ben-Akiva et al., 1991; Bonsall, 1992; Friesz et al., 1994; Jayakrishnan et al., 1994; Hall, 1996; Bierlaire, 1996). Since then, various studies strive to investigate the impact of the evolving technologies on traffic flow as well as to employ new technologies to intervene in users' route choice behavior (Ramos et al., 2018; de Moraes Ramos et al., 2020; Sohrabi and Lord, 2022). Among other aspects, such studies prove that more sustainable travel behavior can be promoted by utilizing emerging smartphone applications (apps) (Sunio and Schmöcker, 2017; Andersson et al., 2018).

The share of drivers that comply with travel information is called the compliance rate, and a large body of literature exists in identifying the factors affecting the compliance rate (Bonsall and Joint, 1991; Chen et al., 1999; Chen and Jovanis, 2003; Chorus et al., 2009; Arentze et al., 2012; Kerkman et al., 2012; Djavadian et al., 2014; Ardeshiri et al., 2015; Klein and Ben-Elia, 2018; van Essen et al., 2019, 2020; Mariotte et al., 2021). Among all, quality, credibility, accuracy, and reliability of information are found significantly effective in complying with advice (Bonsall and Joint, 1991; Chen et al., 1999; Srinivasan and Mahmassani, 2000; Ardeshiri et al., 2015; Cao and Zhang, 2016). Drivers' personalities such as being risk averse (Klein and Ben-Elia, 2018), habits (van Essen et al., 2019), moral personality (Szep et al., 2023), and the behavior of other drivers (Bonsall and Joint, 1991) are also found influential on the rate of complying with route advice.

The type of information delivered to drivers is also identified as a key factor in determining the compliance rate with the advice where the highest is achieved under the incentives strategy compared to the nudge strategy (Klein and Ben-Elia, 2018). Djavadian et al. (2014) also confirmed that incentives positively affect complying with the routing advice compared to the other information strategies in a driving simulation environment. They benefitted from point incentives that can be used to unlock features of a navigation application on a smartphone, raising the question of whether rewarding drivers with cash would outperform points. A study in the US (Wang et al., 2020) argues that different types of incentives have the potential to influence the mobility decisions of specific groups of people. They showed that, for example, large cash coupons are more interesting to people with higher incomes and people living with children, while people with no children are more interested in the 10% discount.

In previous studies, the difference between SRR travel time and the fastest route, which represents TTS, is considered a key influential factor in the compliance rate. In line with this, Kerkman et al. (2012), applying a model to SP data, showed that the travel time difference between the SRR and the fastest route is more meaningful, compared with the absolute value of travel time. Djavadian et al. (2014) stated that, if TTS was very high, drivers would not be willing to comply with the routing advice. In a study with two routes, the main route with a traffic signal and an alternative route without, the share of compliance with the advice dropped from 60% to 20% as the difference between the travel time of the alternative route and the main route changes from 0 to 100% of the red-light duration in the main route (Ringhand and Vollrath, 2018). van Essen et al. (2019), using RP data collected in the US, proved that, when the difference between two routes' travel time is small, the compliance rate with the "switch" recommendation is 42%, while a large difference between the two routes' travel time leads to 39% of compliance rate. Whereas many studies tested TTS in a short range of a few minutes, Mariotte et al. (2021) proposed various levels of TTS, up to 50%, to investigate the compliance rate for congestion alleviation and emission reduction, using SP data. They observed a high compliance rate of 80% when TTS is 10% of the shortest travel time and almost a linear decline in compliance rate with an increase in TTS. In their study, TTS at the level of 30% of the shortest travel time is introduced as a threshold after which the compliance rate drops significantly.

The impact of TTS on compliance rates for different trip purposes and various social goals is also examined. Kerkman et al. (2012), using SP data, proposed that TTS has a stronger effect on complying with the advice on work trips, compared with shopping and social visiting. Interestingly, Mariotte et al. (2021) found that, with an increase in TTS, the compliance rate for emission reduction drops slower than for congestion alleviation. Still, the impact of social goals on TTS is unclear.

In the field of social routing behavior where studies investigate complying with the route advice, discrete choice models are often employed to determine influential factors on compliance rates. Concerning the nature of compliance behavior, Logit and Probit models are the most commonly used in previous studies (Chen et al., 1999; Srinivasan and Mahmassani, 2000; Jou et al., 2005; Abdel-Aty and Fathy Abdalla, 2006; Cao and Zhang, 2016; Mariotte et al., 2021). However, it should be noted that standard Logit models developed based on the assumption of independence of irrelevant alternatives (IIA) are not capable of modeling the correlation among unobserved utilities in panel data (Revelt and Train, 1998), where each agent makes numerous decisions in different situations. Hence, Mixed Logit models that relax the IIA assumption are used to investigate factors affecting compliance rates in various studies (Chen et al., 1999; Kerkman et al., 2012; Shiftan et al., 2011; Ben-Elia et al., 2013; Cao and Zhang, 2016; Klein and Ben-Elia, 2018; van Essen et al., 2019, 2020; Mariotte et al., 2021; Szep et al., 2023).

It is found that various types of data make substantial differences in the compliance rate. Ardeshiri et al. (2015) compared the compliance with a variable message sign that displays the fastest route among a set of three routes, using SP data, as well as a driving simulation experiment. The results demonstrate that for specific levels of TTS (5 and 15 min), the compliance rate in SP data is lower than in the driving simulator. They explained that the reason might be the perception of travel time and congestion in the driving simulator. Comparing SP and RP data, van Essen et al. (2020) showed that TTS, type of information given to drivers, and drivers' personalities do not affect complying with the advice in RP data while they are significantly influential in SP data. They also investigated the reasons why drivers in the revealed choice experiment did not follow the suggested route. Their results revealed that only 3 out of 13 drivers did not take the SRR due to large TTS, suggesting that TTS in the route choice decision is not as important as expected. It is worth mentioning that their sample size is very small, so the statistical inference is hard to derive, and TTS is bounded in a short range of 2–7 min. Nonetheless, no study has been found to investigate the factors affecting the acceptance of TTS by car users either with SP or RP data. Hence, this study aims to provide insights into TTS behavior using both stated choice and revealed choice experiments.

3. Methodology

The methodological structure of this study is split into two stages: (1) defining a framework to collect suitable data for analyzing drivers' TTS behavior which includes both SP and RP data, and (2) proposing a discrete choice model that accounts for the characteristics of data (i.e., both ordinal and mixed effects of TTS). To propose this framework, it is necessary to identify factors that are needed to be collected in the data and behavioral models that are generally used in this field, which can be attained through the literature review, in Section 2.

3.1. Data collection

Two common methods for collecting data to assess travelers' behavior are running stated choice and revealed choice experiments. Although SP data might be biased, it is usually used because it allows the researchers to define several scenarios and have full control over the variables with a lower operational effort and cost, compared with RP data (Hensher et al., 2005; de Dios Ortúzar and Willumsen, 2011). Evaluating TTS with both types of data reveals not only the key elements affecting social routing behavior but also the differences between SP and RP data. In the following subsections, the method of data collection and the design of both stated and revealed choice experiments are presented.

3.1.1. Stated choice experiment

To analyze factors influencing TTS, we designed an online questionnaire comprising three main parts. The first part collects background information, consisting of sociodemographics, driving-related experience, typical travel patterns, and work/study status. In the second part, drivers' attitudes towards the environment, sustainability, traffic jam, and the willingness to change driving patterns to support more sustainable traffic flow are surveyed. Collecting this additional information is important to understand the specific factors influencing users' acceptance of TTS.

Finally, in the third part, which is related to stated choices, respondents are asked to imagine a hypothetical commute trip towards the city center, where two different routes are available: a baseline (fastest) route that takes, e.g., 20 min and the SRR that has a longer travel time but contributes to one of the predefined social goals. According to the information that respondents receive in each scenario, they have to choose the maximum level of TTS they would accept, among 4 options: (i) 0; (ii) up to 2 min; (iii) up to 5 min; or (iv) up to 8 min. These TTS levels are equal to 10%, 25%, and 40% of the fastest route travel time, respectively, and originate from findings of an SP analysis (Kröller et al., 2021) in which 5 min and 8 min detours are found more compelling than 13 min and 20 min ones. By discretizing the TTS in 4 levels, SP data contains less information, however, it is easier for participants to respond.

To design a stated choice experiment in the third part of the questionnaire, we need to define the hypothetical situations (scenarios) under which participants choose their preferred outcomes. These scenarios are generated based on the factors that are likely to have an impact on the choices being investigated. Thus, in the first place, we need to identify the factors. Since no study has been conducted about the factors that significantly influence TTS, factors of interest must be considered as those frequently emerging in compliance behavior studies. In this study, we considered that the type of information delivered to the drivers and the social goal of the detour are two main factors that might influence how individuals perceive and make decisions about their TTS.

Also, factor levels have to be determined to measure the change in each factor's influence. To investigate the drivers' inclination to TTS for various social goals, three goals are introduced to the participants that are among the most important challenges that cities encounter due to urbanization, and set by the municipalities: *liveability* (e.g., avoiding residential areas), *safety* (e.g., avoiding school zones), and emission reduction. Also, three information strategies are developed, called *nudge*, *social reinforcement*, and *incentive*, to steer participants towards taking the longer route. Note that the naming of the first two strategies is taken from van Essen et al. (2020). Each strategy with a specific level of information aims at influencing personal route choice to improve network efficiency. The levels of information given to the drivers under each information strategy are as follows:

- *Nudge strategy*: respondents receive travel time of both routes, as well as the positive aspects of the SRR, as shown in Fig. 1(a).
- *Social reinforcement strategy*: in addition to the information of the nudge strategy, a participant receives information on the choices of other drivers, i.e., the percentage of drivers who have been asked to take the SRR and complied with routing advice, as shown in Fig. 1(b). Drivers have more tendency to comply with the advice when they know about the choice of other drivers (Djavadian et al., 2014). While van Essen et al. (2020) assumed that the share of other drivers who comply with the routing advice is constant (72%) in their experiments, in this survey, we assume three different levels of compliance to determine the effect of various levels of reinforcement on TTS: 50%, 70%, and 90%.
- *Incentive strategy*: this strategy advises drivers to take another route than the fastest, and in return, they receive a (monetary) reward. Thus, besides the information on the nudge strategy,

a driver is informed about the rewards (see Fig. 1(c)). We define two forms of monetary incentives: a gamification approach, where participants receive 10 points, equivalent to 2€, that can be spent on city activities, or direct 1€ cash.

A full factorial design, encompassing all factors and their respective levels, then, can be used to define all the possible scenarios, however, the resulting number of scenarios would be large and may cause response fatigue. So, the number of scenarios must be reduced to a manageable size. In our case, we define a scenario with a specific information strategy denoted by I and a specific social goal denoted by G, which is symbolized as $I + G$, where G can be one of the three social goals of a detour ($Live$: increasing liveability, $Safe$: improving safety, and $Emis$: emission reduction), and I can be one of the six information strategies (Nud: nudge, $ReiXX$: social reinforcement with XX% of compliance of other drivers where XX is 50, 70, or 90, $Inc10p$: 10-point incentive, and $Inc1€$: one Euro cash incentive). Considering the possible combinations, 18 different scenarios are definable. To prevent participants from dropping out, in the end, we decided to limit our experiment scenarios. The 10 chosen scenarios are $Nud + Live$, $Nud + Safe$, $Nud + Emis$, $Rei50 + Live$, $Rei70 + Live$, $Rei90 + Live$, $Inc10p + Live$, $Inc10p + Safe$, $Inc10p + Emis$, and $Inc1€ + Live$, i.e., we excluded the investigation of some combinations including the three reinforcement strategies and the 10-point incentive strategy in tandem with the goals of emission reduction and safety improvement. This pruning aims to strike a balance between comprehensive coverage and participant commitment. The scenarios are chosen in a way that all information types cover at least one specific goal to ensure that the experimental design remains focused on the investigation of all types of information impacts on TTS (e.g., liveability is more general than the other goals). Still, there are two information strategies covering all three social goals enabling us to compare the impacts of various social goals of detours on the acceptance of TTS.

3.1.2. Revealed choice experiment

Revealed choice experiments are related to the actual choices of drivers in real-world situations. Therefore, a tool such as a smartphone app is required to influence drivers' behavior, record their chosen route, and monitor if they are following the suggested route. In this study, we employ a navigation app called *Code the Streets AmiGO*, developed by TomTom, which operates on a route plan made before the trip (i.e., pre-trip navigation). Each participant receives an activation code to install the mobile navigation app after completing the questionnaire in the stated choice experiment. Consequently, the sociodemographics, drivers' attitudes, and other factors collected in the online questionnaire are useful for exploring the factors influencing users' acceptance of TTS.

Since our aim is that this experiment reflects the SP survey results, the app is designed in a way that users are presented with the fastest route and the SRR, for every trip they make in the real world, as shown in Fig. 2. The user interface is adjusted to display the SRR for liveability which avoids certain neighborhoods and for safety which avoids school zones during the arrival and departure times of the students. However, emission reduction, which is taken into account in the stated choice experiment, cannot be implemented in the navigation app due to technical limitations. The only information strategy applied to the navigation app is the nudge strategy. Hence, two social goals (liveability and safety), and one information strategy (nudge) are assessed as the perceptions indicators presented to the respondents through RP data. It should be noted that RP data is typically more limited than SP data.

When a destination is chosen, two route options are displayed on the app, with information on the respective travel times. If the fastest route and the SRR are the same, only a single route without notification is provided. By clicking on the SRR, a banner with header text appears, mentioning the social goal that the route takes into account. "Take

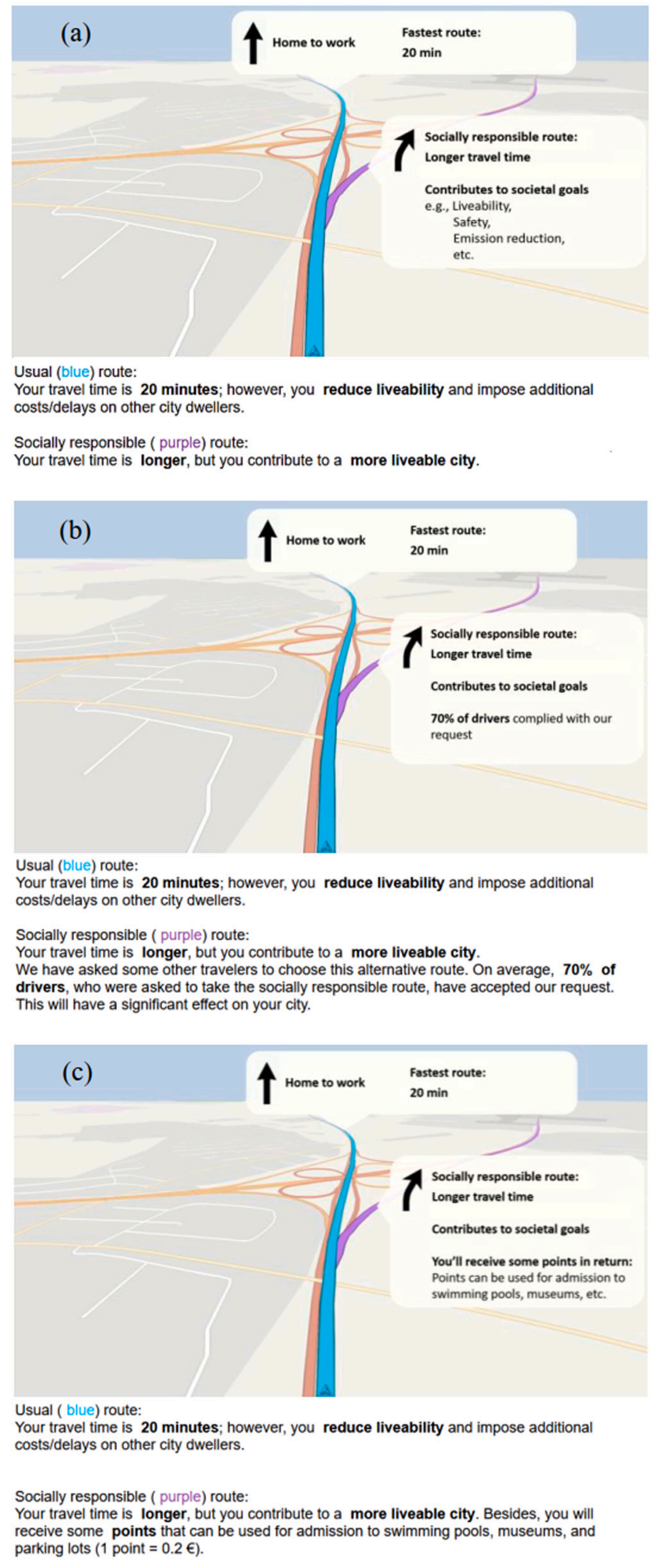

Fig. 1. The different types of information strategies presented to participants in the stated choice experiment: (a) nudge, (b) social reinforcement, and (c) incentive.

this route to keep our city safe.", "Contribute to a safer city! Take this route.", and "Keep children safe. Take this route." are the three banners that appear for safety. Three different header texts for each social goal are embedded into the app so as not to create a routine within the driving habits of the users or overload them with distracting nudges.

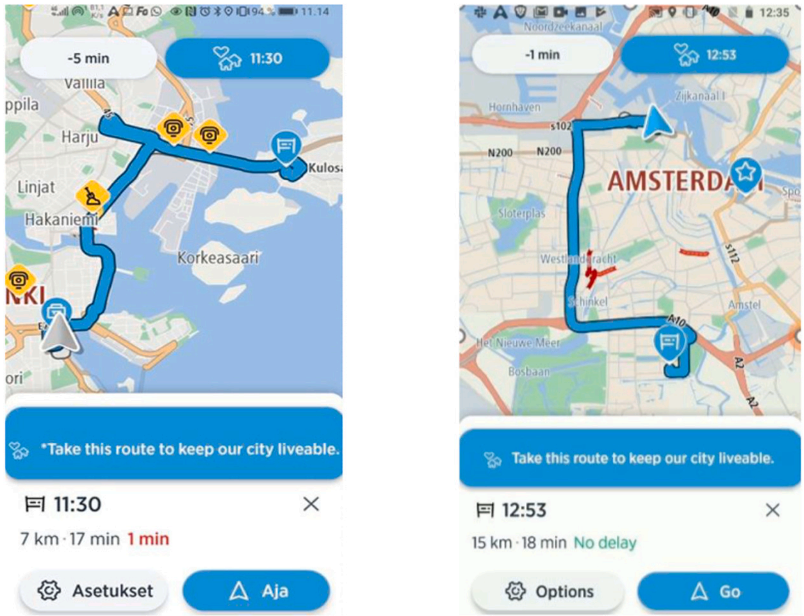

Fig. 2. Code the streets AmiGO navigation app (by TomTom) used for the revealed choice experiment.

More detailed information can be shown explaining why the drivers are asked to take the SRR by clicking on the banner with the header text. For instance, "The City of Amsterdam kindly asks you to take this social route to contribute to a safe city. This route avoids school zones as much as possible." is one of the detailed information provided to the participants for safety. Finally, a thank-you message, e.g., "Thanks for your social contribution", is sent to the drivers at their destination if they have followed the SRR. Note that the TTS in RP data, which is computed by subtracting the travel times of the two routes, is a continuous variable. Besides, TTS in RP data is an exogenous variable since respondents are asked to make a trade-off between two routes with specific travel times, while TTS in SP data is an endogenous choice variable. However, to make the RP outputs comparable with SP, TTS in RP data is discretized and considered an endogenous variable.

3.2. Model specification

Discrete choice models are widely used to provide a better understanding of the factors affecting discrete decisions (Ben-Akiva and Lerman, 1985; Hensher et al., 2005; Greene, 2009). Since in this study, TTS, as the dependent variable, is measured on an ordinal scale and each participant makes multiple choices (e.g., 10 successive responses in SP data and several trips in RP data), a model that accounts for the ordinal nature of the dependent variable, as well as the panel effect of data, is needed. As a result, a Mixed Ordered-Response Logit (MORL) model (Bhat and Srinivasan, 2005; Srinivasan et al., 2006; Azimi et al., 2020), which estimates relationships between an ordered categorical dependent variable and a set of independent variables when the observations are not independent, is applied to the data to determine the factors influencing TTS.

MORL models are also called Random-Effects Ordinal Logit in the literature (Hedeker and Gibbons, 1994) since they are able to capture heterogeneity among responses by having coefficients that vary in the population, i.e., they can consider both fixed effects and random effects of variables. Let us denote the fixed-effect coefficient β and the random-effect coefficient γ_j, where j $(= 1, \dots, M)$ represents a cluster consisting of n_j observations; coefficient γ_j is allowed to randomly vary across the individuals, meaning that different decision-makers may have different preferences.

In the ordered logit models, the dependent variable is assumed to have an underlying continuous latent variable. Assuming k is a possible outcome $(k = 1, \dots, K)$, the utility that the ith person in cluster j obtains from outcome k, U_{kij}, in this study served as the latent measure of TTS experienced by drivers, is described by a linear function of explanatory variables, as:

$$U_{kij} = \beta X_{ij} + \gamma_j Z_{ij} + \epsilon_{kij} + \nu_{kij} \tag{1}$$

where X_{ij} and Z_{ij} are vectors of explanatory variables affecting the utility of person i in cluster j; ϵ_{kij} is the independent extreme value-distributed error term with zero mean; and ν_{kij} is the zero-mean error term that captures taste variation and correlation across unobserved utility components, implying that the IIA assumption is no longer held. It should be noted that X_{ij} does not contain a constant term because its effect is absorbed into the cutpoints that separate the outcome categories, and the dependence of U_{kij} on X_{ij} is suppressed.

The ordered response structure needs the latent variable, to be assigned to one of the K ordered outcomes. This allocation is accomplished using cutpoints, which convert the latent utility into TTS levels by defining the boundaries at which the utility transitions between two TTS levels. If κ_k is the kth cutpoint that separates the outcome category k from $k+1$, we can introduce:

$$T_{ij} = \begin{cases} 1 & U_{ij} < \kappa_1 \\ 2 & \kappa_1 \le U_{ij} < \kappa_2 \\ \dots & \\ K & \kappa_{K-1} \le U_{ij} \end{cases}, \tag{2}$$

which shows how the ordinal TTS levels are produced by the linear continuous latent propensity, through the cutpoints, where κ_0 and κ_K are taken as $-\infty$ and $+\infty$, respectively.

Then, the probability of observing outcome k is computed as follows:

$$P_k = Pr(T_{ij} = k) = Pr(\kappa_{k-1} < U_{ij} < \kappa_k). \tag{3}$$

Coefficients, β and γ_j, and cutpoints, $\kappa_1 \dots \kappa_{K-1}$, of MORL models can be estimated automatically by statistical software (e.g., Stata) simultaneously, using, e.g., a maximum likelihood method which maximizes the likelihood of the observed data.

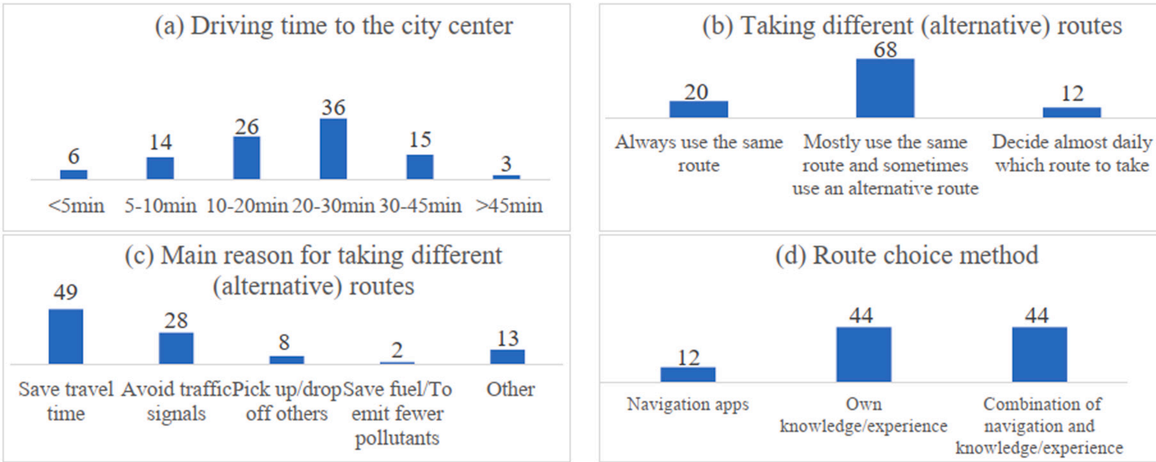

Fig. 3. Sample driving-related characteristics and travel pattern.

4. Statistical analysis of data

4.1. Participants

The study was conducted in two European cities, Amsterdam, the Netherlands, and Helsinki, Finland. The SP survey was delivered via an online questionnaire to 90 registered participants, who were informed about the survey through social media/websites and registered based on a self-assessment of eligibility (which included driving regularly a car to the city center and having an Android phone), from September to November 2021. In the end, 66 participants (44 from Helsinki and 22 from Amsterdam) completed the questionnaire. Every person who participated in the stated choice experiment received an activation code to utilize The Code the Streets AmiGO app. In total, 36 participants (28 from Helsinki and 8 from Amsterdam) installed and used the navigation app from October to December 2021. In total, 452 route requests have been recorded, 94% (423) of the requests were in Helsinki and 6% (29) in Amsterdam.

Table 1 summarizes the sociodemographic characteristics of the sample, including respondents from Helsinki and Amsterdam. The sample shows an overrepresentation of male respondents (75%); all age classes are well represented, although the number of participants over 60 years old is relatively small. Regarding education, 66% and 91% of participants have a university degree in Helsinki and Amsterdam, respectively. Regarding annual household income, all classes are well represented in Helsinki, but not in Amsterdam. In both cities, the biggest share of respondents belongs to families with a size of 2 people. These numbers can be representative of the cities unless the shares of one-person households that participated in the experiment are less than the shares of one-person households presented in the population statistics of both Helsinki[3] (49%) and Amsterdam[4] (39%), while the shares of households with 4 people or more are higher than the city statistics.

In Fig. 4, some driving-related characteristics and travel patterns of the sample are shown, where the number on each bar represents the percentage of respondents. According to Fig. 3(a), participants' travel time to the city center has a bell-shaped distribution with a mean of around 20 min, which validates our assumption about the baseline travel time (20 min) in the stated choice experiment. Among respondents, 20% always use the same route for going to the city center, as shown in Fig. 3(b), but others at least sometimes take an alternative route. The most frequent reasons for taking a different route are stated saving time (49%) and avoiding traffic signals (28%), as depicted in Fig. 3(c). Fig. 3(d) shows that 44% of the respondents rely only on their knowledge and experience for route choice and have not used navigation apps for route choice. Providing routing advice via navigation apps possibly does not change this group's route choice behavior significantly. There are 12% of participants rely only on navigation apps. 44% of respondents combine their experience with information from navigation apps to decide about the routes. This group might be the main target of such studies since they most probably get nudges.

Table 1
Sample sociodemographic characteristics.

Variable	Category/level	Both (N = 66) %	Helsinki (N = 44) %	Amsterdam (N = 22) %
Gender				
	Male	75	76	73
	Female	23	24	23
	Other	2	0	4
Age				
	18–29	16	14	18
	30–39	28	33	18
	40–49	31	29	36
	50–59	23	24	23
	≥60	2	0	5
Education				
	High-school diploma	19	25	4
	Bachelor	39	34	50
	Master	36	34	41
	Other	6	7	5
Annual household income				
	<20K	2	2	0
	20K–40K	9	10	9
	40K–60K	16	2	5
	60K–80K	19	19	18
	80K–100K	14	17	9
	>100K	17	17	18
	Prefer not to answer	23	14	41
Household size				
	1	17	17	18
	2	44	40	50
	3	16	19	9
	≥4	23	24	23

4.2. Compliance rate

In all scenarios of SP data, more than 93% of the respondents claim to comply with the advice and take the SRR with different levels of

[3] https://www.hel.fi/hel2/tietokeskus/julkaisut/pdf/21_06_09_Helsinki_facts_and_figures_2021.pdf.

[4] https://www.cbs.nl/en-gb/figures/detail/82905ENG.

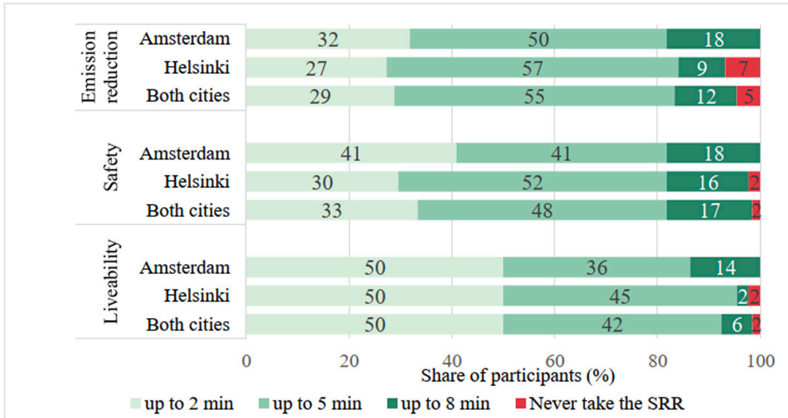

Fig. 4. TTS for various social goals under the nudge strategy ($Nud + G$) in Helsinki and Amsterdam.

Table 2
Compliance rate (%) for various social goals in Helsinki and Amsterdam, in SP data.

City	$Nud + Live$	$Nud + Safe$	$Nud + Emis$	$Rei50 + Live$	$Rei70 + Live$	$Rei90 + Live$	$Inc10p + Live$	$Inc10p + Safe$	$Inc10p + Emis$	$Inc1€ + Live$
Helsinki	98	98	93	95	93	93	98	98	98	98
Amsterdam	100	100	100	100	100	100	100	100	100	100
Both	98	98	95	97	95	95	98	98	98	98

TTS. Table 2 shows the SP compliance rate for all social goals and information types in Amsterdam and Helsinki. The compliance rates, in this study, are significantly higher than what was reported in previous studies (e.g., 57% in van Essen et al. (2020) and 49% in Mariotte et al. (2021) for congestion alleviation) probably due to offering a route with up to 2-min longer travel time that is a quite intangible increase in travel time. Interestingly, the compliance rate in Amsterdam is 100% for all scenarios. This may be caused by a biased sample with an insufficient number of participants (22 responses).

On the other hand, the overall compliance rates, in RP data, in Helsinki and Amsterdam are computed to be 47% and 62%, respectively. The compliance rates, in previous studies, are smaller, for instance, they are reported as 31% in Enschede, the Netherlands (Van Essen et al., 2019), and 21%–28% depending on information strategy in a laboratory experiment in Rotterdam, the Netherlands (Djavadian et al., 2014). In this study, the compliance rate for liveability and safety are computed to be 48% and 42%, respectively, in Helsinki. It implies that people care about liveability more than safety in Helsinki. While, in Amsterdam, the compliance rate for safety is higher than for liveability (75% and 60%, respectively).

The compliance rate of SP is significantly higher than RP data, demonstrating the bias of SP data caused by hypothetical situations for both liveability (98% vs. 49%) and safety (98% vs. 44%). In SP data, a 10% longer SRR than the fastest route is always presented to the participants. Considering the route requests in which the maximum TTS is 10% of the fastest route, in RP, the compliance rate for liveability and safety are computed to be 57% and 60%, respectively, which are still significantly lower than the SP compliance rate.

Similar differences between SP and RP data have been reported in van Essen et al. (2020) regarding the compliance rate. The difference between SP and RP data has been studied for many years and is widely discussed in different fields (Börjesson, 2008; Haghani and Sarvi, 2017). Since SP and RP data have both advantages and limitations, the potential for combining SP and RP data has grown (Lavasani et al., 2017; Guzman et al., 2021; Arellana et al., 2022) to overcome their deficiencies.

4.3. Travel time sacrifice

Table 3 shows the share of drivers who accept up to 2, 5, and 8 min of TTS in all scenarios of SP data. For liveability, half of the respondents take the SRR with 10% longer travel time under the nudge strategy, while under 5 other strategies, the biggest shares of drivers are likely to take the SRR with 25% longer travel time, demonstrating that less TTS for liveability is accepted under the nudge strategy, compared with the other strategies. If drivers are informed that 90% of other drivers who received social routing advice for liveability follow it, the share of drivers willing to take longer routes increases. With a 90% of compliance rate, the percentage of drivers who take the SRR with 40% longer travel time is 7% higher than with a 50% compliance rate (15% vs. 8%).

Interestingly, monetary incentives flatten the results for different goals; that is, regardless of the goal, drivers accept bigger TTS compared with the nudge strategy. Almost half of the drivers take SRR with 25% longer travel time, and more than 30% of the drivers take 40% longer SRR for all three social goals. However, the two types of incentives do not produce substantial differences. This implies that less amount of cash incentive works as effectively as higher values of points in order to achieve liveability. This is in line with the discussion that, in the employment context, there is a preference for cash over non-cash incentives (Jeffrey, 2009).

Figs. 4 and 5 present the share of respondents with different levels of TTS, in SP data, for different social goals, in Helsinki and Amsterdam, under nudge and incentive strategies. In Amsterdam, under the nudge strategy, participants make the biggest TTS for emission reduction where 18% and 50% of respondents state that they take SRR with 40% and 25% longer travel time, respectively. In Helsinki, participants make the biggest TTS for safety, where 16% of respondents stated that they take 40% longer SRR. However, according to Fig. 5, under the incentive strategy, the biggest TTS is for emission reduction in Helsinki and for safety in Amsterdam (i.e., it is the opposite of the previous case), although the differences are rather small. This finding implies that the effects of information strategies on TTS vary geographically.

Table 4 shows the average travel time of the fastest routes and the suggested SRR followed by the TTS, in RP data, in Helsinki and Amsterdam. Overall, drivers in Helsinki make a more considerable TTS. In fact, the average TTS in Helsinki is computed to be 3.7 min while it is 1.7 min in Amsterdam, which are equal to 22% and 6% of the average fastest route travel time, respectively.

In RP data, TTS for safety is lower than for liveability. However, it is the opposite in SP data, implying that people are more likely to take longer routes for the sake of a safer city. Drivers are likely to take SRR

Table 3
Share of drivers (%) who sacrifice up to 2, 5, and 8 min in SP data.

TTS	$Nud+Live$	$Nud+Safe$	$Nud+Emis$	$Rei50+Live$	$Rei70+Live$	$Rei90+Live$	$Inc10p+Live$	$Inc10p+Safe$	$Inc10p+Emis$	$Inc1€+Live$
Up to 2 min[a]	50	33	29	36	36	30	20	26	17	15
Up to 5 min[b]	42	48	55	53	48	50	48	42	48	50
Up to 8 min[c]	6	17	12	8	11	15	30	30	33	33

[a] 10% of the shortest travel time.
[b] 25% of the shortest travel time.
[c] 40% of the shortest travel time.

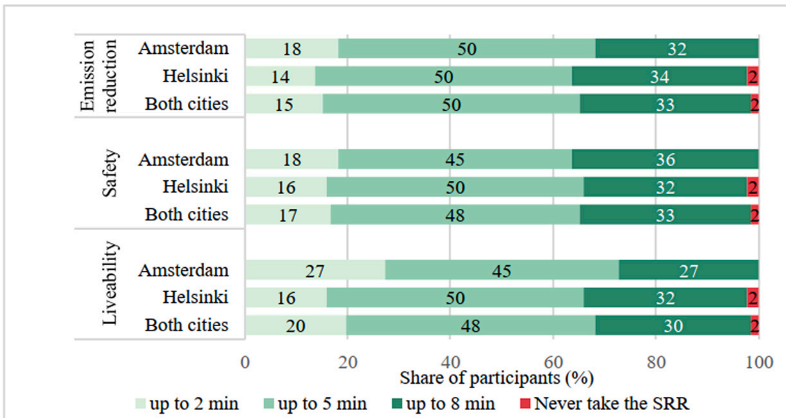

Fig. 5. TTS for various social goals under the incentive strategy ($Inc10p+G$) in Helsinki and Amsterdam.

Table 4
TTS and travel time (min) in Helsinki and Amsterdam in RP data.

	Helsinki	Amsterdam	Both
Avg. travel time of the fastest route	21.3	31.6	22.0
Avg. travel time of the SRR	25.9	33.7	26.5
Avg. travel time of the fastest route when SRR is selected	21.7	42.9	23.3
Avg. travel time of the SRR when SRR is selected	25.4	44.6	26.9
Avg. TTS	3.7	1.7	3.6
Avg. TTS for liveability	3.8	1.7	3.6
Avg. TTS for safety	2.8	1.9	2.7

with 18% (21%) longer travel time for liveability, while they are likely to take 22% (18%) longer SRR for safety, based on SP (RP) data.

5. Model results and interpretations

Two MORL models are estimated for SP and RP data, and are called the SP model and RP model, respectively. Stata 17 is employed for data analysis and model calibration. Table 5 presents the estimation results of the two models with 660 (66 respondents × 10 scenarios) and 447 observations for SP and RP data, respectively. The Wald chi-squared test in both models results in a p-value (Prob > χ^2) being very close to zero, indicating that there is evidence to reject the null hypothesis that all coefficients are zero. This implies that the models are statistically significant. Additionally, the McFadden Pseudo R-squared values (McFadden et al., 1973) are calculated to be 28% and 13% for the SP and RP models, respectively, suggesting that the models explain a substantial portion of the variation in the dependent variable compared to the null model, indicating a good fit for discrete models.

In Table 5, the empty cells in this table show that the associated variables are not significant in the model, while cells with dash signs illustrate that the corresponding variables do not exist in the data. We categorized the variables into different groups and discuss the impacts of each category in the rest of this section.

(a) Social goal
Looking at the results in Table 5 related to the SP model, drivers are more likely to accept higher levels of TTS for safety and emission reduction, compared with liveability. However, it should be noted that safety and emission reduction are actually part of the broader concept of liveability. This finding, therefore, demonstrates that avoiding generality and being more specific about the goal of detour lead to acceptance of higher levels of TTS. Furthermore, TTS for safety is not significantly different from emission reduction in both models.

(b) Information strategies
Regarding the way routing advice is intended, the performances of $Rei50$ and $Rei70$ are not significantly different from the nudge strategy. However, $Rei90$ and both incentive strategies positively influence TTS, implying that, under these information strategies, drivers accept higher levels of TTS than with the nudge strategy. Still, the impact of the incentive strategies is stronger than Rei90. In line with the findings from the statistical analysis of data in Section 4, no significant difference is observed between the two types of monetary incentives, demonstrating that 1€ cash is as strong as 10 points (=2€).

(c) Sociodemographics
Among various sociodemographic variables collected in the survey, age and education seem to have significant impacts on levels of TTS, and their impacts are similar for both SP and RP models. Elderly drivers make bigger TTS than younger drivers. Having a university degree, interestingly, is negatively correlated with levels of TTS, meaning that drivers with university degrees are less willing to accept higher levels of TTS, which might be due to their potentially tight schedules. The same impact has been observed for compliance rate that is negatively correlated with the level of education (Chen and Jovanis, 2003).

(d) Drivers' attitudes
In the SP model, the more people care about the environment and sustainability, the higher levels of TTS they accept. Besides, drivers who are more willing to change their routes to contribute to a safer city make bigger TTS. These variables are not found significant in the RP model. People who have a high desire for

Table 5
Mixed Ordered-Response Logit model results for SP and RP data.

	SP			RP		
	Coeff.	t value	P>|t|	Coeff.	t value	P>|t|
Social goals (Ref.: Liveability)						
Safety	0.60	2.37	0.02	−0.49	−1.56	0.12
Emission reduction	0.52	2.07	0.04	–	–	–
Information strategies (Ref.: Nudge)						
$Rei50$	0.22	0.69	0.49	–	–	–
$Rei70$	0.22	0.68	0.50	–	–	–
$Rei90$	0.64	1.97	0.05	–	–	–
$Inc10p$	1.48	6.95	0.00	–	–	–
$Inc1€$	1.47	4.45	0.00	–	–	–
Sociodemographics						
Age >50 years	0.82	3.87	0.00	1.67	5.91	0.00
Having a university degree	−0.64	−3.16	0.00	−2.52	−7.73	0.00
Drivers' attitudes						
High-level importance of the environment and sustainability	2.31	10.00	0.00			
High-level acceptance of an unfamiliar route recommended by a navigation app	0.57	2.70	0.01	0.75	3.03	0.00
High-level desire for changing routes to contribute to a safer city	1.12	5.70	0.00			
High-level desire for receiving nudges	0.94	4.84	0.00	1.13	4.36	0.00
Car-/driving-/trip-related attributes						
Driving a petrol car	−0.79	−4.53	0.00			
Driving an electric car				2.15	2.37	0.02
High-level familiarity with the road network in the city center	0.44	2.25	0.02	1.74	4.31	0.00
Using a personal vehicle (almost) daily				0.54	2.09	0.04
Running errands is the regular purpose of trips to the city center	0.52	2.17	0.03	0.77	2.81	0.01
Driving time between home and city center longer than 30 min				−0.69	−1.90	0.06
Normal route choice behavior						
Saving time is the main goal of route choice	−0.30	−1.76	0.08			
Relying on my knowledge/experience	−0.35	−1.92	0.06			
Relying on navigation apps				2.33	3.33	0.00
Characteristics of suggested SRR						
Distance of the SRR (km)	–	–	–	0.01	−1.73	0.08
Cutpoints						
κ_1	−1.09	−2.46	0.02	1.41	2.91	0.00
κ_2	2.79	6.42	0.00	2.51	5.12	0.00
κ_3	6.05	12.47	0.00	3.62	7.24	0.00
Wald Chi-squared test	258.81 (Prob. > χ^2 = 0.00)			89.76 (Prob. > χ^2 = 0.00)		
Number of observations	660			447		

receiving nudges, as well as people who are likely to accept unfamiliar routes recommended by navigation apps, are more willing to make heavier TTS, for both SP and RP models.

(e) Car-, driving-, and trip-related attributes
Based on the SP model, owners of petrol cars are less likely to accept bigger levels of TTS, compared with drivers who own other types of cars (e.g., electric, hybrid, and diesel). However, these variables are not found significant in the RP model. Instead, using an electric vehicle is positively correlated with the levels of TTS, in the RP model. Having an electric car might be translated to a higher importance of the environment to the driver, as its impact is explained in the previous item (d). Nonetheless, the pairwise correlation between these two variables is 0.19, meaning that no high correlation is found between these two features.
People who use their cars daily or almost daily are more inclined to accept higher levels of TTS, compared with the drivers who use cars less frequently, in the RP model. Furthermore, people who drive more than 30 min to get to the city center are less likely to accept higher levels of TTS. These findings demonstrate that frequent car users and people who are close to the city center act more socially, probably due to a clearer perception of traffic externalities.
Drivers who regularly travel to the city center for running errands are more likely to make higher TTS, compared with work commuters and individuals driving for other purposes (e.g., shopping), in both models. Also, the higher familiarity with the road network, the higher willingness to accept greater TTS.

(f) Route choice behavior
As expected, drivers who choose their routes in order to minimize travel time are reluctant to accept high levels of TTS. Participants who rely on their experience/knowledge for route choice are also less inclined to make bigger TTS, compared with the people who choose routes based on a combination of personal knowledge and navigation apps or solely via navigation apps, in the SP model. Conversely, in the RP model, drivers who choose their routes relying on navigation apps make bigger TTS, compared with the people who choose routes based on a combination of personal knowledge and navigation apps or solely via their knowledge.

(g) Characteristics of suggested SRR
As travel distance is measured in the revealed choice experiment, the distance of the SRR is used as an explanatory variable in the RP model. The result indicates that a longer distance of the SRR leads to less tendency towards higher levels of TTS.

6. Conclusion

Digitalization offers the opportunity to provide real-time information to navigate traffic in line with city values. The information and routing advice can be conveyed through a navigation app, aiming at rerouting traffic flow in specific areas, at specific times, and for specific reasons. As it is reasonable to assume that the bigger the share of compliance with the routing advice, the better the network efficiency, offering compatible route advice with drivers' preferences leads to better use of the existing road infrastructure while moving towards city values. Despite the fact that one of the main components affecting complying with the routing advice is the level of TTS, little attention is paid to the amount of TTS that drivers are ready to accept for various social goals under different information strategies. Accordingly, this study develops a framework including data collection and a choice model to address factors affecting TTS and determine the suitable information strategy based on required TTS for achieving a specific social goal.

To this end, this study designed a methodology that includes stated choice and revealed choice experiments in Helsinki, Finland, and Amsterdam, the Netherlands, and Mixed Ordered-Response Logit models applied to both SP and RP data to provide insights into social routing behavior, as well as investigate the difference between SP and RP data. The outcomes of the study contribute to a better understanding and prediction of influential factors on TTS, which will be useful for future traffic demand management policies and strategies by offering individual-specific social routes for particular reasons and improving the performance of the transportation network.

The data suggests that people in different countries might have different priorities, as shown in Figs. 4 and 5. Therefore, a more detailed comparison between TTS behavior in different geographical locations with sufficient records will be of interest. The outputs of the models indicate that the type of information given to drivers, the goal for the detour, sociodemographics, drivers' normal route choice behavior, and drivers' attitudes towards the environment, sustainability, and navigation apps significantly affect social routing behavior.

According to the performance of various information strategies, if a higher level of TTS is needed, the road authority might consider implementing monetary incentives. Reinforcement with higher levels of compliance (e.g., 90%) is at the next level. Regarding the type of monetary incentive, we did not find a significant difference between 1€ cash and 10 points (=2€) to stimulate drivers to contribute to a more liveable city. Besides, under the incentive strategy, no significant difference is found between various social goals, meaning that offering monetary incentives in return for choosing SRR smooths the effects of goals. It is essential to recognize the inherent risk in any incentive scheme, as there is a potential for attracting travelers from other modes to car traffic and inducing demand by decreasing the cost of travel. Our approach focuses on reducing the cost of longer routes to offset the additional travel time, thereby encouraging drivers to consider alternative routes aligned with social goals. Notably, we underscore that offering high incentives capable of generating additional revenue for drivers should be deliberately avoided.

Several significant variables in the SP model are not found significant in the RP model, and vice versa. Besides, the compliance rates are found different under the two data. Revealed choice experiments usually suffer from low numbers of observations due to high operation costs. This is why this study and earlier studies in this field have small RP sample sizes. For instance, Djavadian et al. (2014) recruited 25 people, van Essen et al. (2020) hired 28 people, and this study recruited 36 people in total. Hence, there is always a trade-off between running stated and revealed choice experiments. A solution to overcome the limitations of both data is combining SP and RP data by scaling SP data to obtain the same variance in both data. Thus, the analysis in this paper could be extended by employing a joint SP–RP model to investigate how much the variances of unobserved utility within both data are different. If they are not different, one can pool the two data to enrich the data and dominate the deficiency of the data.

Despite the attempts made in this study to investigate factors affecting TTS, there are certain limitations, mostly regarding data, that need to be addressed in the future. We acknowledge the bias presents in the SP data caused by asking respondents about their maximum level of TTS, and using a fixed baseline travel time in SP data (e.g., 20 min). Although the effect of cultural differences exists in our sample, we could not control that to avoid biased results as single samples are small. The small sample size also could potentially limit the statistical power of the analysis. With a larger dataset, traditional validation approaches like splitting into training and validation sets could enhance the assessment of our model's performance. Additionally, the absence of directly comparable studies in the existing literature posed challenges in validating our model outputs against established patterns. Thus, the outcomes of this study, although not fully suitable for shaping comprehensive policy recommendations, contribute significantly to our understanding of drivers' social routing behavior, and offer a foundation for further investigation and exploration in this area. Furthermore, a comprehensive comparison between SP and RP data was not possible due to RP's limited information about the incentive strategy and the goal of emission reduction. Having the same nature of TTS (e.g., either continuous or discrete) in both data can enhance result reliability.

CRediT authorship contribution statement

Shaghayegh Vosough: Conceptualization, Methodology, Software, Formal analysis, Writing – review & editing, Visualization. **Claudio Roncoli:** Conceptualization, Methodology, Writing – review & editing, Visualization, Supervision, Funding acquisition.

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.

Data availability

The authors do not have permission to share data.

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