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# Understanding preferences for mobility-on-demand services through a context-aware survey and non-compensatory strategy

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ABSTRACT

The potential lack of realism in stated-preference surveys is particularly acute in contexts where disaggregate real-world data is challenging to obtain. Mobility-on-Demand (MOD) services present one such context. The MOD context is unique due to factors such as service reliability (difference in stated vs. actual travel and waiting time) and current mode inertia which affect the choice of MOD services and are difficult to infer from revealed preference data. Further, travel mode choices are repetitive and constitute a relatively easy choice situation. Consequently, individuals may utilize simple non-compensatory strategies. In this study, we design a survey to mimic real-world choice sets using a joint revealed and stated- (RP-SP) preference survey approach. We construct the complete journey of individuals taking into account departure time, access and egress mode, current primary mode and origin–destination pair. A Choquet Integral (CI)-based choice model with endogeneity correction is employed, thereby allowing to approximate non-compensatory behaviour. Results confirm the presence of non-compensatory behaviour across all mode users (car, public transport and bike). Reliability and inertia effects are most pronounced for car users including the potential for a combined departure time-mode shift towards MOD. Owing to non-compensatory behaviour and inertia, higher travel costs cannot be fully compensated by shorter waiting and travel times and a differential pricing strategy may be required to increase MOD market share. Failure to account for common unobserved factors between the RP and SP choices results in inflated attribute importance.

## 1. Introduction and motivation

Mobility-on-demand (MOD) services such as Uber and DiDi may potentially offer substantial economic and environmental benefits (Teubner and Flath, 2015). Using a simulation model, Alonso-Mora et al., (2017) concluded that 3000 four-passenger cars could serve 98 % of New York taxi demand assuming perfect sharing compatibility. Despite such proclaimed benefits, MOD services market share has been comparatively low, especially for regular trips. According to a report by DBS Asian Insights (2019), the penetration of ridesharing services is still under 1 % of total passenger vehicle trips of up to 30 miles in the United States. It is, therefore, crucial to gain a better understanding of the underlying behavioural determinants which impact travellers' choices in the presence of MOD alternatives. This will enable us to cater service operations as well as design Mobility as a Service (MaaS) platforms, where MOD is expected to play an important role, so as to target specific user groups.

Several studies have attempted to understand the factors affecting the propensity of individuals towards MOD service. In particular,

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indicative socio-demographic indicators and trip purpose (Dias et al., 2019; Sikder, 2019), the effect of reliability (Bansal et al., 2020; Bailey, 2022), and competition/complementarity between MOD and existing modes (Jin et al., 2019; Cats et al., 2022). While such studies have enhanced our understanding, we identify two key limitations pertaining to data collection and modelling strategy.

The vast majority of studies rely on stated-preference (SP) surveys due to the scarcity of publicly available individual-level trip data with detailed information such as trip purpose, access/egress mode and household configuration. However, the use of hypothetical scenarios reduces the validity and transferability of the results (Beck et al., 2016). To overcome these issues, researchers have turned to either a pivot-based SP approach or recently developed SP surveys based on real-world options encountered by an individual through API (application programming interface) and GPS (global positioning system) systems. Using the pivot approach is appealing (Krueger et al., 2016; Weiss et al., 2019) as it enables the generation of attributes thereby leading to a reduced risk of generating alternatives that lack meaning and are not engaging (Fifer et al., 2014; Cherchi and Hensher, 2015). However, it may not enable a true representation of real-world decision strategy due to a high discrepancy between stated and true values. Further, such an approach induces endogeneity (Train and Wilson, 2008; Guevara and Hess, 2019). The use of API and GPS can help construct fully context-aware surveys with engaging choice sets (Frei et al., 2017; Song et al., 2018; Danaf et al., 2019) as evidenced by the high hit rate in personalized menu providers (Song et al., 2018). SP studies tend to include all the existing travel options (car, public transport, bike and walk) depending on the origin–destination information in the SP choice set in addition to MOD option(s). Such a choice set construction can introduce bias in parameter estimates due to the inclusion of irrelevant alternatives (Ng'ombe and Brorsen, 2022) in the absence of an explicit choice set construction procedure in such an independent availability logit (IAL) model. A significant share of trips made on weekdays involves regular trips such as commutes, grocery shopping and school/college trips. Travel mode decisions for regular/repeated tasks tend to be habit and attitude-driven (Ramos et al., 2020). Therefore, an individual may only compare the new MOD service(s) with the currently used mode (car, public transport, bike and walk) in the context of regular trips. Such an assumption is not unfounded and empirical evidence of such behaviour does exist in transportation (Thøgersen, 2006; Gao et al., 2020) and other contexts such as agricultural economics and marketing (Chang et al., 2009; Eliaz and Spiegler, 2011).

Constructing individual-specific SP choice sets may also help reduce the divergence between true and modelled decision strategies. A considerable body of empirical evidence points to the usage of simpler non-compensatory behavior in the context of familiar repeated choices (Hoyer, 1984, Aarts et al., 1997; Innocenti et al., 2013). Yet, such mode-specific evidence has been difficult to establish in the context of MOD service choices due to the use of generic SP choice sets and data/context-specific non-compensatory models in past studies.

An additional advantage of excluding irrelevant options (especially existing travel mode options) from the SP choice set is allowing researchers to expand the scope of the study. For example, one can include options to capture the preference of MOD service for first, last or both legs or departure window preference (early or late) with a minimal increase in task complexity (Swait and Adamowicz, 2001). Expanding the scope also helps obtain unspurious parameter estimates.

In this study, we model the preferences related to MOD services for regular trips through the use of an API-based SP survey and a discrete choice model (DCM) based on a Choquet-Integral aggregation function (Dubey et al., 2022). We utilize Google Map API to extract trip features (access and egress modes, main mode, travel time and cost of various legs depending on the mode) and construct individual-specific SP choice sets. The SP choice set includes a primary mode (reported by the individual for a particular regular trip and purpose) and four MOD options (representing early and late departure windows). We also include service reliability (stated vs. actual travel and waiting time) for the MOD options. The novel inclusion of departure window and service reliability in the SP choice set enables the quantification of temporal mode-shift, inertia effects (mode-specific and time-specific) and regret concerning future choices. We choose to use a CI-based DCM as it requires no a-priori assumptions. The CI can approximate various functional forms such as weighted sum (compensatory behaviour), ordered weighted sum, and minimum or maximum of an attribute value. It can also approximate conjunctive and disjunctive behaviour through the use of endogenous attribute cut-offs. Other non-compensatory behaviour approximation models such as attribute cut-off-based approach (Swait, 2001; Martínez et al., 2009) and utility-regulating functions (Elrod et al., 2004) either require pre-knowledge of cut-offs or are computationally cumbersome.

This study makes several non-trivial substantial and empirical contributions. Our survey design and subsequent model estimations are developed to quantify and capture the impacts of heterogeneity and uncertainty in MOD-related travel choice, both key aspects in the simulation and optimization of new shared mobility solutions. In particular, our contributions are fivefold. First, the study sets out to empirically estimate the extent to which non-compensatory behaviour is exercised and accordingly develops an SP survey with greater realism and estimates choice models that are capable of eliciting a non-compensatory behaviour. Second, we add two important mode choice aspects: temporal mode shift and reliability in the context of mobility-on-demand (MOD) services. To the best of our knowledge, this is the first data collection effort that allows for such an analysis. Third, due to the inclusion of individual-specific primary mode in the SP choice set, endogeneity corrections must be applied. In our estimation framework, we control for endogeneity through a covariance approach. To the best of our knowledge, this is the first empirical application in the context of MOD choice through context-aware surveys to account for endogeneity. Due to the size of the choice set and the longitudinal nature of survey data, the endogeneity correction approach needed to be modified using a composite-marginal likelihood approach to render the estimation computationally feasible. The modified estimation approach will enable a wider application of endogeneity correction in future empirical works. Fourth, we methodologically demonstrate and empirically quantify how inertia and the effect of past choices can be included in the preference evaluation. Finally, we also highlight through the analysis of service fee derivation how false assumptions about the underlying behavioural mechanism can lead to erroneous planning and design decisions. We show that the impact of MOD services on public transport is likely to be limited. Furthermore, we demonstrate the implications of our findings for the design of differential pricing strategies and related revenue management techniques.

The remainder of the paper is organized as follows: Section 2 provides an overview of the literature on the determinants of MOD choice dimensions followed by a description of survey design in Section 3. Section 4 provides the description of the Choquet-Integral followed by model formulation and estimation strategy. Section 5 provides the description of survey data, model results and performance measures. Conclusions, limitations, and avenues of future research are discussed in Section 6.

## 2. Determinants of MOD choice

Elicitation of respondents' preferences as a function of travel time, waiting time, and travel cost is straightforward in the SP survey. However, the inclusion of service reliability and departure time preference requires careful consideration as it may affect the size of the choice set. In this section, we provide a discussion on the importance of these factors and their measurement in the survey.

### *2.1. Service reliability*

Reliability (certainty) plays an important role in travel mode and route choice. Evidence suggests that information on bus arrival and any unexpected delay tends to reduce the perceived waiting time, reduce the feeling of uncertainty and even increase ease of use (Dziekan and Kottenhoff, 2007; Watkins et al., 2011). In the context of MOD, a user may opt to pay higher costs for a more reliable service provider or may budget extra time to cope with the negative implications of an unreliable service. Hence, over a long period, modal choice depends largely on an individual's ability to learn about service reliability, i.e., variability of travel and waiting time, ceteris paribus (see Li et al., 2010 for an excellent review).

In the context of mode choice, the reliability effect is captured in the SP survey design by providing travel time information as ranges or an additional possible increment due to uncertainty (Bhat and Sardesai, 2006; Tam et al., 2011) and as an indicator variable (late or early departure) due to uncertainty (Wakabayashi et al., 2003). Similar to travel mode literature, route choice literature offers several avenues to quantify the effect of reliability (Gao et al., 2010; Ben-Elia et al., 2013a; Ghader et al., 2019). One way to include the uncertainty in the design is by considering travel time as either probabilistic, range or a combination of fixed and probabilistic values (Razo and Gao, 2013). Alternatively, feedback (generally upon making a choice) or some external information is provided to respondents in an iterative choice-making setting (Avineri and Prashker, 2005; Avineri and Prashker, 2006; Ben-Elia and Shiftan, 2010; Cats and Gkioulou, 2017).

The feedback approach is appealing as it offers a process-oriented approach (difference between expected and actual travel and waiting times) to model the regret depending upon the degree of risk aversion exercised by the individual (Ben-Elia et al., 2013b). Over time individuals learn about the reliability of a service and may change their behaviour accordingly. Therefore, we convey the reliability of the MOD service through the feedback approach in the survey.

### *2.2. Departure time window*

A change in departure time (early or late) is tied to both the cost and reliability of the service. In a systematic review of congestion pricing and its impact on car usage and change in departure time window, Li and Hensher (2012) observed that peak-hour pricing led to a decrease in car usage and social trips (Saleh and Farrell, 2005, Ubbels and Verhoef, 2006; van Amelsfort et al., 2008). Several other studies also indicate some level of trip reduction among car users but not so among public transport users (Jaensirisak et al., 2005; Hu and Saleh, 2005). Owing to the temporal flexibility of MOD services, users can choose when to depart depending on the trip's purpose and cost. Since MOD service prices are relatively higher in peak hours as compared to non-peak hours (Garg and Nazerzadeh, 2021), there might be a financial incentive on the part of users to adjust the departure time window. Reliability, on the other hand, can lower the financial incentive. A traveller would likely plan to depart early when faced with an unreliable service, ceteris paribus (Gaver, 1968).

Departure time is usually represented in the SP survey as an additional attribute (Arellana et al., 2012). For modelling purposes, they are treated as categorical variables (early, current or late). To represent the departure time preference in the survey, we adopt the same approach. However, we represent the departure time as a time window (restricted to 15 min) as compared to the point value used in the literature. The time window approach facilitates the estimation of demand on a continuous time scale (discretized on an interval of 15 mins).

The inclusion of departure time preference can lead to an increase in the size of the choice set depending on the availability of other modes. To circumvent this problem, we utilize the concept of a two-stage choice process in the survey.

### *2.3. Choice set construction*

As postulated by Manski (1977), choice is a two-stage process where the first stage involves the elimination of irrelevant alternatives followed by a careful examination of relevant alternatives in the second stage to make a choice. The SP survey design can be modified to include highly relevant alternatives in the choice set. In particular, for a given trip purpose and departure time window, the choice set (displayed to the respondent) may only include the primary mode (currently used mode for the specific trip purpose) and MOD alternatives. This has two advantages. First, it reduces the size of the choice set and therefore is cognitively less demanding (Swait and Adamowicz, 2001). Second, it enhances the model performance and parameter sensitivity (Ng'ombe and Brorsen, 2022).

## 3. Mode choice survey

In this section, we provide details of the survey design. The survey was designed using the Qualtrics platform and is a web-based survey.

### 3.1. Survey description

The survey consists of a two-step process devised to elicit user modal preferences based on their choice from a relevant and relatable choice set. In the first step (revealed choice/preference: RC/RP), respondents are asked to provide trip details of their most frequent daily trip: origin–destination (OD), departure time window (restricted to a 15-minute window), trip purpose (work-related, school/college, family and personal care, and social or recreational), and currently used primary trip mode (car, train/metro, bus, tram/light rail, and bicycle). To collect origin and destination locations, we provide users with an embedded Google Map interface where they can directly type the addresses of their origin and destination or nearby locations (e.g., in case of limited information or privacy concerns). Fig. 1 provides a screenshot of the origin information collection module in the survey. In this illustration, the user chooses School/college trip as their most frequent daily trip purpose. A similar interface is also used for destination information collection with appropriate wording. Next, the primary trip mode is defined as the mode which covers the largest distance. Trips with walking as the primary mode or bikes with a trip distance of less than 2 km were screened out to ensure reasonable parity between MOD travel and pick-up time. Based on trip information, travel time, waiting time (if any), and cost are obtained using Google Map API (Distance Matrix Calculation API). In case public transport is the primary mode, respondents are asked to provide information on origin–destination stop and access and egress modes. With the help of this additional information, accurate access time, waiting time at the stop, in-vehicle time, egress time and trip cost are obtained through Google Map API. Fig. 2 presents a typical public transport trip. In this example, the respondent reported a departure window of 7:00 – 7:15. We therefore set the trip start time to 7:07. This information along with the option 'walking' is fed into Google API to obtain the time (i.e., 10 min) and distance to the nearest bus stop. The waiting time at the bus stop is obtained using the respondent's time of arrival at the stop and the next bus's arrival at the stop.

The procedure is followed until reaching the indicated destination for each leg of the trip to obtain the total time, distance and cost of the performed trip. The public transport fare (€) is obtained by applying the distance-based fare structure used by the public transport authorities in the Netherlands ($0.96 + 0.162 * \text{distance [km]}$). For the car mode, travel cost is determined based on per-km car operating cost obtained through information on the user's car mileage, maintenance cost, parking and toll, registration and insurance, kilometre driven per year, age of the car, and ownership (own vs. rented).[1]

In the second step (stated preference: SP), we present respondents with a series of choice experiments where each experiment consists of a total of five alternatives composed as a combination of mode and departure time window restricted to 15-minute intervals:

1. Primary mode at reported departure window
2. MOD option 30 min earlier
3. MOD option 15 min earlier
4. MOD option at reported departure window
5. MOD option 15 min later

### 3.2. SP efficient design

Using a D-efficient design in Ngene, we generated two blocks of 15 choice tasks each. In the D-efficient design, six attributes with three levels each (continuous variables) and one attribute with two levels were used as shown in Table 1.1.

To ensure that the price of a shared MOD is not greater than the one for the non-shared MOD (irrespective of the MOD label defined through departure window value), appropriate constraints on price attribute level were defined for each of the four MOD options in Ngene.

### 3.3. SP survey example

Fig. 3a provides a screenshot of the choice experiment module in the survey for train users. Relevant mode features (travel time, waiting time, travel cost and a dummy variable indicating whether the MOD service is shared or private) are provided. A pop-up window is provided to aid respondents in the event of symbol clarification as shown in Fig. 3b (screenshots of the choice experiment and symbol explanation for car users are provided in the supplementary sheet section S.1). Before the start of the choice experiment module, an information page is displayed detailing the meaning of every symbol and terminology used in the choice experiment. Upon making a choice, respondents receive information about the actual travel and waiting time as shown in Fig. 4. The feedback information is only provided if the respondent selected one of the MOD options. We decided to not provide feedback in case the primary mode has been chosen as it may interfere with the respondent's existing experience.

In the choice experiment, the cost of the primary mode is kept unchanged, i.e., we display the actual cost obtained from the Google

[1] If the user reports ownership as own, then the total amount paid or monthly instalment (whichever is applicable) is appropriately recorded. In the event of ownership as leased, the monthly instalment is recorded.

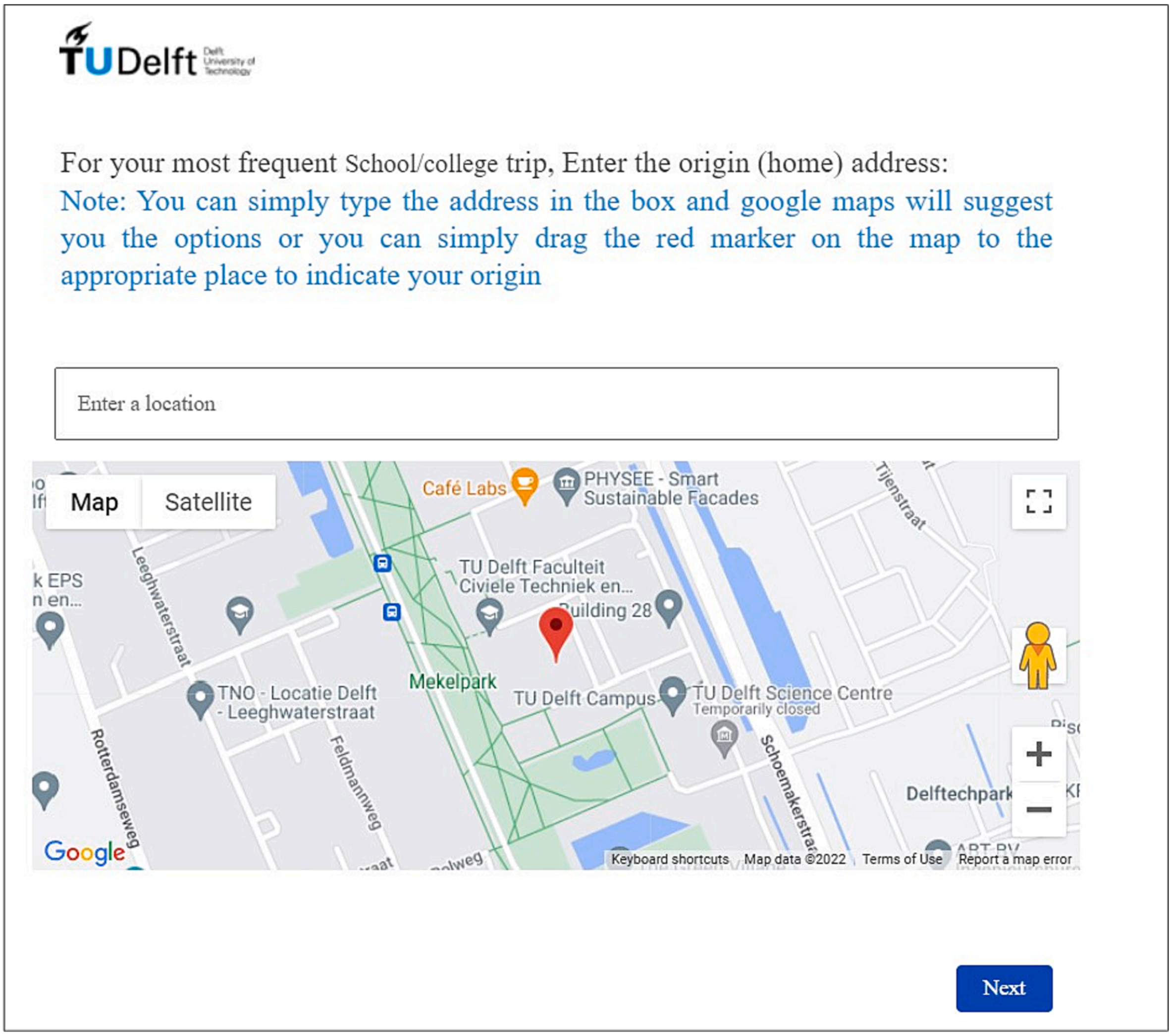


**Fig. 1.** Origin-Destination module in the survey.

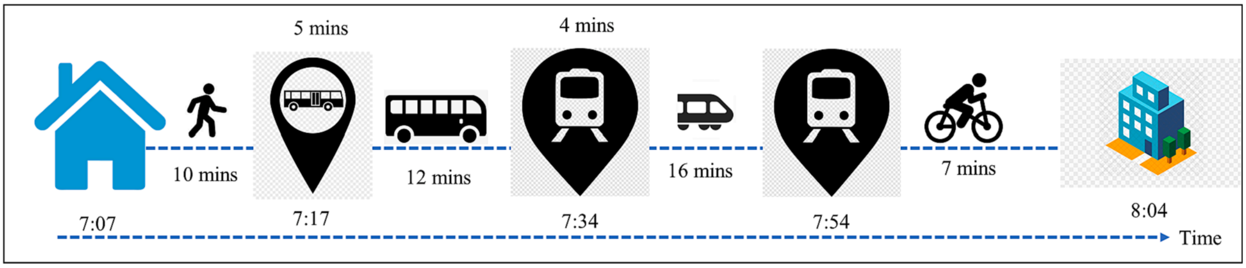


**Fig. 2.** Illustration of a public transport trip.

API for the reported OD pair. The MOD travel times are based on car travel time obtained through the Google API, i.e., the same base travel time is used for all options in the case of car users. In the case of non-car users, public transport and car travel times are used for the PT option and other MOD options, respectively. The access and egress times of the public transport (primary mode) for the non-motorized modes (walking and biking) are also kept unchanged. All the other values of travel time, waiting time, cost, access and egress time values are drawn from their respective ranges (attribute level) with an equal probability (uniform distribution) as shown in Table 1.1. In the event of the same price level of a shared and non-shared ride, numbers are drawn until the implied value of the non-shared ride is greater than the shared ride. Finally, the actual travel and waiting times displayed on the experience screen are uniformly

**Table 1.1**
Attribute levels

| Attributes | Levels | | |
|---|---|---|---|
| | 1 | 2 | 3 |
| Travel time | [tt-3, tt + 2] | [tt-1, tt + 2.5] | [tt + 1, tt + 3] |
| Waiting time for MOD | [2, 5) | [5, 10) | [10, 15] |
| Travel cost/km for a private ride | [0.3, 0.6) | [0.6, 0.9) | [0.9, 1.15] |
| Travel cost/km for shared ride | [0.3, 0.5) | [0.5, 0.8) | [0.8, 0.9] |
| Shared indicator | Yes (1) | No (0) | |
| Access time (AT) (applicable for motorized access mode and public transport as primary mode) | AT * [1, 1] | AT * (1, 1.2] | AT * (1.2, 1.4] |
| Egress time (ET) (applicable for motorized egress mode and public transport as primary mode) | ET * [1, 1] | ET * (1, 1.2] | ET * (1.2, 1.4] |

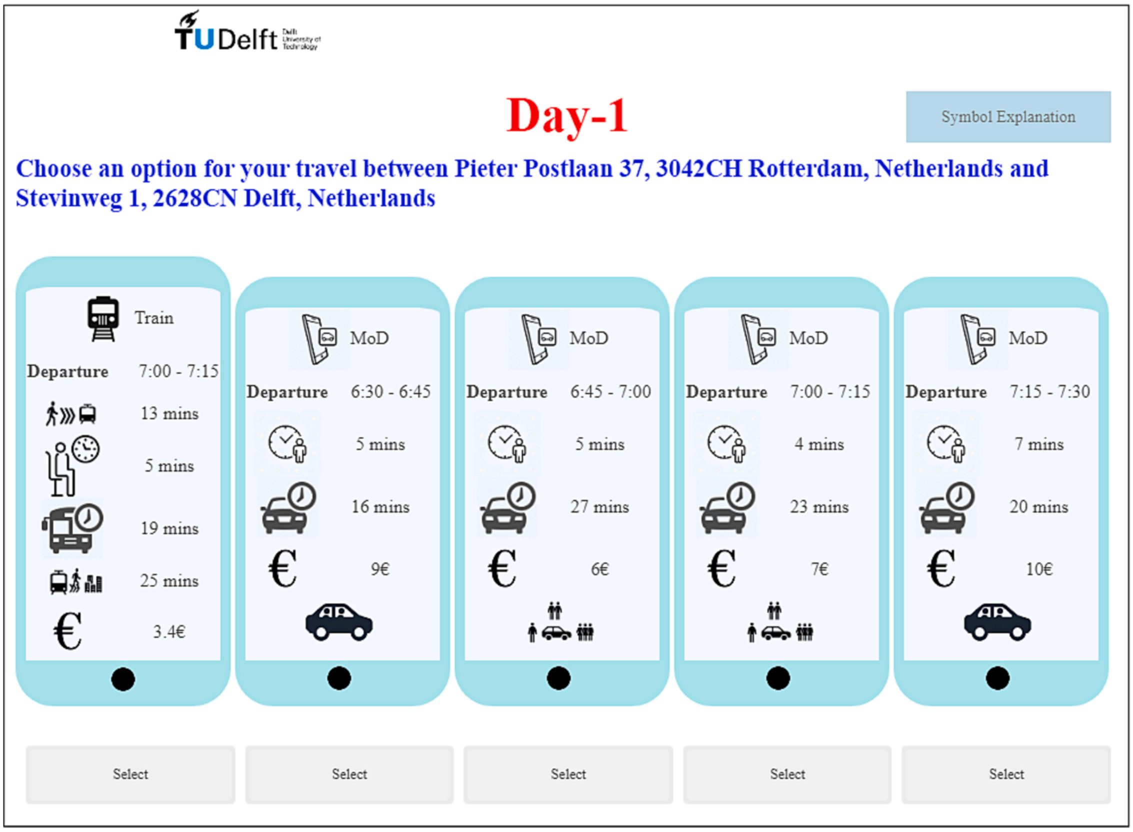


**Fig. 3a.** Choice experiment for the train users.

drawn from a range as shown in Table 1.2. Since the actual travel and waiting times are always longer than the expected travel and waiting times, our estimate of reliability differs in interpretation from those reported in earlier works (Ben-Elia and Shiftan, 2010; Ben-Elia et al., 2013b) where the focus was on understanding long-term route/mode convergence. Such a setting is not feasible in the current survey due to the relatively larger choice set (5 options). Therefore, to an extent, we measure the trade-off between increased travel and waiting time in future choices.

In the survey, each respondent completes a total of 15 choice tasks with each choice task framed as a 'Day' progressing from Day-1 to Day-15.

## 4. Choquet Integral

It is impossible to cover the entire non-compensatory literature and associated modelling methodology. We encourage the readers to refer to Lew and Whitehead (2020) for an excellent review of non-compensatory literature and Dubey et al., (2022) for methodological limitations of such frameworks. Below we provide a brief introduction of Choquet-Integral to highlight its mathematical properties.

Let $K$ be the total number of attributes and $Z(\{\phi\}, \{1\}, \{2\}, ..., \{K\}, \{1, 2\}, ..., \{1, 2, ..., K\})$ denote the collection of all subsets (size:

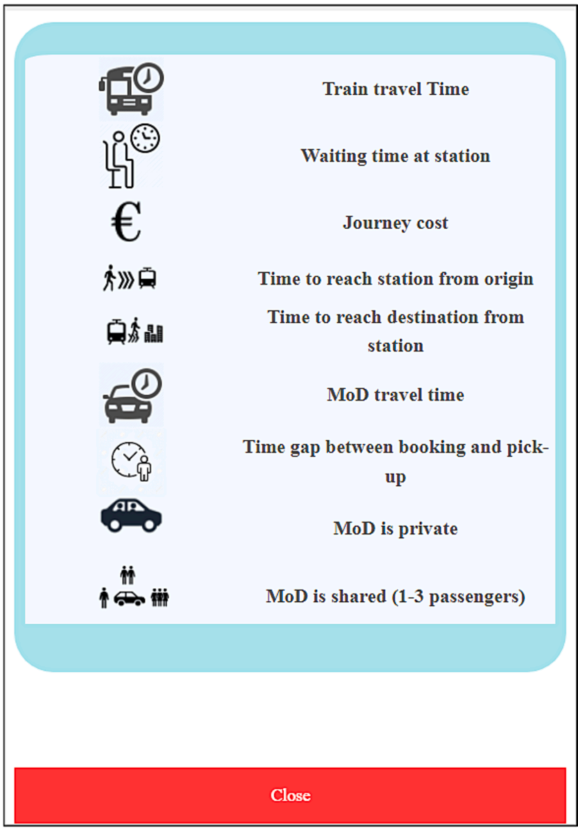


**Fig. 3b.** Pop-up window of “Symbol Explanation” for train users.


**Fig. 4.** Feedback information.

**Table 1.2**
Reliability band

| Car travel time (CTT) | Actual travel time | Actual waiting time |
|---|---|---|
| CTT <= 20mins | [1.25*DTT, 1.30*DTT] | [1.25*DWT, 1.30*DWT] |
| 20 mins < CTT <= 40mins | [1.25*DTT, 1.30*DTT] | [1.25*DWT, 1.30*DWT] |
| CTT > 40mins | [1.10*DTT, 1.20*DTT] | [1.10*DWT, 1.20*DWT] |

*DTT: displayed travel time, DWT: displayed waiting time.

$2^K$) of $K$ including the null set ($\{\phi\}$). Each element in set Z is called a ***coalition***. The amount of information (contribution towards probability) a coalition in Z offers in the absence of other attributes is called as value of coalition. Further, larger the coalition, higher the amount of information ($\mu(1,2) \geqslant \mu(1) + \mu(2)$) known as monotonicity in the number of attributes. The value of all coalitions is captured by a characteristic function ($\mu : 2^K \to \mathbb{R}$). Choquet Integral (CI) is one such function that can be used to represent the characteristic function. CI is a fuzzy integral based on fuzzy measures ($\mu$), which can be used to represent the coalition structure of attributes (Choquet, 1954; Grabisch, 1996; Alfonso, 2013). The CI aggregation function for a set of $K$ attributes can be expressed as follows:

$$CI = \sum_{k=1}^{K} h(x_{\pi_k})(\mu(A_k) - \mu(A_{k-1})) \tag{1}$$

where $A_k$ is the set of cardinality $k$ formed using permutation of attributes ($x$), $k \in \{1, 2, ..., K\}$ is the index for attributes, and

$$\begin{aligned} & h(x_{\pi_k}) \to h(x_{\pi_1}) \geqslant h(x_{\pi_2}) \geqslant ... \geqslant h(x_{\pi_K}) \geqslant 0;\ \ 0 \leqslant h(x_{\pi_k}) \leqslant 1 \\ & \mathbf{A}_K = \{x_1, x_2, ..., x_K\} \\ & \mu(\phi) = 0,\ \ \mu(\mathbf{A}_K) = 1,\ \ \mu(\mathbf{C}) \leqslant \mu(\mathbf{D}); \mathbf{C} \subseteq \mathbf{D} \subseteq \mathbf{A}_K;\ \ 0 \leqslant \mu() \leqslant 1 \end{aligned} \tag{2}$$

The function $h()$ represents the numerical value of attributes ($x$) in a descending order bounded between 0 and 1. $\mu()$ represents the fuzzy measure also bounded between 0 and 1. The number of fuzzy measures is a function of attributes, i.e., for a $K$ attribute configuration, a total of $2^K - 1$ fuzzy measures will be estimated (excluding the null set as the fuzzy measure value for a null set is 0).

The transformation $x \to h(x)$ is generally achieved through attribute normalization across alternatives. Let $\psi(x_k) = \{x_k^1, x_k^2, ..., x_k^I\}$ be the collection of the $k^{th}$ attribute values across all alternatives $I(i = 1, 2, ..., I)$. For attributes with a positive effect on choice outcome (higher the value, better the attribute), normalization can be performed as follows:

$$h(x_k^i) = \frac{x_k^i - \min(\psi(x_k))}{\max(\psi(x_k)) - \min(\psi(x_k))} \tag{3}$$

Similarly, for attributes with a negative effect on choice outcome (lower the value, better the attribute), normalization can be performed as follows:

$$h(x_k^i) = \frac{\max(\psi(x_k)) - x_k^i}{\max(\psi(x_k)) - \min(\psi(x_k))} \tag{4}$$

Next, monotonicity constraints in Eq. (2) are represented using fuzzy measures [$\mu()$]. Since fuzzy measures are constrained between 0 and 1. The monotonicity constraints are typically represented using an unconstrained transformation called Möbius transformation to reduce the problem complexity (see Dubey et al., 2022 for a detailed explanation). The transformation can be written as follows:

$$\begin{aligned} & \sum_{H \subseteq A_K} m(H) = 1 \quad where\ A_K = \{x_1, x_2, ..., x_K\} \\ & \sum_{H \subseteq A_K \backslash k} m(H \cup k) \geqslant 0 \forall k; \\ & where\ A_K \backslash k\ represents\ the\ collection\ of\ all\ attributes\ except\ the\ k^{th} attribute \\ & \qquad \cup\ represents\ the\ union\ of\ two\ sets \\ & \\ & m(.)\ is\ the\ Möbius\ representation\ of\ \mu(.)\ and\ one-to-one\ mapping\ between\ them\ is\ as\ follows: \\ & m(H) = \sum_{F \subseteq H} (-1)^{H \backslash F} \mu(F) \\ & \mu(F) = \sum_{H \subseteq F} m(H) \end{aligned}$$

Next, one can also obtain explicit attribute importance value based on CI estimates using Eq. (5) known as the Shapley value

$$S(k) = \sum_{A \subset Z \backslash k} \frac{Fact(|K| - |A| - 1)Fact(|A|)}{Fact(|K|)} [\mu(A \cup \{k\}) - \mu(A)]; \quad 0 \leqslant S(k) \leqslant 1, \tag{5}$$

where $Fact()$ represents the factorial, $||$ indicates the cardinality of the set and $\mathbf{K} = \{1, 2, ..., K\}$ is the set of all attributes. The Shapley value is interpreted as the average marginal contribution of an attribute $k$ in all coalitions, i.e., attributes can be ranked based on their Shapley value to quantify the importance of an attribute in the overall decision-making, a concept equivalent of Shapley additive explanation (SHAP) in machine learning (Lundberg and Lee, 2017).[2]

[2] Readers are highly encouraged to refer Mazzanti (2020) and Tran (2021) for an excellent non-technical explanation of SHAP values.

### 4.1. Choquet integral as a non-compensatory approximation function

Consider the following configuration of fuzzy measures for a three-attribute scenario.

$$\mu(1) = 0.00, \mu(2) = 0.94, \mu(3) = 0.00, \mu(12) = 1.00, \mu(13) = 0.29, \mu(23) = 0.94, \mu(123) = 1.00$$

Next, consider the following normalized attribute values $(x_k^i)$ for an alternative

$$\psi(x_k^i) = \left\{x_{1_1}^i, x_2^i, x_3^i\right\} = \{0.2, 0.7, 0.1\}$$

Hence $h(x_k^i) \rightarrow h(x_2^i) > h(x_1^i) > h(x_3^i)$.
With this, the CI can be written as follows:

$$\begin{aligned} CI_i &= x_2^i * \mu(2) + x_1^i * [\mu(12) - \mu(2)] + x_3^i * [\mu(123) - \mu(12)] \\ &= 0.7*0.94 + 0.2(1.00 - 0.94) + 0.1(1.00 - 1.00) \\ &= 0.66 + 0.01 + 0.00 \\ &= 0.67 \end{aligned}$$

Three observations can be made based on the calculation of CI. First, $(x_3^i)$ does not impact the choice probability as long as it is below a normalized value of 0.2. Second, the impact of $(x_1^i)$ on overall probability calculation is negligible. Third, since the normalization of attributes is based on the range across all alternatives in the choice set. It ensures that the normalized values are task and context-dependent leading to task-specific approximation of non-compensatory behaviour.

### 4.2. Choice model formulation with endogeneity correction

In studies involving the SP-off-RP approach, pivoting around the chosen RP attributes can lead to endogeneity in the SP experiment (Train and Wilson, 2008; Guevara and Hess, 2019). The endogeneity issue arises due to the use of RP-chosen alternative attributes as a base value to create the attributes of SP alternatives. Pivoting in such a way can transfer the unobserved effects from the RP stage to the SP stage. The endogeneity issue is typically corrected by estimating a joint RP-SP model with a shared un-observed parameter between the RP-chosen alternative and the corresponding SP alternative.

Although the current survey is an SP-off-RP approach, the attribute construction performed in the SP stage differs from the usual RP pivot approach. For example, if the user reported train as their primary mode in the RP stage, then the SP stage does not use train mode attributes to construct MOD mode attributes. Rather, the MOD mode attributes are created based on car attributes (car-based travel time for the reported OD pair and departure time derived using Google API, per-km travel cost and waiting time is pre-determined as reported earlier (see supplementary sheet section S.1). The same process is used for all four primary modes in the SP stage. Furthermore, all the attributes (MOD and reported primary mode) have three levels (see section 3) and hence attribute values change from one choice situation to the other. This ensures that the endogeneity issue is minimized in the SP stage. Nevertheless, from an econometric point of view, one should still perform a joint RP-SP estimation with shared unobserved factors between the RP-reported mode and the corresponding SP stage mode. This translates into the estimation of an $(19 \times 19)$[3] error-covariance matrix. Such a large error-covariance matrix can cause numerical instability during model estimation, especially in logit-kernel-based models due to the simulation-based estimation approach. Hence, we use a probit-kernel-based framework to build a Choquet-Integral-based choice model framework.

Let $t$ be the index for the choice occasion $(t = 1,2,\ldots,T)$(15 repeated choice scenarios in the SP stage), $i$ be the index for alternative $(i = 1, 2, \ldots, I)$ and $k$ be the index for the number of attributes $(k = 1,2,\ldots,K)$ (travel time, waiting time, and travel cost). Then, we can write the utility of alternative $i$ in the time period $t$ as follows:

$$U_{i,t} = CI_{i,t} + \varepsilon_{i,t} \tag{6}$$

where $CI_{i,t}$ is the CI value of the $i^{th}$ alternative at the time $t$ and $\varepsilon_{i,t}$ is a normally distributed error term.
Further, the $CI_{i,t}$ can be written as follows:

$$CI_{i,t} = \sum_{k=1}^{K} h\left(x_{N_k}^{i,t}\right)\left(\mu_i\left(A_k^{i,t}\right) - \mu_i\left(A_{k-1}^{i,t}\right)\right) \tag{7}$$

Therefore, $CI_{i,t}$ can be termed the observed part of utility calculated using a Choquet aggregation function. Eq. (7) indicates that fuzzy measures are alternative-specific but invariant across time periods. The $x^{i,t} \rightarrow h\left(x_{N_k}^{i,t}\right)$ transformation can be performed using Eq. (3) and Eq. (4).

Normalization requires that attribute values take a real number with a definite direction (effect on choice outcome). Hence, only

[3] A $(3 \times 3)$ block for the RP stage and a $(4 \times 4)$ SP block for each of the four primary mode users.

ordered data types (continuous, count and ordinal) can be used inside CI. The inclusion of unordered data types requires a special normalization approach (Wang et al., 2006). To keep the model complexity to a minimum, we revert to a weighted sum (WS)[4] approach to account for the effect of non-continuous/un-ordered attributes.[5] Therefore, Eq. (6) can be extended as follows:

$$U_{i,t} = CI_{i,t} + \boldsymbol{\beta}_i^{'}\mathbf{x}_{i,t} + \varepsilon_{i,t} \tag{8}$$

where $\mathbf{x}_{i,t}$ is a $(k \times 1)$ vector of exogenous variables, $\boldsymbol{\beta}_i$ is the corresponding $(k \times 1)$ vector of coefficients, and $\boldsymbol{\beta}_i^{'}\mathbf{x}_{i,t}$ is the observed part of utility derived using a weighted-sum (WS) aggregation function.

Next, we can include the effect of reliability (as induced through a feedback mechanism) as follows:

$$U_{i,t} = CI_{i,t} + \boldsymbol{\beta}_i^{'}\mathbf{x}_{i,t} + R_{i,t} + \varepsilon_{i,t} \tag{9}$$

where $R_{i,t} = 1 - e^{\left[\rho\left[\vartheta\left(TT(\text{experienced})_{i_{t-1}} - TT(\text{displayed})_{i_{t-1}}\right) + \tau\left(WT(\text{experienced})_{i_{t-1}} - WT(\text{displayed})_{i_{t-1}}\right)\right]\right]}$

In Eq. (9), $\rho(0,\infty)$ is a regret aversion factor with $\rho = 0$ indicating no regret. The term $\vartheta\left(TT(\text{experienced})_{i_{t-1}} - TT(\text{displayed})_{i_{t-1}}\right)$ represents the weighted difference between experienced and displayed travel time. Similarly, the term $\tau\left(WT(\text{experienced})_{i_{t-1}} - WT(\text{displayed})_{i_{t-1}}\right)$ represents the weighted difference between experienced and displayed weighting/pick-up time.

Eq. (9) can be written in a matrix format with the help of additional notations. For brevity, a detailed description of matrices/notations is provided in Appendix Section A.1.

With the help of notations, Eq. (9) can be written in matrix notations as follows:

$$\boldsymbol{U} = \left[sumc[(\boldsymbol{\beta}.^*\ \boldsymbol{X})^{'}] + \boldsymbol{CI} + \boldsymbol{R} + \boldsymbol{\psi}\right] \tag{10}$$

where $\boldsymbol{R} = \boldsymbol{I}_T - \exp\{\vartheta^* sumc[((\widehat{X}_{TE} - \widehat{X}_{TD}).^*\widehat{X}_{Chosen})^{'}] + \tau^* sumc[((\widehat{X}_{WE} - \widehat{X}_{WD}).^*\widehat{X}_{Chosen})^{'}]\}$, $\boldsymbol{I}_T$ is a column vector of size $T$ filled with a value of 1, and the operator $sumc[\,]$ returns the sum of columns of a matrix. Here we assume a time-invariant error-covariance matrix, i.e., $\varepsilon_{i,t} = \eta_i$.

$\boldsymbol{\eta} = (\eta_1, \eta_2, ..., \eta_I)^{'}$ $[(I \times 1)$ vector$]$ and $\boldsymbol{\psi} = [\text{ones}(T,1)\ .^*.\ \boldsymbol{\eta}][(TI \times 1)$ vector$]$.

Eq. (10) provides a general framework to write a utility specification including all three components: Choquet-Integral, Weighted sum, and regret due to differences in stated vs. actual travel and wait times. In our survey, we essentially have five dependent variables: one RP stage choice, and four SP stage choices depending on the reported RP stage mode (car, train/metro, bus/tram/light-rail, and bike). Below, we write the utility equation for all five dependent variables.

$$\begin{aligned}
\boldsymbol{U}_{RP} &= \left[sumc[(\boldsymbol{\beta}\ .^*\ \boldsymbol{X})^{'}]_{RP} + \boldsymbol{\psi}_{RP}\right] \\
\boldsymbol{U}_{car-SP} &= \left[sumc[(\boldsymbol{\beta}\ .^*\ \boldsymbol{X})^{'}]_{car-SP} + \boldsymbol{CI}_{car-SP} + \boldsymbol{R}_{car-SP} + \boldsymbol{\psi}_{car-SP}\right] \\
\boldsymbol{U}_{train/metro-SP} &= \left[sumc[(\boldsymbol{\beta}\ .^*\ \boldsymbol{X})^{'}]_{train/metro-SP} + \boldsymbol{CI}_{train/metro-SP} + \boldsymbol{R}_{train/metro-SP} + \boldsymbol{\psi}_{train/metro-SP}\right] \\
\boldsymbol{U}_{bus/tram/light-rail-SP} &= \left[sumc[(\boldsymbol{\beta}\ .^*\ \boldsymbol{X})^{'}]_{bus/tram/light-rail-SP} + \boldsymbol{CI}_{bus/tram/light-rail-SP} + \boldsymbol{R}_{bus/tram/light-rail-SP} + \boldsymbol{\psi}_{bus/tram/light-rail-SP}\right] \\
\boldsymbol{U}_{bike-SP} &= \left[sumc[(\boldsymbol{\beta}\ .^*\ \boldsymbol{X})^{'}]_{bike-SP} + \boldsymbol{CI}_{bike-SP} + \boldsymbol{R}_{bike-SP} + \boldsymbol{\psi}_{bike-SP}\right]
\end{aligned} \tag{11}$$

Now, we can combine the individual RP and SP stage choice models into a single framework using a covariance approach as follows:

$$\boldsymbol{U} = \mathbf{B} + \boldsymbol{\xi} \tag{12}$$

where

$$\mathbf{B} = \begin{bmatrix} sumc[(\boldsymbol{\beta}.^*\boldsymbol{X})^{'}]_{RP} \\ sumc[(\boldsymbol{\beta}.^*\boldsymbol{X})^{'}]_{car-SP} + \boldsymbol{CI}_{car-SP} + \boldsymbol{R}_{car-SP} \\ sumc[(\boldsymbol{\beta}.^*\boldsymbol{X})^{'}]_{train/metro-SP} + \boldsymbol{CI}_{train/metro-SP} + \boldsymbol{R}_{train/metro-SP} \\ sumc[(\boldsymbol{\beta}.^*\boldsymbol{X})^{'}]_{bus/tram/light-rail-SP} + \boldsymbol{CI}_{bus/tram/light-rail-SP} + \boldsymbol{R}_{bus/tram/light-rail-SP} \\ sumc[(\boldsymbol{\beta}.^*\boldsymbol{X})^{'}]_{bike-SP} + \boldsymbol{CI}_{bike-SP} + \boldsymbol{R}_{bike-SP} \end{bmatrix} [\{I_{RP} + 4^*I_{SP}^*T\} \times 1]\,vector,$$

[4] The weighted sum (WS) approach is also known as additive utility function in the discrete choice literature. However, we use the term weighted sum throughout the paper to distinguish the functional form of CI from the additive utility.

[5] We refrain from using Wang et al. (2006) approach for two reasons. First, a simulation evaluation will be required to assess the performance of the approach which is beyond the scope of this work. Second, out of four mode attributes (travel time, waiting time, travel cost, private/shared), three are continuous. Hence, we can afford to keep the model complexity to minimal and still achieve the necessary outcome.

$$\boldsymbol{\xi} = \begin{bmatrix} \boldsymbol{\psi}_{RP} \\ \boldsymbol{\psi}_{car-SP} \\ \boldsymbol{\psi}_{train/metro-SP} \\ \boldsymbol{\psi}_{bus/tram/light-rail-SP} \\ \boldsymbol{\psi}_{bike-SP} \end{bmatrix}, \begin{matrix} I_{RP} = 4(\#\ of\ options\ in\ RP\ stage),\ I_{SP} = 5(\#\ of\ options\ in\ SP\ stage), \\ and\ T = 15(\#\ of\ choice\ occassions\ in\ SP\ stage) \end{matrix}$$

Let $\widetilde{\boldsymbol{\Omega}}$ be the covariance matrix of $\boldsymbol{\eta}$.

$$\text{Therefore,}\ \boldsymbol{U} \sim MVN[\mathbf{B}, \widetilde{\boldsymbol{\Theta}}] \tag{13}$$

where

$$\mathbf{B} = \begin{bmatrix} \mathbf{B}_{RP} \\ \mathbf{B}_{SP1} \\ \mathbf{B}_{SP2} \\ \mathbf{B}_{SP3} \\ \mathbf{B}_{SP4} \end{bmatrix},\ and\ \widetilde{\boldsymbol{\Theta}} = \begin{bmatrix} \widetilde{\boldsymbol{\Omega}}_{RP} & \widetilde{\boldsymbol{\Omega}}^{'}_{RP,SP1} & \widetilde{\boldsymbol{\Omega}}^{'}_{RP,SP2} & \widetilde{\boldsymbol{\Omega}}^{'}_{RP,SP3} & \widetilde{\boldsymbol{\Omega}}^{'}_{RP,SP4} \\ \widetilde{\boldsymbol{\Omega}}_{RP,SP1} & \mathbf{I}_T.^*.\widetilde{\boldsymbol{\Omega}}_{SP1} & \mathbf{0} & \mathbf{0} & \mathbf{0} \\ \widetilde{\boldsymbol{\Omega}}_{RP,SP2} & \mathbf{0} & \mathbf{I}_T.^*.\widetilde{\boldsymbol{\Omega}}_{SP2} & \mathbf{0} & \mathbf{0} \\ \widetilde{\boldsymbol{\Omega}}_{RP,SP3} & \mathbf{0} & \mathbf{0} & \mathbf{I}_T.^*.\widetilde{\boldsymbol{\Omega}}_{SP3} & \mathbf{0} \\ \widetilde{\boldsymbol{\Omega}}_{RP,SP4} & \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{I}_T.^*.\widetilde{\boldsymbol{\Omega}}_{SP4} \end{bmatrix}$$

where $\mathbf{I}_T$ is an identity matrix of size $(T \times T)$, and the subscript SP1, SP2, SP3 and SP4 correspond to the car, train/metro, bus/tram/light-rail, and bike, respectively.

In the joint RP-SP covariance matrix, the covariance is only allowed between RP and SP variables and not between SP variables (indicated by zero in the matrix $\widetilde{\boldsymbol{\Theta}}$) as respondents only complete one SP task depending on the RP stage mode.

Eq. 13 can be solved by taking the utility difference w.r.t the chosen alternative and calculating the cumulative distribution function (cdf) of a multivariate normal (MVN) distribution at corresponding differenced utility values. Since, only the difference in utility matters, we work with utility differences. It means, only differenced error-covariance matrix is identified. Moreover, the top left element of the differenced error-covariance matrix is fixed to 1 to set the scale of utility (Train, 2009). Thus, for $I$ alternative, only $[I^*(I-1)^*0.5]-1$ covariance elements are identifiable. Further, since all the differenced error covariance matrices must originate from the same undifferenced error covariance matrix, we specify the matrix $\boldsymbol{\Theta}$ as follows:

$$\boldsymbol{\Theta} = \begin{bmatrix} \boldsymbol{\Omega}_{RP} & \boldsymbol{\Omega}^{'}_{RP,SP1} & \boldsymbol{\Omega}^{'}_{RP,SP2} & \boldsymbol{\Omega}^{'}_{RP,SP3} & \boldsymbol{\Omega}^{'}_{RP,SP4} \\ \boldsymbol{\Omega}_{RP,SP1} & \mathbf{I}_T.^*.\boldsymbol{\Omega}_{SP1} & \mathbf{0} & \mathbf{0} & \mathbf{0} \\ \boldsymbol{\Omega}_{RP,SP2} & \mathbf{0} & \mathbf{I}_T.^*.\boldsymbol{\Omega}_{SP2} & \mathbf{0} & \mathbf{0} \\ \boldsymbol{\Omega}_{RP,SP3} & \mathbf{0} & \mathbf{0} & \mathbf{I}_T.^*.\boldsymbol{\Omega}_{SP3} & \mathbf{0} \\ \boldsymbol{\Omega}_{RP,SP4} & \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{I}_T.^*.\boldsymbol{\Omega}_{SP4} \end{bmatrix}$$

where

$$\boldsymbol{\Omega}_{RP} = \begin{bmatrix} 0 & \mathbf{0}_{1\times(I_{RP}-1)} \\ \mathbf{0}_{(I_{RP}-1)\times 1} & \widetilde{\boldsymbol{\Omega}}_{(I_{RP}-1)\times(I_{RP}-1)} \end{bmatrix},\ \text{and}\ \boldsymbol{\Omega}_{SP} = \begin{bmatrix} 0 & \mathbf{0}_{1\times(I_{SP}-1)} \\ \mathbf{0}_{(I_{SP}-1)\times 1} & \widetilde{\boldsymbol{\Omega}}_{(I_{SP}-1)\times(I_{SP}-1)} \end{bmatrix}$$

For a respondent, we only need to calculate the MVN-cdf function using the RP observation and one of the SP observations depending on the RP-reported mode. Hence, we construct a set of metrics below to appropriately select elements from the matrix $\mathbf{B}$ and $\boldsymbol{\Theta}$ to perform utility difference. Also, for ease of notation, we re-write the differenced error-covariance matrix $\widetilde{\boldsymbol{\Theta}}$ as follows:

$$\widetilde{\boldsymbol{\Theta}} = \begin{bmatrix} \widetilde{\boldsymbol{\Omega}}_{RP} & \widetilde{\boldsymbol{\Omega}^{'}}_{RP,SP1} & \widetilde{\boldsymbol{\Omega}^{'}}_{RP,SP2} & \widetilde{\boldsymbol{\Omega}^{'}}_{RP,SP3} & \widetilde{\boldsymbol{\Omega}^{'}}_{RP,SP4} \\ \widetilde{\boldsymbol{\Omega}}_{RP,SP1} & \widetilde{\boldsymbol{\Omega}}_{SP1} & \mathbf{0} & \mathbf{0} & \mathbf{0} \\ \widetilde{\boldsymbol{\Omega}}_{RP,SP2} & \mathbf{0} & \widetilde{\boldsymbol{\Omega}}_{SP2} & \mathbf{0} & \mathbf{0} \\ \widetilde{\boldsymbol{\Omega}}_{RP,SP3} & \mathbf{0} & \mathbf{0} & \widetilde{\boldsymbol{\Omega}}_{SP3} & \mathbf{0} \\ \widetilde{\boldsymbol{\Omega}}_{RP,SP4} & \mathbf{0} & \mathbf{0} & \mathbf{0} & \widetilde{\boldsymbol{\Omega}}_{SP4} \end{bmatrix}$$

Next, define a set of matrices as follows:

$\boldsymbol{H}_{error} = zeros(I_{RP} + I_{SP} - 2, I_{RP} + 4I_{SP} - 5), \boldsymbol{H}_{mean} = zeros(I_{RP} + I_{SP}, I_{RP} + 4I_{SP}),$

$\boldsymbol{H}_{error}[1 : (I_{RP} - 1), 1 : (I_{RP} - 1)] = \boldsymbol{I}_{I_{RP}-1},$

$\boldsymbol{H}_{error}\left[(I_{RP} - 1) + 1 : I_{RP} + I_{SP} - 2, I_{RP} + \left(i_{m,RP} - 1\right)(I_{SP} - 1) : I_{RP} + \left(i_{m,RP}\right)(I_{SP} - 1)\right] = \boldsymbol{I}_{SP-1},$

$\boldsymbol{H}_{mean}[1 : I_{RP}, 1 : I_{RP}] = \boldsymbol{I}_{I_{RP}},$

$\boldsymbol{H}_{mean}\left[I_{RP} + 1 : I_{RP} + I_{SP}, (I_{RP} + 1) + \left(i_{m,RP} - 1\right)(I_{SP}T) : (I_{RP} + 1) + \left(i_{m,RP}\right)(I_{SP}T)\right] = \boldsymbol{I}_{SP*T},$

$\boldsymbol{I}_{I-1} : identity\ matrix\ of\ size\ (I - 1),$

$$i_{m,RP} = \left\{ \begin{array}{c} 1, \textit{if} \text{ car is reported as primary mode} \\ 2, \textit{if} \text{ train/metro is reported as primary mode} \\ 3, \textit{if} \text{ bus/tram/light - rail is reported as primary mode} \\ 4, \textit{if} \text{ bike is reported as primary mode} \end{array} \right\}$$

Now, we can appropriately select elements from the matrix $\mathbf{B}$ and $\widetilde{\boldsymbol{\Theta}}$ as follows:

$$\widehat{\mathbf{B}} = \boldsymbol{H}_{mean}\mathbf{B},\ and\ \widehat{\boldsymbol{\Theta}} = \boldsymbol{H}_{error}\widetilde{\boldsymbol{\Theta}}\boldsymbol{H}'_{error}$$

Next, define a matrix $\mathbf{D}$ to convert a differenced error matrix $\widehat{\boldsymbol{\Theta}}$ into an undifferenced matrix as follows:

$\mathbf{D} = zeros(I_{RP} + I_{SP}, I_{RP} + I_{SP} - 2),$
$\mathbf{D}[2 : I_{RP}, 1 : I_{RP} - 1] = \boldsymbol{I}_{RP-1},$
$\mathbf{D}[I_{RP} + 2 : I_{RP} + I_{SP}, I_{RP} : I_{RP} + I_{SP} - 2] = \boldsymbol{I}_{SP-1},$
$\boldsymbol{I}_{I-1} : identity\ matrix\ of\ size\ (I - 1),$
$\widehat{\boldsymbol{\Theta}} = \mathbf{D}\widehat{\boldsymbol{\Theta}}\mathbf{D}'$

The utility/disutility (as a direct function of mode attributes) and regret (due to experienced differences between expected and actual in-vehicle and/or waiting times) in a given time period may also affect the decision in subsequent time periods. To incorporate the effect of past experiences, we use an auto-regressive (AR) structure on overall utility. We consider an AR structure of order 1 (AR-1). With an AR-1 structure, one may write the utility specification for an alternative $i$ in the time period $t$ as follows:

$$U_{i,t} = \pi U_{i,t-1} + U_{i,t} \tag{14}$$

where $U_{i,t} = V_{i,t} + \sigma_{i,t}$, and $0 \leqslant \pi \leqslant 1$ regulates the effect of past utility and regret on the current decision. The use of AR-1 structure is often found sufficient in empirical studies to incorporate past experiences (Blake et al., 2020). However, one can also use AR-2 or higher-order AR structures to explicitly account for the direct and indirect effects of past experiences. For example, in an AR-1 structure, only the direct impact is identified for the immediate previous day $(t-1)$ and the effect (indirect effect) of remaining lag days $(t-2, t-3, ..., 1)$ is mediated through the $(t-1)^{th}$ day. On the other hand, in an AR-2 structure, the direct impact is identified for both $(t-1)^{th}$ and $(t-2)^{th}$ days and the effect (indirect effect) of remaining lag days $(t-3, t-4, ..., 1)$ is mediated through both $(t-1)^{th}$ and $(t-2)^{th}$ days. For an $r-order$ AR structure, Eq. (14) can be re-written as follows:

$$U_{i,t} = \pi_1 U_{i,t-1} + \pi_2 U_{i,t-2} + \ldots + \pi_r U_{i,t-r} + U_{i,t}; 0 \leqslant \pi_j \leqslant 1 \forall j = 1 : r \text{ and } t > r \tag{15}$$

Further, assume a time-invariant error-covariance matrix, i.e., $\sigma_{i,t} = \eta_i$. Therefore, we can re-write Eq. (15) as follows:

$$U_{i,t} = \left(U_{i,t} + \eta_i\right) + \pi_1\left(U_{i,t-1} + \eta_i\right) + \pi_2\left(U_{i,t-2} + \eta_i\right) + \ldots + \pi_r\left(U_{i,t-r} + \eta_i\right) \tag{16}$$

While it may be tempting to use an $(T-1)order$ AR structure $(T = \#\ of\ choice\ occassions)$, it is advised to iteratively estimate models with 1-order increments to avoid estimation issues, especially for highly non-linear models.

Using the AR framework, we now introduce correlation between time periods in the SP choices. Let $\pi_{SP1} = (\pi_1, \pi_2, ..., \pi_r)'[(r \times 1) \text{ vector}], and \pi_{SP} = (\pi'_{SP1}, \pi'_{SP2}, ..., \pi'_{SP4})'[(4 \times r) \text{ matrix}]$.

Define a matrix $\boldsymbol{F}_{TI}$ of size $[TI_{SP} \times TI_{SP}]$ with all the elements being equal to zero. Now, follow the pseudo-code provided below to fill in the cells of the matrix $\boldsymbol{F}$.

```
π_curr = π_SP[i_m,RP, :]'
for i = 1 to r
      for j = i + 1 to T
            for m = 1 to I
                  F[(j − 1)*I_SP + m, (j − 2)*I_SP + m − (i − 1)*I_SP] = π_curr[i]
            end
      end
end
```

Next, re-write the vector $\widehat{\mathbf{B}}$ and matrix $\widehat{\mathbf{\Theta}}$ as follows:

$$\widehat{\mathbf{B}} = \begin{bmatrix} \widehat{\mathbf{B}}_{RP}(I_{RP} \times 1) \\ \widehat{\mathbf{B}}_{SP}(TI_{SP} \times 1) \end{bmatrix}, \widehat{\mathbf{\Theta}} = \begin{bmatrix} \widehat{\mathbf{\Theta}}_{RP}(I_{RP} \times I_{RP}) & \widehat{\mathbf{\Theta}}'_{RP,SP} \\ \widehat{\mathbf{\Theta}}_{RP,SP} & \widehat{\mathbf{\Theta}}_{SP}(I_{SP} \times I_{SP}) \end{bmatrix}$$

Now, we can expand the vector $\widehat{\mathbf{B}}$ and matrix $\widehat{\mathbf{\Theta}}$ to include correlation across time periods in the SP choices as follows:

$$\widehat{\mathbf{B}}_{SP} = \mathbf{S}\widehat{\mathbf{B}}_{SP}, \ and \ \widehat{\mathbf{\Theta}}_{SP} = \mathbf{S}\left[\left(\mathbf{I}_T.^*.\widehat{\mathbf{\Theta}}_{SP}\right)\right]\mathbf{S}',$$
$$where \ \mathbf{S} = \left[\mathbf{I}_{TI_{SP}} - \mathbf{F}_{TI_{SP}}\right]^{-1}$$

Therefore, the expanded vector $\widehat{\mathbf{B}}$ and matrix $\widehat{\mathbf{\Theta}}$ can be written as follows:

$$\widehat{\mathbf{B}} = \begin{bmatrix} \widehat{\mathbf{B}}_{RP}(I_{RP} \times 1) \\ \widehat{\mathbf{B}}_{SP}(TI_{SP} \times 1) \end{bmatrix}, \widehat{\mathbf{\Theta}} = \begin{bmatrix} \widehat{\mathbf{\Theta}}_{RP}(I_{RP} \times I_{RP}) & \left(\boldsymbol{1}_T.^*.\ \widehat{\mathbf{\Theta}}_{RP,SP}\right)' \\ \left(\boldsymbol{1}_T.^*.\ \widehat{\mathbf{\Theta}}_{RP,SP}\right) & \widehat{\mathbf{\Theta}}_{SP}(TI_{SP} \times TI_{SP}) \end{bmatrix}$$

Next, to perform utility difference, we construct a matrix $\mathbf{M}$ of size $[(I_{RP} - 1) + T(I_{SP} - 1) \times (I_{RP}) + T(I_{SP})]$ using the pseudo-code provided in Appendix Section A.2. Essentially, it is a matrix with elements 1 and $-1$ to subtract the utility of the chosen alternative with all the non-chosen alternatives. We can write the distribution of utility differences as follows:

$$\bar{\boldsymbol{U}} \sim MVN_{(I_{RP}-1)+T(I_{SP}-1)\times(I_{RP}-1)+T(I_{SP}-1)}(\bar{\mathbf{B}}, \bar{\mathbf{\Theta}})$$
$$where \ \bar{\mathbf{B}} = \mathbf{M}\widehat{\mathbf{B}}, \ \text{and} \ \bar{\mathbf{\Theta}} = \mathbf{M}\widehat{\mathbf{\Theta}}\mathbf{M}'$$

Thus, the likelihood of the decision-maker $n$ can be written as:

$$L_n(\boldsymbol{\theta}) = \int_{-\infty}^{\bar{\mathbf{B}}} f_{(I_{RP}-1)+T(I_{SP}-1)}(\mathbf{r}|\bar{\mathbf{B}}, \bar{\mathbf{\Theta}})d\boldsymbol{r} \tag{17}$$

The likelihood (constrained) maximization problem can be written as follows:

$$\max_{\boldsymbol{\theta}} \sum_{n=1}^{N} Log(L_n(\boldsymbol{\theta})) \tag{18}$$

**Such that for each SP stage choice $\forall i$**

$$\begin{aligned} &\sum_{H\subseteq A_K} m(H) = 1; \ \text{where } A_K = \{x_1, x_2, \ldots, x_K\} \\ &\sum_{H\subseteq A_K\backslash k} m(H \cup k) \geqslant 0 \forall k; \forall i \\ &\text{where } A_K\backslash k \text{ represents collection of all attributes except the } k^{th} \text{ attribute} \\ &\qquad \cup \text{ represents the union of two sets} \end{aligned} \tag{19}$$

Since *Möbius* parameters are unconstrained and has a one-to-one mapping with fuzzy measures, we convert fuzzy measures $\mu()$ into their corresponding Möbius parameters $m()$ and solve the above-constrained optimization problem. The decision variables in the constrained maximisation problem are $\boldsymbol{\theta} = \left[\text{Vech}(\mathbf{m}), \text{Vech}(\boldsymbol{\beta}), \vartheta, \rho, \tau, \pi, \text{Vech}(\widetilde{\mathbf{\Omega}})\right]$, where the Vech(.) operator vectorises the unique element of a matrix and the vector $\mathbf{m}$ contains all the Möbius parameters.

The likelihood function involves the computation of a $(I_{RP} - 1) + T(I_{SP} - 1)$ dimensional multi-variate normal cumulative density function (MVNCDF) for each decision-maker. One can use Geweke, Hajivassiliou and Keane (GHK) simulator (Geweke, 1991; Hajivassiliou et al., 1996; Keane, 1994; Genz, 1992) or analytical approximation methods (Bhat, 2011; Bhat, 2018) to accurately evaluate the multivariate normal cumulative distribution function (MVNCDF). However, none of the methods can estimate a high dimensional MVNCDF with reasonable accuracy and their performance starts to deteriorate beyond an integral dimension of 10. In our empirical analysis, the dimensionality of integration is $63[(4-1)+15(5-1)]$. No combinations of starting parameter values can provide a value numerically indifferent from zero. Further, estimation-time and memory requirements for such high dimensional integral are unreasonably high. To overcome this issue, we use the composite marginal likelihood (CML) approach (Varin, 2008). In the CML approach, a low-dimensional surrogate function is approximated to estimate a high-dimensional function.

The likelihood function (Eq. (17) can be written as follows using the CML approach:

$$L_{CML}(\boldsymbol{\theta}) = \left(\prod_{r=1}^{T-1}\prod_{r'=r+1}^{T}\Pr(i_r = i_{m,SP,r}, i_{r'} = i_{m,SP,r'}, i_{RP} = i_{m,RP})\right) \tag{20}$$

$$L_{CML}(\boldsymbol{\theta}) = \left(\prod_{r=1}^{T-1}\prod_{r'=r+1}^{T}\int_{-\infty}^{\bar{\mathbf{B}}_{rr'}} f_{(I_{RP}-1)+2(I_{SP}-1)}(\mathbf{r}|\bar{\mathbf{B}}_{rr'}, \bar{\mathbf{\Theta}}_{rr'})d\boldsymbol{r}\right)$$

where $\bar{\mathbf{B}}_{rr'} = \mathbf{L}\bar{\mathbf{B}}$, $\bar{\mathbf{\Theta}}_{rr'} = \mathbf{L}\bar{\mathbf{\Theta}}\mathbf{L}'$ and the matrix $\mathbf{L}$ is constructed as follows:

$$\begin{aligned}
&\mathbf{L} = zeros((I_{RP}-1)+2(I_{SP}-1), (I_{RP}-1)+T(I_{SP}-1)),\\
&\mathbf{L}[1:(I_{RP}-1), 1:(I_{RP}-1)] = \mathbf{I}_{I_{RP}-1},\\
&\mathbf{L}[I_{RP}:(I_{RP}-1)+(I_{SP}-1), (I_{RP}-1)+(r-1)(I_{SP}-1)+1:(I_{RP}-1)+r(I_{SP}-1)] = \mathbf{I}_{I_{SP}-1},\\
&\mathbf{L}[(I_{RP}-1)+(I_{SP}-1)+1:(I_{RP}-1)+2(I_{SP}-1), (I_{RP}-1)(r'-1)(I_{SP}-1)+1:(I_{RP}-1)+r'(I_{SP}-1)] = \mathbf{I}_{I_{SP}-1},\\
&\mathbf{I}_{I-1} : identity\ matrix\ of\ size\ (I-1)
\end{aligned}$$

In the above CML expression, the highest dimension of integration is $(I_{RP}-1)+2(I_{SP}-1)$. For the approximate computation of the $(I_{RP}-1)+2(I_{SP}-1)$ dimensional MVNCDF function, we use a GHK simulator with 600 Halton Draws (Bhat, 2003; Train, 2000). Further, since Eq. (17) is a constrained optimization problem, the Broyden–Fletcher–Goldfarb–Shanno (BFGS) algorithm (Fletcher, 2000) can no longer be used. Therefore, we use the sequential least-square programming (SLSQP) algorithm to solve the constrained loglikelihood maximization problem. Readers are referred to (Nocedal and Wright, 2006)) for a detailed discussion of the SLSQP algorithm. We use the SLSQP algorithm's off-the-shelf implementation in Python's Scipy package.

In the current empirical analysis, there are three explanatory variables in the CI. Hence, the equality and inequality constraints (for each alternative) to ensure $0\leqslant\mu()\leqslant1$ and monotonicity can be written as follows:

**Equality constraint (for each SP stage choice):**

$$m(TT)+m(WT)+m(TC)+m(TT,WT,TC)+m(TT,TC)+m(WT,TC)+m(TT,WT,TC)=1$$

**In-equality constraints (for each SP stage choice):**

$$\begin{aligned}
&m(TT)\geqslant0 \Rightarrow \mu(TT)\geqslant0\\
&m(WT)\geqslant0 \Rightarrow \mu(WT)\geqslant0\\
&m(TC)\geqslant0 \Rightarrow \mu(TC)\geqslant0\\
&m(TT)+m(TT,WT)\geqslant0 \Rightarrow \mu(TT,WT)-\mu(WT)\geqslant0\\
&m(TT)+m(TT,TC)\geqslant0 \Rightarrow \mu(TT,TC)-\mu(TC)\geqslant0\\
&m(WT)+m(TT,WT)\geqslant0 \Rightarrow \mu(TT,WT)-\mu(TT)\geqslant0\\
&m(WT)+m(WT,TC)\geqslant0 \Rightarrow \mu(WT,TC)-\mu(TC)\geqslant0\\
&m(TC)+m(TT,TC)\geqslant0 \Rightarrow \mu(TT,TC)-\mu(TT)\geqslant0\\
&m(TC)+m(WT,TC)\geqslant0 \Rightarrow \mu(WT,TC)-\mu(WT)\geqslant0\\
&m(TT)+m(TT,WT)+m(TT,TC)+m(TT,WT,TC)\geqslant0 \Rightarrow \mu(TT,WT,TC)-\mu(WT,TC)\geqslant0\\
&m(WT)+m(TT,WT)+m(WT,TC)+m(TT,WT,TC)\geqslant0 \Rightarrow \mu(TT,WT,TC)-\mu(TT,TC)\geqslant0\\
&m(TC)+m(TT,TC)+m(WT,TC)+m(TT,WT,TC)\geqslant0 \Rightarrow \mu(TT,WT,TC)-\mu(TT,WT)\geqslant0
\end{aligned}$$

**Ensuring differenced error-covariance matrix is positive-definite**

To ensure the non-singularity of the error-covariance matrix, we perform the model estimation in Cholesky space. Let $\boldsymbol{L}_{chol}$ is the lower Cholesky decomposition of the covariance matrix $\widetilde{\Theta}$. Then, we pass the unique elements of the $\boldsymbol{L}_{chol}$ matrix to the optimization function. Further, we need to ensure that the implied covariance matrix based on optimized $\boldsymbol{L}_{chol}$ results in a matrix with the top left element for each of the RP and SP choice variables is equal to 1. To ensure such condition, follow the pseudocode described below:

$$Num\_Options = (I_{RP}, I_{SP1}, I_{SP2}, I_{SP3}, I_{SP4})$$
$$Num\_Options = Num\_Options - 1$$
$$Num\_Options\_Rsum = cumsum(Num\_Options)$$
$$\text{for } i = 2 \text{ to } len(Num\_Options)$$
$$\quad \text{row\_num} = Num\_Options\_Rsum[i-1]$$
$$\quad \text{row\_curr} = \boldsymbol{L}_{chol}[\text{row\_num},:]$$
$$\quad \text{row\_curr} = (\text{row\_curr})^2$$
$$\quad \text{denom} = (1 + sum(\text{row\_curr}))^{0.5}$$
$$\quad \text{for } j = 1 \text{ to row\_num}$$
$$\qquad \text{if } j \mathrel{!=} \text{row\_num}$$
$$\qquad\quad \boldsymbol{L}_{chol}[\text{row\_num}, j] = \boldsymbol{L}_{chol}[\text{row\_num}, j] \big/ \text{denom}$$
$$\qquad \text{else}$$
$$\qquad\quad \boldsymbol{L}_{chol}[\text{row\_num}, j] = 1 \big/ \text{denom}$$
$$\quad \text{end}$$
$$\text{end}$$

### 4.3. Choice set construction and additional RP stage explanatory variables

As discussed in section 3.1, the first step of the survey includes obtaining information about the most frequent trip of an individual. Respondents are asked to provide details of the most frequent trip along with the respective travel mode. We do not elicit the revealed preference (RP) choice using conjoint analysis to keep the survey time reasonable. Instead, we construct the RP choice set and mode-specific travel time, wait time, and cost post-survey. In particular, we consider four modes: car, train, bus/tram and bike. For each of the modes, relevant mode attributes (in-vehicle travel time, access and egress distance and travel cost[6]) are obtained using Google API based on respondent-reported OD-pair and departure time.

Access to various modes is determined through a combination of additional survey-based information and obtained mode attributes. Access to the car (deterministic: yes or no) is obtained based on the answers to two survey questions which asked respondents to indicate household vehicle ownership (binary: yes or no) and possession of driving license by the respondent (binary: yes or no). For both train/metro and bus/tram/light-rail, access to mode (deterministic: yes or no) is determined based on in-vehicle travel time (IVTT). If the obtained (through Google API) IVTT is greater than zero, the mode is considered available to the respondent. Finally, the bike is considered universally available. Table 2 provides the distribution of overall access to various primary modes obtained in the survey.

We further enrich the data by appending four-digit postcode-level socio-economic data as a proxy for individual-level socio-economic details available from the Dutch Central Bureau of Statistics (Dutch Central Bureau of Statistics, 2017).[7] Finally, the sample is split into 80/20 for estimation and validation purposes.

**Table 2**
Revealed choice mode availability

| Mode | Available (%) |
|---|---|
| Car | 93 |
| Train/metro | 95 |
| Bus/tram/light-rail | 97 |
| Bike | 100 |

[6] Travel cost for car is calculated assuming a 0.5 euros/km cost based on sample average operating cost (see Fig. 6). Public transport travel cost is calculated using the equation discussed in section 3.

[7] In the survey, information on household income was not mandatory and about 15% respondents did not report their personal or household level income. The distribution of socio-economic variables at zip code level is available in the supplementary sheet section S.2.

## 5. Sample description and estimation results

In this section, we provide a description of sample statistics and model estimation results.

### 5.1. Sample statistics

Survey dissemination was performed by Qualtrics. Participants were recruited from their survey panel based on age and gender. All the respondents reside and work in the Netherlands. Further, no region restriction was imposed in terms of the respondent's location except that the OD pair should be within the Netherlands.

A total of 2021 responses were collected between September and November 2021. During this period, the COVID-19 restrictions were largely lifted in the Netherlands. In particular, there was no restriction on social gatherings and the mask was only obligatory in public transport. After data cleaning, a total of 1606 responses remained valid for model estimation.[8] Fig. 5a provides the distribution of survey completion time. Based on an initial pilot, respondents with survey completion time shorter than 7 min or longer than 30 min were excluded, resulting in the exclusion of 43 respondents. The average survey completion time is 12.5 min. Figs. 5b to 5e provide the distribution of socio-demographic and reported trip characteristics in the sample. The sample consists of an equal share of males and females. There are sufficient observations in various age categories with the highest proportion of respondents in the age category 55 or older. The sample is fairly balanced in education status with 45 % of respondents with a diploma or less and 55 % with a technical or bachelor's degree or higher. The majority of the respondents in the sample are employed (68 %) with a considerable proportion of retired individuals (16 %). In terms of trip purpose, work or work-related trip constitutes the majority of trips (65 %). There is also a considerable share of family and social care (11 %) and social/recreational (18 %) trips. The majority of the respondents are car users (76.2 %). Public transport (Train/Metro/Bus/Tram/Light-rail) accounts for 14 % of the trips and the active mode (bike) has a substantial share of 10 %. The temporal distribution of trips reflects a peak period during 7–9 AM. There is also a considerable share of trips taking place during the afternoon (12–16) period (23 %).

Fig. 6 provides the distribution of cost and time for car users. The calculated per km car cost is considerably different from the user's perceived cost (labelled as reported in the figure) indicating a downward bias in self-reported values (Elgar et al., 2005). The average car trip time (based on reported OD) is around 25 min and very few trips are over 75 min or longer. Fig. 7 provides the time distribution for various legs of a train/metro trip.[9] The majority of train/metro trips have an access time of 20 min. On average, bike users spend less time compared to other modes in accessing a train/metro station. The same pattern holds for egress time with an average egress time of 18 min. The average in-vehicle travel time is about 45 min for train/metro users. Based on the mode split, the majority of train/metro trips involve accessing the station by bike and covering the last leg of the journey on foot.

Fig. 8 provides the time distribution for various legs of a bus/tram/light-rail trip.[10] The access and egress mode distribution suggests that the majority of respondents have easy access to stop within a walking distance range. The average in-vehicle trip time stands at around 40 min. Finally, bike users have an average biking time of 20 min (Fig. 9).

Next, Figs. 10a and 10b provide the distribution of the primary mode reported by respondents and the choice share of alternatives in the SP choice experiment, respectively. Car is the most commonly used primary mode (75 %) while bus/tram/light-rail is the least used primary mode (3 %). The mode split between train/metro and bike is equal with a 10 % share each. Additionally, car and train/

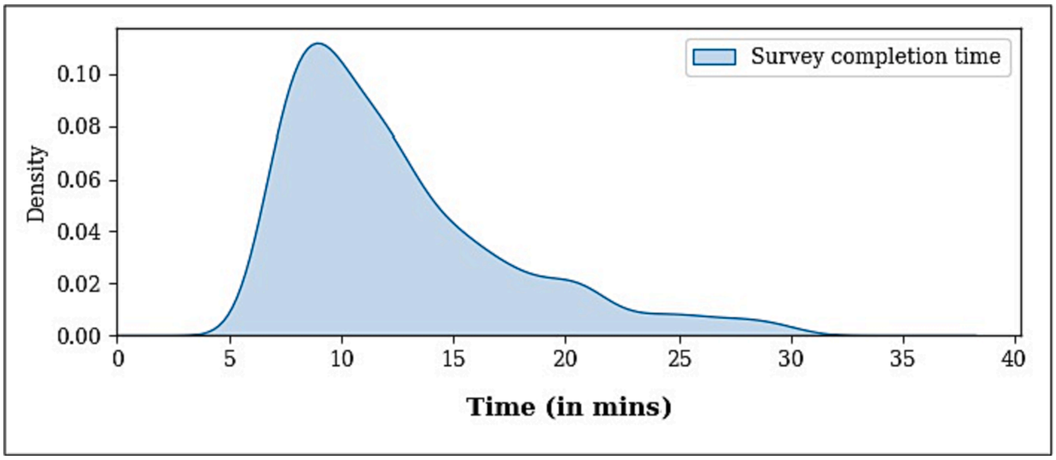


**Fig. 5a.** Survey completion time distribution.

[8] The data cleaning involved checking validity of OD pair, unusual travel times and survey duration.
[9] The PT label included both train/metro and bus/tram/light-rail.
[10] The PT label included both train/metro and bus/tram/light-rail.

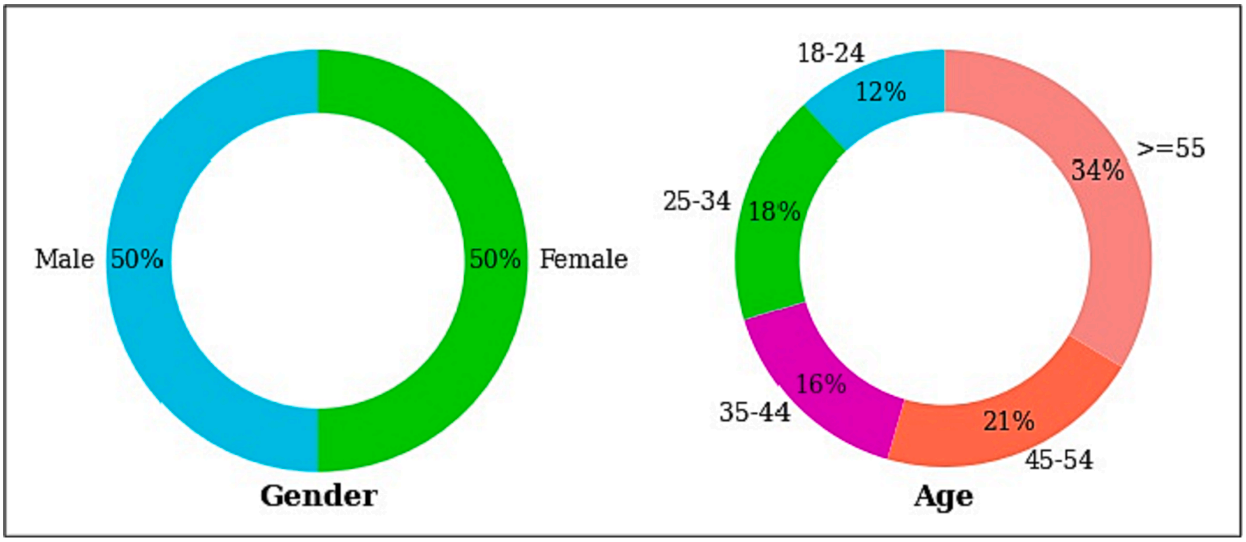


**Fig. 5b.** Age and gender distribution in the sample.

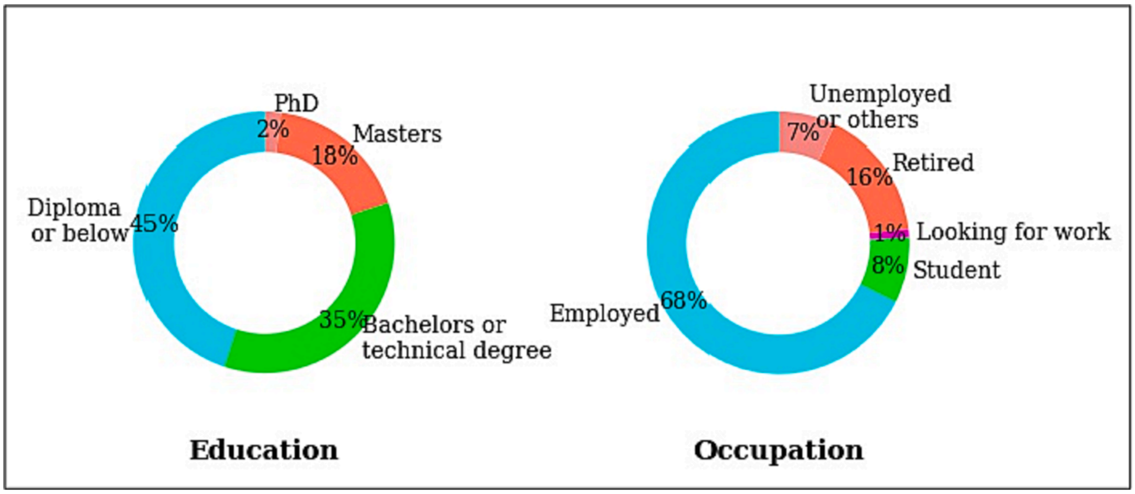


**Fig. 5c.** Education and occupation distribution in the sample.

metro users show the highest affinity towards MOD service followed by bus/tram/light-rail users. It also appears that bike users are least likely to shift towards an MOD service. Motorized mode users also exhibit a propensity to change the departure time window.

### 5.2. Result and discussion

In this section, we discuss the estimation results. First, we discuss the effect of various explanatory variables on the primary mode followed by a discussion of SP-stage estimation results. The explanatory variables in the utility specification for primary mode are modelled using a weighted sum functional form. The SP-stage choices (trade-off between primary mode and MOD option) are modelled as a combination of Choquet-Integral and weighted sum functional form. In our discussion of SP stage results, we focus on the following important areas:

1. Approximation of non-compensatory behaviour in the context of MOD choice and comparison of CI model with traditional WS model at a behavioural level
2. Regret due to the difference in stated vs. actual travel and wait time difference
3. Inertia effect due to longitudinal choices
4. Propensity for the departure time change in the presence of MOD service
5. Endogeneity effect
6. Price estimate required to achieve critical mass

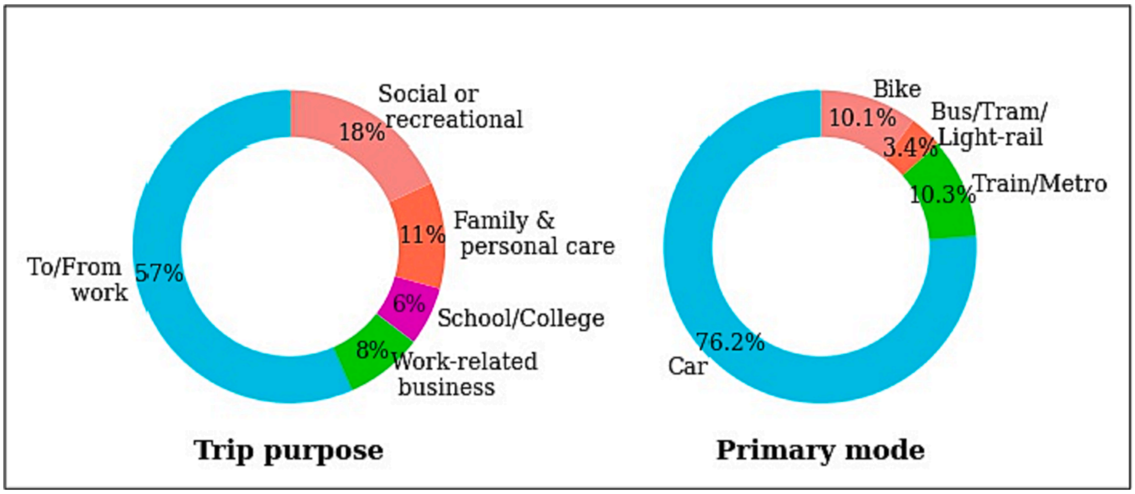


**Fig. 5d.** Trip purpose and primary mode distribution in the sample.

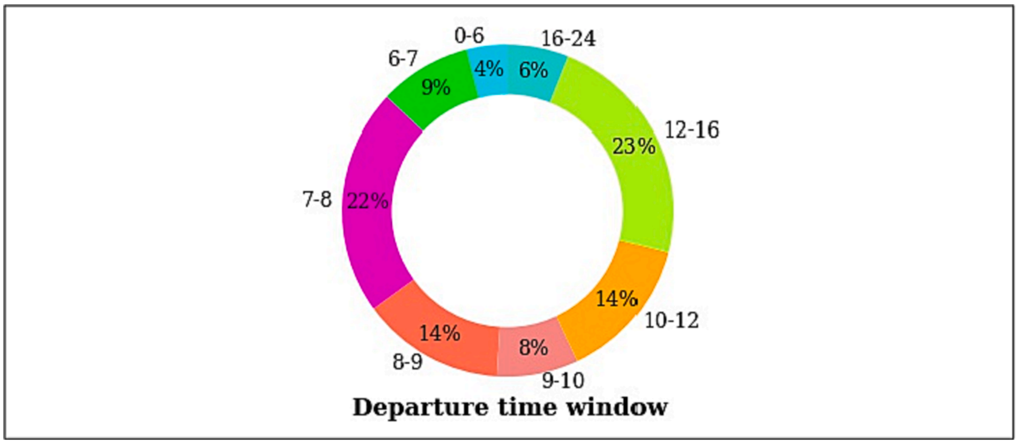


**Fig. 5e.** Temporal distribution of trips in the sample.

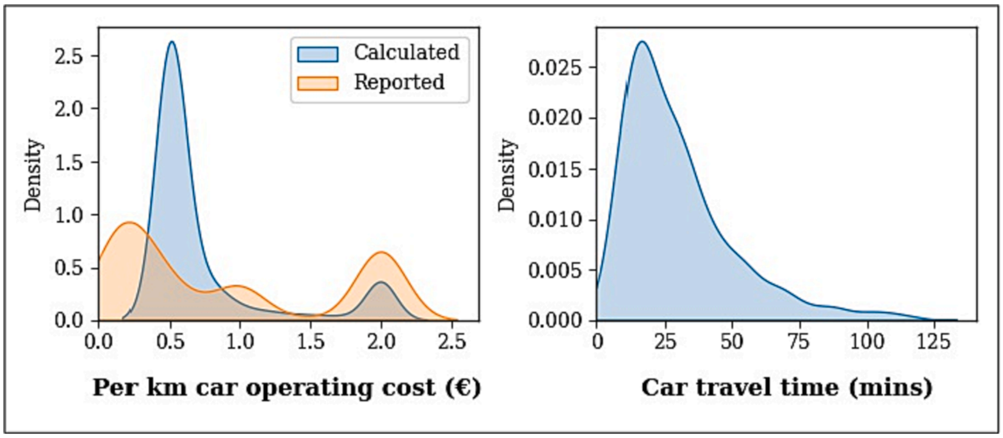


**Fig. 6.** Time and cost distribution for car users.

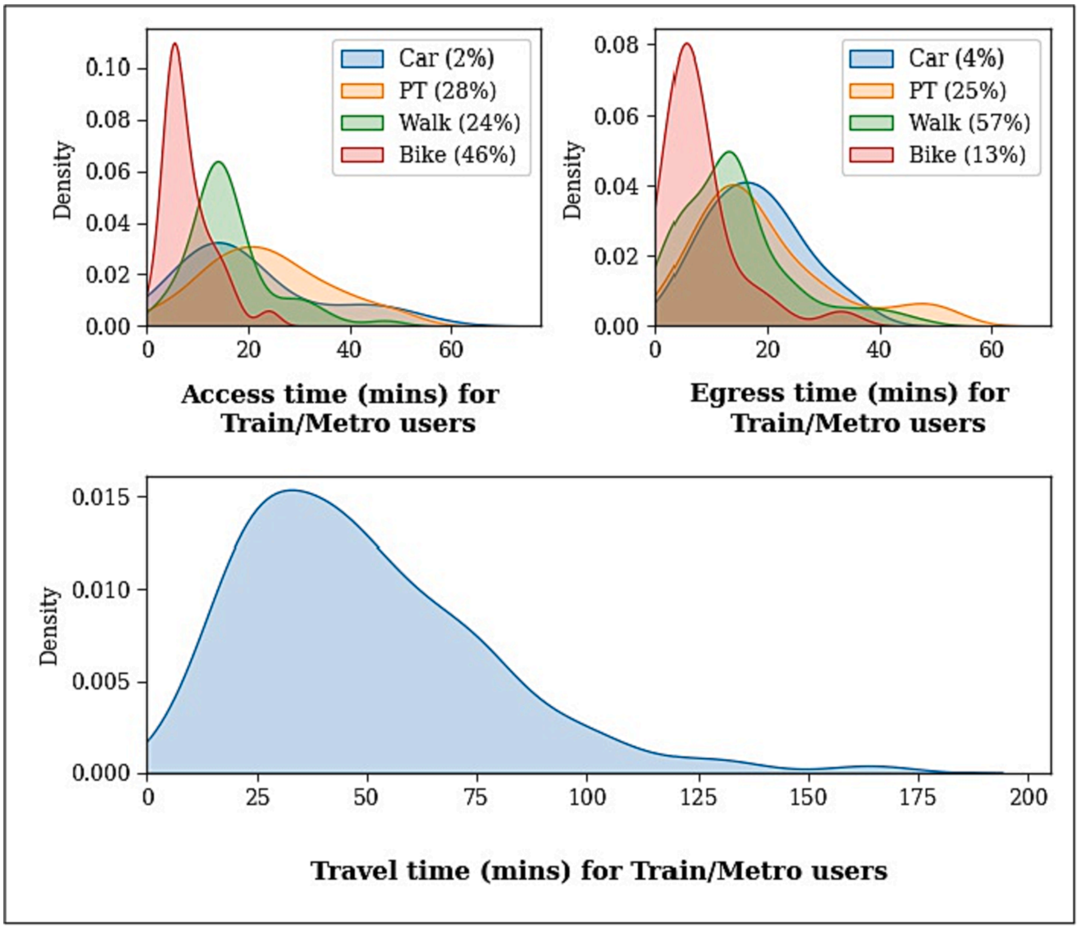


**Fig. 7.** Access, egress and in-vehicle time distribution for Train/Metro users.

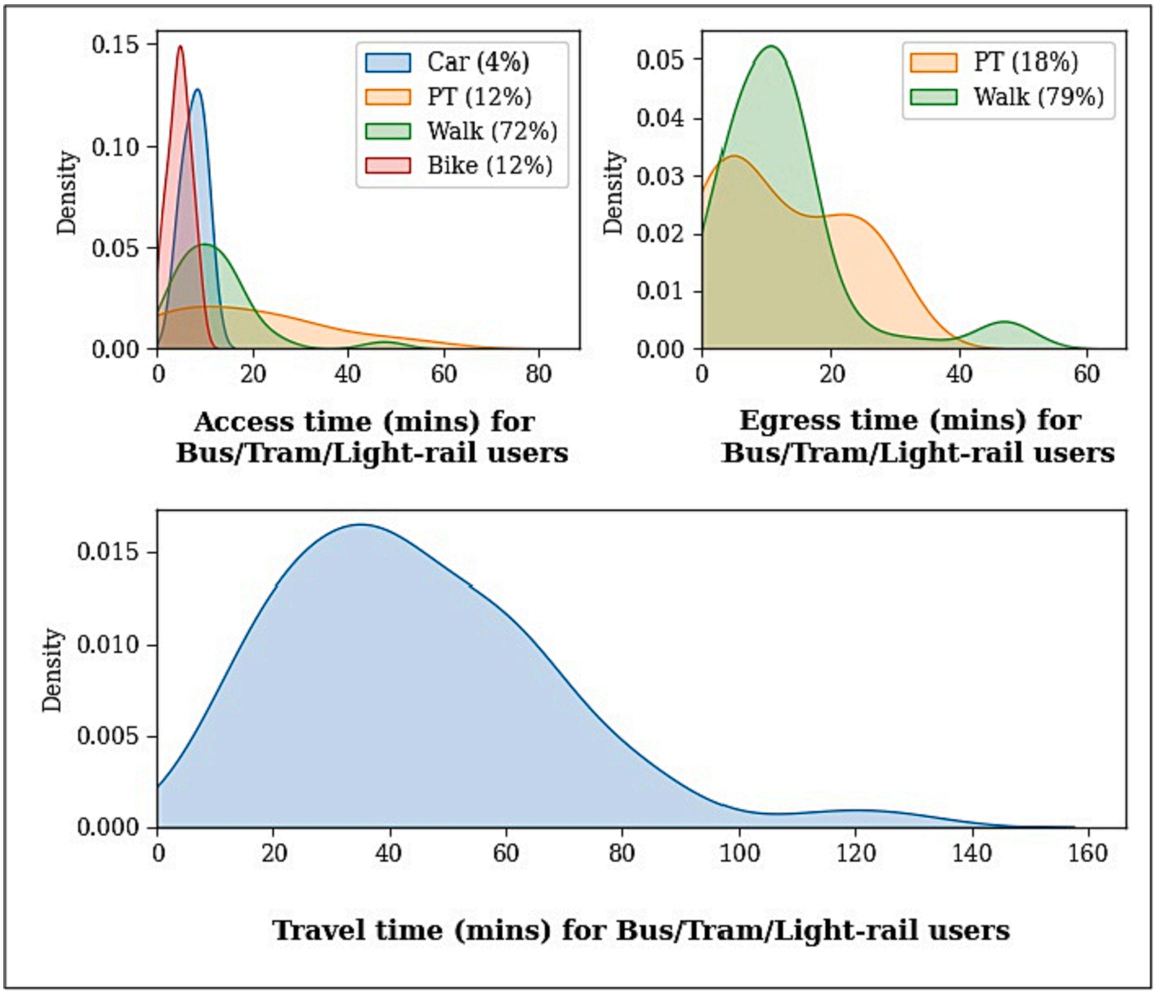


**Fig. 8.** Access, egress and in-vehicle time distribution for Bus/Tram/Light-rail users.

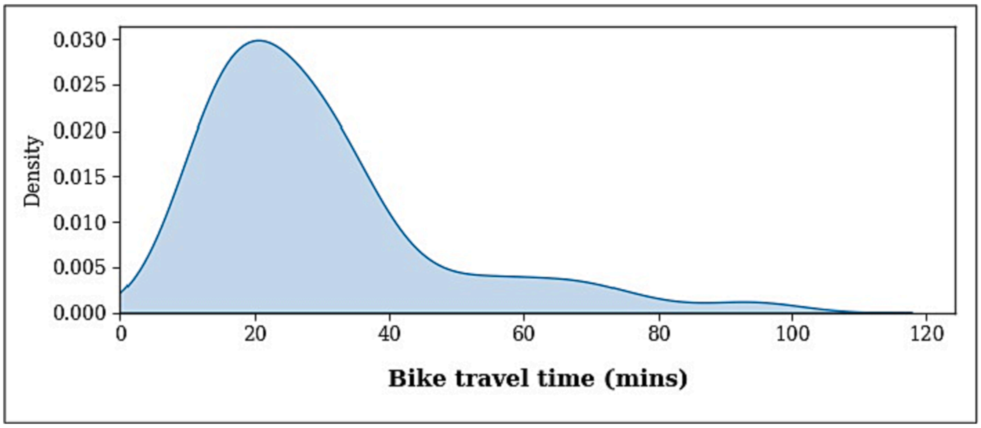


**Fig. 9.** Travel time distribution for bike users.

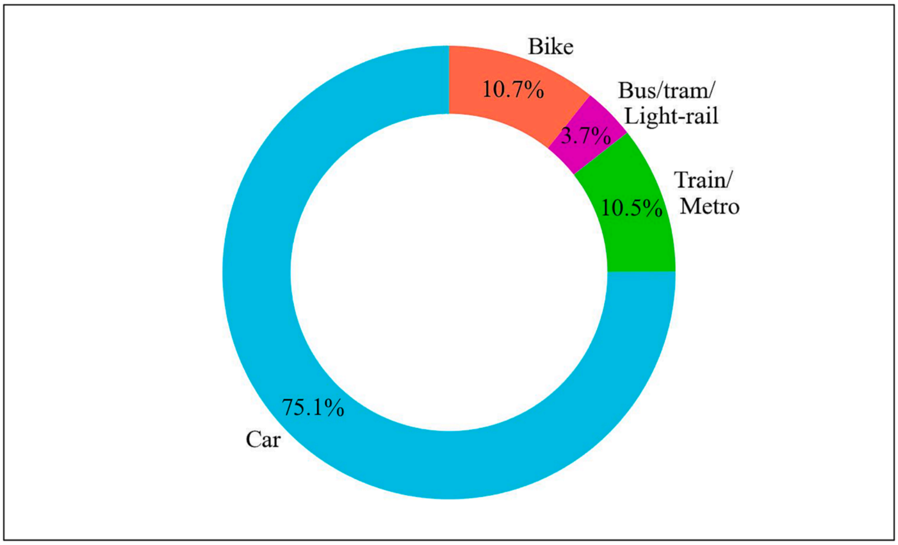


**Fig. 10a.** Revealed preference (Primary) mode share.

*5.2.1. Primary mode results (RP-stage)*

Tables 3.1 and 3.2 provide the estimates of explanatory variables for the primary mode. In particular, Table 3.1 shows the effect of demographic features (age, gender, occupation, and education status), departure time and trip purpose. The effect of in-vehicle travel time, out-of-vehicle distance, travel cost and OD socio-economic indicators are shown in Table 3.2.

As expected, school/college trips are more likely to be performed by public transport (PT) modes as they help avoid traffic jams and require no parking (van Exel and Rietveld, 2009).[11] However, people prefer car or train over bus and bike for trips involving household tasks possibly due to time and space flexibility. Highly educated individuals also have a high propensity towards train/metro, possibly due to reasons such as comfort, greater environmental awareness and a lesser propensity to drive (Fisher et al., 2012; Sivak, 2013). Train/metro is mostly preferred in morning rush hours (6–10 am) over other modes as the frequency of trains in the morning is almost 10 trains/hour in large parts of the Netherlands. Trains, in general, are considered the most viable option for medium to long-distance trips (50 km or more) in the Netherlands (van der Waerden and van der Waerden, 2018). Young (18–24) individuals exhibit a high propensity towards train/metro. There are also age group-specific effects on the bus/tram and bike modes with individuals belonging to age groups (45–54) and (25–34) exhibiting low propensity towards bus/tram and bike, respectively. Next, occupation also has a significant impact on the choice of primary mode with non-employed individuals (students, pensioners, and unemployed/looking for work) exhibiting a high propensity towards usage of PT and bike as compared to car. This can be attributed to both lower frequency and higher flexibility of trips performed by such individuals (Kim and Ulfarsson, 2004) and a decrease in the popularity of cars among the younger generation (Hjorthol, 2016).

All mode attributes (in-vehicle travel time, out-of-vehicle distance, and cost) have intuitive signs and are significant. The implied values of time (VOT) for car, train/metro, and bus/tram/light-rail users are 11.50€/h, 7.20€/h, and 6.40€/h, respectively. The VOT values obtained for the car and public transport users in this study are close to the values observed by Kouwenhoven et al., (2014) and Alonso-González et al., (2020) for the Dutch population. Guevara (2017) provides excellent reasons grounded in the microeconomic theory behind higher VOT for private mode as compared to public transport modes which are not dependent on income. Since the car is usually more expensive than public transport and hence likely to be used by individuals with high-income levels. This leads to a higher VOT for car users coupled with the fact that the travel time by car is generally shorter than public transport. Beyond this income-implied VOT effect, Guevara (2017) provides two additional reasons for higher VOT based on mode-valued differences (Wardman, 2004). The first explanation is related to the marginal consumption of resources. In public transport setting, the user is not the operator. Hence any additional consumption of resources such as oil has no direct impact on the user as fare is exogenous. On the other hand, the car user is both a user and an operator and hence extra resource consumption has an indirect effect on car users' utility. Hence, the mode-valued VOT for car users is likely to be higher as compared to public transport users due to consumption-related effects. The second reason behind higher VOT for car users is related to activity scheduling. Car is faster and can access a large number of places. This allows for complex trip chaining as compared to public transport. The ability to perform many tasks in a short period by car allows for a higher level of utility achieved by the user leading to a higher VOT (Guevara et al., 2015).

In addition to the mode and demographic variables, the land-use variables also have a significant effect on mode preference. As the density of the (both origin and destination) area decreases, the propensity to use non-car modes decreases. An increase in real-state value at the origin reduces the propensity to use train/metro as compared to bus/tram/light-rail. On the other hand, an increase in

[11] In the Netherlands, high-level bus routes have bus-only lanes.

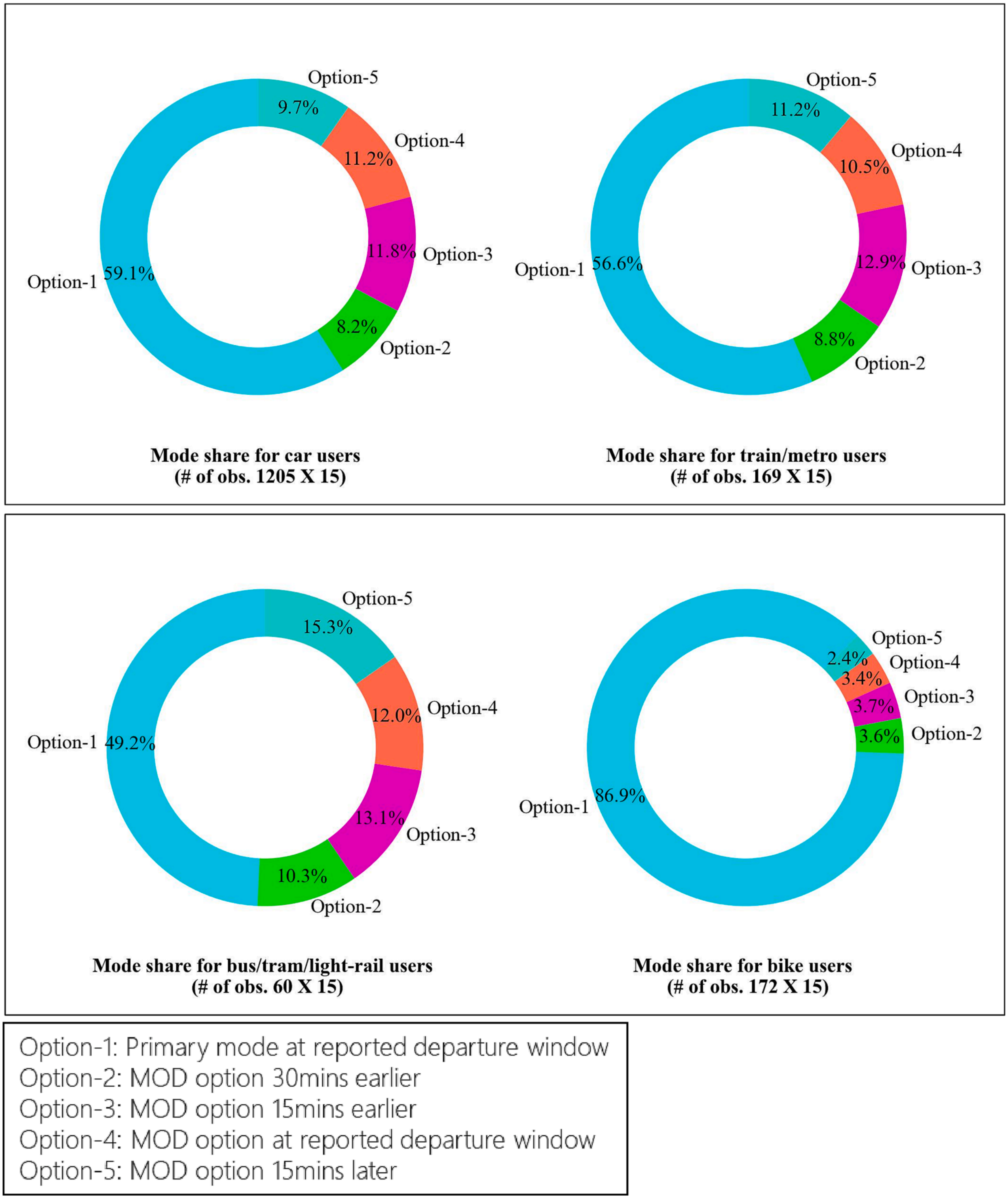


**Fig. 10b.** Mode share distribution in the stated-preference choice experiment.

the real-state value at the destination increases the propensity towards train/metro. Car ownership at the destination negatively impacts the propensity towards train/metro. At the origin level, an increase in distance to the closest supermarket has a positive effect on the likelihood of using the train/metro. However, an increase in distance to the closest primary school has a negative effect on the likelihood of using PT modes. At the destination level, an increase in the distance to the closest supermarket has a positive effect on the bike. Overall, the high-density areas positively affect the propensity of PT modes as also reported by (Limtanakool et al., 2006) who

**Table 3.1**
Choquet-Integral based MNP model estimation results (t-statistics in brackets)

| Dependent variable | Alternatives | Explanatory variables | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | | | *Trip purpose (base: To/from work)* | | | | *Education status (base: high school diploma or less)* | |
| | | Intercept | Work-related | Going to university | House related work | Social trip | Bachelor's degree | Master's or PhD degree |
| ***Primary mode*** | Car | | | | | | | |
| | Train/Metro | −0.753 (-19.78) | — | 0.775 (29.17) | — | — | 0.188 (15.38) | 0.202 (13.73) |
| | Bus/Tram/Light-rail | −0.508 (-12.31) | — | 1.357 (23.14) | −0.735 (-7.53) | — | — | — |
| | Bike | −0.309 (-16.75) | — | — | −0.188 (-14.57) | — | — | — |
| ***Car users*** | Car at the reported 15-minute departure window | | | | | | | |
| | MOD 30 mins earlier | −1.170 (-8.49) | — | — | — | — | — | 0.056 (1.04) |
| | MOD 15 mins earlier | −0.530 (-5.59) | — | — | −0.085 (-1.85) | — | — | — |
| | MOD at the reported 15-minute departure window | −0.382 (-5.37) | −0.062 (-1.72) | — | −0.133 (-2.80) | −0.075 (-1.57) | — | 0.043 (1.48) |
| | MOD 15 mins later | −0.417 (-5.58) | −0.091 (-1.90) | — | −0.133 (-2.47) | −0.073 (-1.62) | — | 0.056 (1.89) |
| ***Train/ metro users*** | Train/metro at the reported 15-minute departure window | | | | | | | |
| | MOD 30 mins earlier | 0.45 0 (1.52) | — | — | — | — | — | — |
| | MOD 15 mins earlier | 0.569 (2.16) | — | — | — | — | — | — |
| | MOD at the reported 15-minute departure window | 0.337 (1.22) | — | — | — | — | — | — |
| | MOD 15 mins later | 0.597 (2.47) | — | — | — | — | — | — |
| ***Bus/tram/ light-rail users*** | Bus/tram/light-rail at the reported 15-minute departure window | | | | | | | |
| | MOD 30 mins earlier | −0.945 (-1.00) | — | — | — | — | — | — |
| | MOD 15 mins earlier | 0.099 (0.41) | — | — | — | — | — | — |
| | MOD at the reported 15-minute departure window | −0.010 (-0.04) | — | — | — | — | — | — |
| | MOD 15 mins later | 0.238 (0.51) | — | — | — | — | — | — |
| ***Bike users*** | Bike at the reported 15-minute departure window | | | | | | | |
| | MOD 30 mins earlier | −1.577 (-1.41) | — | — | 0.343 (1.100) | — | — | — |
| | MOD 15 mins earlier | −0.484 (-1.05) | — | — | — | — | — | — |
| | MOD at the reported 15-minute departure window | −0.367 (-0.83) | — | — | — | — | — | — |
| | MOD 15 mins later | −0.900 (-1.03) | — | — | — | — | — | — |

| Dependent variable | Alternatives | Explanatory variables | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | *Departure window (base: 7–8)* | | | | | | | | | |
| | | 0–6 | 6–7 | 8–9 | 9–10 | 10–12 | 12–16 | 16–17 | 17–18 | 18–19 | 19–24 |
| ***Primary mode*** | Car | | | | | | | | | | |
| | Train/Metro | — | 0.291 (16.48) | 0.253 (13.79) | — | −0.346 (-19.96) | −0.384 (-19.10) | −0.833 (-14.92) | −0.833 (-14.92) | −0.833 (-14.92) | −0.833 (-14.92) |
| | Bus/Tram/Light-rail | — | — | — | — | — | — | — | — | — | — |
| | Bike | — | — | — | — | — | — | −0.610 (-16.31) | −0.610 (-16.31) | −0.610 (-16.31) | −0.610 (-16.31) |
| ***Car users*** | Car at the reported 15- | | | | | | | | | | |

(*continued on next page*)

**Table 3.1** (*continued*)

| Dependent variable | Alternatives | Explanatory variables | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | ***Departure window (base: 7–8)*** | | | | | | | | | |
| | | 0–6 | 6–7 | 8–9 | 9–10 | 10–12 | 12–16 | 16–17 | 17–18 | 18–19 | 19–24 |
| | minute departure window | | | | | | | | | | |
| | MOD 30 mins earlier | — | — | — | 0.159 (2.51) | — | 0.060 (1.18) | — | — | — | — |
| | MOD 15 mins earlier | — | — | — | — | — | — | — | — | — | — |
| | MOD at the reported 15-minute departure window | −0.064 (-1.21) | — | 0.043 (1.48) | — | — | — | — | — | — | — |
| | MOD 15 mins later | — | — | — | — | 0.079 (2.21) | 0.047 (1.70) | — | — | — | — |
| ***Train/metro users*** | Train/metro at the reported 15-minute departure window | | | | | | | | | | |
| | MOD 30 mins earlier | — | — | 0.136 (1.83) | — | — | — | — | — | — | — |
| | MOD 15 mins earlier | — | — | — | — | — | — | — | — | — | — |
| | MOD at the reported 15-minute departure window | — | — | — | 0.116 (1.95) | — | — | — | — | — | — |
| | MOD 15 mins later | — | — | — | 0.060 (1.67) | — | — | — | — | — | — |
| ***Bus/tram/light-rail users*** | Bus/tram/light-rail at the reported 15-minute departure window | | | | | | | | | | |
| | MOD 30 mins earlier | — | — | — | — | — | — | — | — | — | — |
| | MOD 15 mins earlier | — | — | — | — | — | — | — | — | — | — |
| | MOD at the reported 15-minute departure window | — | — | — | — | — | — | — | — | — | — |
| | MOD 15 mins later | — | — | — | — | — | — | — | — | — | — |
| ***Bike users*** | Bike at the reported 15-minute departure window | | | | | | | | | | |
| | MOD 30 mins earlier | — | — | — | — | — | — | — | — | — | — |
| | MOD 15 mins earlier | — | — | — | — | — | — | — | — | — | — |
| | MOD at the reported 15-minute departure window | — | — | — | — | — | — | — | — | — | — |
| | MOD 15 mins later | — | — | — | — | — | — | — | — | — | — |

| Dependent variable | Alternatives | Explanatory variables | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | ***Age (base: 55 or above)*** | | | | ***Gender (base: female)*** | ***Occupation (base: employed)*** | | |
| | | 18–24 | 25–34 | 35–44 | 45–54 | Male | Student | Pensioner | Unemployed/ looking for work |
| ***Primary mode*** | Car | | | | | | | | |
| | Train/Metro | 0.380 (18.13) | — | — | — | — | 0.905 (31.30) | — | 0.312 (11.33) |

(*continued on next page*)

**Table 3.1** (*continued*)

| Dependent variable | Alternatives | Explanatory variables | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | *Age (base: 55 or above)* | | | | *Gender (base: female)* | *Occupation (base: employed)* | | |
| | | 18–24 | 25–34 | 35–44 | 45–54 | Male | Student | Pensioner | Unemployed/ looking for work |
| | Bus/Tram/Light-rail | — | — | — | −0.473 (-5.73) | — | 0.657 (13.09) | 0.186 (4.79) | 0.542 (12.60) |
| | Bike | — | −0.343 (-24.41) | — | — | — | 1.216 (59.26) | — | — |
| ***Car users*** | Car at the reported 15-minute departure window | | | | | | | | |
| | MOD 30 mins earlier | 0.183 (2.38) | 0.080 (1.18) | 0.091 (1.43) | — | — | — | — | — |
| | MOD 15 mins earlier | 0.114 (2.15) | 0.074 (1.67) | 0.065 (1.47) | 0.076 (2.16) | — | — | — | — |
| | MOD at the reported 15-minute departure window | 0.091 (2.00) | 0.083 (2.17) | 0.081 (1.98) | 0.051 (1.31) | — | — | — | — |
| | MOD 15 mins later | 0.068 (1.26) | 0.06 (1.64) | 0.087 (2.19) | — | — | — | — | — |
| ***Train/ metro users*** | Train/metro at the reported 15-minute departure window | | | | | | | | |
| | MOD 30 mins earlier | 0.187 (1.29) | 0.187 (1.29) | — | — | −0.175 (-1.50) | — | — | — |
| | MOD 15 mins earlier | 0.311 (1.57) | 0.311 (1.57) | 0.174 (1.15) | 0.174 (1.15) | −0.251 (-2.08) | — | — | — |
| | MOD at the reported 15-minute departure window | 0.346 (1.82) | 0.346 (1.82) | 0.184 (1.18) | 0.184 (1.18) | −0.246 (-1.63) | — | — | — |
| | MOD 15 mins later | 0.247 (1.21) | 0.247 (1.21) | 0.189 (1.15) | 0.189 (1.15) | −0.332 (-2.34) | — | — | — |
| ***Bus/tram/ light-rail users*** | Bus/tram/light-rail at the reported 15-minute departure window | | | | | | | | |
| | MOD 30 mins earlier | — | — | — | — | — | — | — | — |
| | MOD 15 mins earlier | — | — | — | — | — | — | — | — |
| | MOD at the reported 15-minute departure window | — | — | — | — | — | — | — | — |
| | MOD 15 mins later | — | — | — | — | — | — | — | — |
| ***Bike users*** | Bike at the reported 15-minute departure window | | | | | | | | |
| | MOD 30 mins earlier | — | — | — | — | — | — | — | — |
| | MOD 15 mins earlier | — | — | — | — | — | — | — | — |
| | MOD at the reported 15-minute departure window | — | — | — | — | — | — | — | — |
| | MOD 15 mins later | — | — | — | — | — | — | — | — |

——: highly insignificant, $p > 0.35$.

found that trains are more attractive in high-density areas. Finally, a higher density of financial and recreational establishments discourages bike use. However, people prefer to use the train/metro and bike over car in areas with high density of trade and catering, and business services.

### 5.2.2. Choice between the currently used primary mode and a MOD service (SP-stage)

In this section, we discuss the presence/absence of non-compensatory behaviour, the effect of reliability, and other explanatory variables on the choice between a current mode and a MOD alternative. In particular, we start our discussion with the evidence for non-compensatory behaviour in the context of MOD mode choice and highlight how one can compare CI and WS models at a behavioural level using feature importance. We also compare two models using aggregate and disaggregate data-fit statistics to statistically validate the underlying behavioural findings. Subsequently, we discuss the effect of past choices/experiences, inertia effect, propensity of temporal mode shift and effect of other trip characteristics such as purpose, and access and egress mode on an individual's choice of a mode.

**Table 3.2**
Choquet-Integral based MNP model estimation results (t-statistics in brackets)

| Explanatory variables | Dependent variable: *Primary mode* | | | |
|---|---|---|---|---|
| | **Car** | **Train/Metro** | **Bus/Tram/Light-rail** | **Bike** |
| ***Mode characteristics*** | | | | |
| In-vehicle travel time (hours) | −0.207 (-5.27) | −0.295 (-5.78) | −0.550 (-7.47) | −1.907 (-8.59) |
| Out-of-vehicle distance (km) | | −0.096 (-13.42) | −0.253 (-12.92) | — |
| Travel cost (€) | −0.018 (-3.46) | −0.041 (-7.93) | −0.086 (-19.36) | |
| ***Trip origin area characteristics*** | | | | |
| ***Area type*** (base: very strong urban (≥2000 addresses per km$^2$)) | | | | |
| Strongly urban (1500–2000 addresses per km$^2$) | | — | — | −0.168 (-16.03) |
| Moderately urban (1000–1500 addresses per km$^2$) | | — | — | — |
| Few urban (500–1000 addresses per km$^2$) | | — | — | — |
| Non-urban (<500 addresses per km$^2$) | | −0.536 (-12.24) | 0.443 (9.36) | — |
| Average value of real-state (in 1000 euros) | | −0.721 (-6.89) | — | — |
| Number of cars per household | | — | — | — |
| Average distance to the closest supermarket (in km) | | 0.252 (11.76) | — | — |
| Average distance to closest primary school (in km) | | −0.543 (-17.99) | −0.694 (-11.27) | — |
| ***Trip destination area characteristics*** | | | | |
| ***Area type*** (base: very strong urban (≥2000 addresses per km$^2$)) | | | | |
| Urban (1000–2000 addresses per km$^2$) | | −0.249 (-17.07) | −0.31 (-13.58) | −0.209 (-17.41) |
| Non-urban (up to 1000 addresses per km$^2$) | | −0.497 (-18.75) | −0.491 (-11.86) | −0.307 (-17.82) |
| Average value of real-state (in 1000 euros) | | 1.038 (13.84) | — | — |
| Number of cars per household | | −0.521 (−23.12) | — | — |
| Average distance to the closest supermarket (in km) | | — | — | 0.136 (18.67) |
| Average distance to the closest primary school (in km) | | — | — | — |
| ***Number of establishments per industry*** (in 100 s) | | | | |
| Agriculture, forestry and fisheries | | — | — | — |
| Industry and energy | | — | — | — |
| Trade and catering | | 0.348 (24.93) | — | — |
| Transport, information and communication | | — | — | — |
| Financial services, real estate | | — | — | −0.729 (-16.62) |
| Business services | | — | — | 0.515 (22.31) |
| Culture, recreation, other services | | −0.58 (-19.54) | — | −0.404 (-11.18) |

——: highly insignificant, $p > 0.35$.

*5.2.2.1. Non-compensatory behaviour*

Table 3.4 reports the CI fuzzy measure estimates.[12] Readers will note that fuzzy measures are generic and not alternative-specific, i.e., the same set of fuzzy measures are estimated for all alternatives for a given primary mode user. In our analysis, we attempt to estimate alternative-specific fuzzy measures ($\mu()$). However, it turned out to be insignificant and, in some cases, led to the singularity of the first-order matrix. This suggests that either an alternative-specific preference is not empirically identifiable in the current dataset or that users attach the same preference (i.e., same attribute importance) for their primary mode and MOD service, i.e., a concise choice set may offer better insights into the decision process. Further, the waiting time variable for public transport options (train/metro and bus/tram/light-rail) is the sum of the access time to the station/stop, waiting time at the station/stop, and egress time to the destination. We created the aggregate waiting time since an alternative-specific CI could not be estimated.[13]

In the case of car users, none of the fuzzy measures are zero. Therefore, car users utilize all the information in their decision-making. However, travel time is considered the least important as implied by its very small fuzzy measure coefficient. It suggests that travel time does not play a significant role in the decision process of car users when comparing the car with MOD options. Similarly, in the case of public transport (train and bus), the fuzzy measure value for travel time is zero. Therefore, no attribute trade-off (zero marginal contribution) occurs in some regions of attribute ranges (see section 4.1) depending on the distribution of attribute values. Between train and bus users, the degree of no-trade-off is stronger among bus users. Finally, bike users exhibit behaviour similar to public transport users with low importance attached to waiting time.

Such a direct inference of non-compensatory behaviour is not possible in models with WS aggregation functions. Therefore, we need to examine another avenue to make a comparison between CI and WS models at the behavioural level. One such avenue can be feature/attribute importance (Shapley value, see Eq. (5) in section 4). One can expect the feature importance values obtained from CI and WS-based models to be significantly different in the event of an underlying non-compensatory behaviour. For example, since the fuzzy measure value of travel time and waiting time is relatively small for bus users, we can infer that the implied feature importance of these two attributes may be close to zero (non-significant role in the decision process of bus users when comparing

[12] When the observed utility function is a combination of weighted sum and CI, a multiplicative scale factor may be estimated to account for difference in range of value. In the current empirical models, we could not statistically distinguish the factor from 1.

[13] The attribute normalization can only be performed if an attribute is applicable for at least two alternatives. We also attempted to estimate attribute-specific membership to overcome the issue of access and egress time non-availability for MOD options in order to estimate separate parameters for those variables. However, the estimates could not be empirically identified.

**Table 3.3**
Choquet-Integral based MNP model estimation results (t-statistics in brackets)

| Dependent variable | Alternatives | Explanatory variables | | | | |
|---|---|---|---|---|---|---|
| | | ***Shared*** | ***Cumulative choice count until time t-1*** | | ***Regret components*** | |
| | | ***(Yes = 1, No = 0)*** | Intercept | Curvature | $ln\left(\frac{ExpectedTT}{ActualTT}\right)$ | $ln\left(\frac{ExpectedWT}{ActualWT}\right)$ |
| ***Car users*** | Car at the reported 15-minute departure window | | 0.209 (7.08) | 1.462 (29.17) | | |
| | MOD 30 mins earlier | 0.201 (4.03) | 0.512 (6.42) | 2.768 (6.29) | 0.451 (1.87) | −0.356 (-1.49) |
| | MOD 15 mins earlier | 0.172 (4.80) | 0.36 (5.99) | 5.303 (2.98) | | |
| | MOD at the reported 15-minute departure window | 0.241 (6.69) | 0.300 (5.77) | 3.295 (4.98) | | |
| | MOD 15 mins later | 0.033 (1.24) | 0.313 (6.07) | 2.295 (7.30) | | |
| ***Train/ metro users*** | Train/metro at the reported 15-minute departure window | | 0.666 (2.58) | 1.847 (8.72) | | |
| | MOD 30 mins earlier | 0.127 (1.44) | 0.048 (1.80) | 1 (fixed) | −0.420 (-1.59) | 0.434 (1.61) |
| | MOD 15 mins earlier | — | — | 1 (fixed) | | |
| | MOD at the reported 15-minute departure window | 0.11 (1.39) | — | 1 (fixed) | | |
| | MOD 15 mins later | — | — | 1 (fixed) | | |
| ***Bus/tram/ light-rail users*** | Bus/tram/light-rail at the reported 15-minute departure window | | — | 1 (fixed) | | |
| | MOD 30 mins earlier | — | — | 1 (fixed) | — | — |
| | MOD 15 mins earlier | — | — | 1 (fixed) | | |
| | MOD at the reported 15-minute departure window | — | — | 1 (fixed) | | |
| | MOD 15 mins later | — | — | 1 (fixed) | | |
| ***Bike users*** | Bike at the reported 15-minute departure window | | — | 1 (fixed) | | |
| | MOD 30 mins earlier | — | 0.987 (1.82) | 3.042 (1.42) | — | — |
| | MOD 15 mins earlier | — | 0.258 (1.56) | 1 (fixed) | | |
| | MOD at the reported 15-minute departure window | — | 0.238 (1.27) | 1 (fixed) | | |
| | MOD 15 mins later | — | — | 1 (fixed) | | |

| Dependent variable | Alternatives | Explanatory variables | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | ***Access mode*** | | | | ***Egress mode*** | | | |
| | | Public transport | Car | Walk | Bike | Public transport | Bike | Car | Walk |
| ***Car users*** | Car at the reported 15-minute departure window | | | | | | | | |
| | MOD 30 mins earlier | | | | | | | | |
| | MOD 15 mins earlier | | | | | | | | |
| | MOD at the reported 15-minute departure window | | | | | | | | |
| | MOD 15 mins later | | | | | | | | |
| ***Train/ metro users*** | Train/metro at the reported 15-minute departure window | 0.233 (2.24) | — | — | — | — | — | — | — |
| | MOD 30 mins earlier | | | | | | | | |
| | MOD 15 mins earlier | | | | | | | | |
| | MOD at the reported 15-minute departure window | | | | | | | | |
| | MOD 15 mins later | | | | | | | | |
| ***Bus/tram/ light-rail users*** | Bus/tram/light-rail at the reported 15-minute departure window | — | — | — | 0.347 (1.74) | — | — | — | — |
| | MOD 30 mins earlier | | | | | | | | |
| | MOD 15 mins earlier | | | | | | | | |
| | MOD at the reported 15-minute departure window | | | | | | | | |
| | MOD 15 mins later | | | | | | | | |
| ***Bike users*** | Bike at the reported 15-minute departure window | | | | | | | | |
| | MOD 30 mins earlier | | | | | | | | |
| | MOD 15 mins earlier | | | | | | | | |

(*continued on next page*)

**Table 3.3** (*continued*)

| Dependent variable | Alternatives | Explanatory variables<br>*Access mode*<br>Public transport | Car | Walk | Bike | *Egress mode*<br>Public transport | Bike | Car | Walk |
|---|---|---|---|---|---|---|---|---|---|
| | MOD at the reported 15-minute departure window | | | | | | | | |
| | MOD 15 mins later | | | | | | | | |

——: highly insignificant, $p > 0.35$.

**Table 3.4**
Choquet-Integral based MNP model estimation results (t-statistics in brackets)

| Explanatory variables | Dependent variable | | | |
|---|---|---|---|---|
| | *Car users* | *Train/ metro users* | *Bus/tram/ light-rail users* | *Bike users* |
| $\mu(TT)$ | 0.083 (2.21) | 0.000 (0.00) | 0.001 (0.00) | 0.116 (1.36) |
| $\mu(TC)$ | 1.000 (7.83) | 0.820 (2.60) | 0.992 (1.76) | 0.687 (1.66) |
| $\mu(WT)$ | 0.736 (7.69) | 0.266 (1.48) | 0.115 (2.15) | 0.001 (0.00) |
| $\mu(TT, TC)$ | 1.000 (8.00) | 0.927 (2.68) | 1.000 (1.71) | 0.822 (1.29) |
| $\mu(TT, WT)$ | 0.736 (7.63) | 0.266 (1.61) | 0.500 (1.57) | 0.117 (1.33) |
| $\mu(TC, WT)$ | 1.000 (7.89) | 0.967 (2.71) | 0.992 (1.71) | 0.981 (1.45) |
| $\mu(TT, TC, WT)$ | 1.000 (7.88) | 1.000 (2.90) | 1.000 (1.77) | 1.000 (1.43) |

*TT: Travel time, TC: Travel cost, WT: Pick-up time, —: Not significant, $\mu()$: Fuzzy measure.

the currently used mode with MOD options).

*5.2.2.2. Feature importance (Shapley value)*

Fig. 11 shows the feature importance of travel time, travel cost, and waiting time for all primary modes. For the CI-based model, the feature importance is obtained using Eq. (5). In contrast, Eq. (5) cannot be directly employed to obtain feature importance in the WS model as parameters are not constrained between 0 and 1 and are also not monotonic. Hence, we derive the feature importance using marginal effects (change in probability) for the pure WS-based model specification. Such measures are typically used in WS based model to derive the importance of an explanatory variable. In particular, we normalize the absolute marginal effect of a primary mode as a result of improvement in service aspects (travel time, travel cost, and waiting time) of the MOD service, one at a time. The marginal effects resulting from a 20 % reduction in MOD service aspects are provided in the supplementary sheet (section S.4). It is plausible that feature importance derived based on this marginal-effect approach may be different from true feature importance.[14] Nevertheless, this approach would suffice for comparing CI and WS-based models at the behavioural level. Further, we estimate two specifications for WS based model: (a) a specification with no interaction between travel time, waiting time, and cost (MNP-WS(NI)), and (b) a specification with complete interaction between travel time, waiting time, and cost (MNP-WS(AI)). A complete interaction ensures an equal degree-of-freedom in both MNP-CI and MNP-WS(AI) models. Hence, any differences observed between MNP-CI and MNP-WS(AI) models can then be attributed to the way variables are processed by the CI function (marginal contribution-based processing).

An examination of the feature importance values (based on MNP-CI) suggests that travel cost is the most important variable followed by waiting time and travel time. Travel time has negligible importance for both car and train/metro users (0.03 and 0.03). This follows from the fact that the in-vehicle travel time does not differ substantially between MOD option, car and train/metro in most instances. Therefore, it has very low alternative discernability power in distinguishing between alternatives. The importance of the cost variables is significantly different between car and non-car users. Cost plays a very important role for public transport and active mode users followed by waiting time. Due to the overall high-quality alternative offered by public transport in the Netherlands, healthy competition exists between MOD and public transport which leads to the cost being the highly influencing variable. These observations are intuitive and hence suggest that CI can unravel the underlying non-compensatory behaviour.

The behavioural differences between MNP-CI and MNP-WS(NI) are evident in the feature importance ordering. In the case of car users, the MNP-WS(NI) model assigns significant importance to travel time and compensates by decreasing the importance of waiting time. The travel time does not differ significantly between the car and MOD and thus does not aid in decision-making. Hence, the

[14] The Shapley equivalent feature importance in weighted-sum based models can be derived using the approach suggested by Mishra (2016). The approach essentially requires estimation of $2^{\#\text{ of attributes}}$ models with all possible interactions. The data-fit estimate ($R^2$ value) of the models are then used as fuzzy measure values in Eq. (5) to obtain Shapley values.

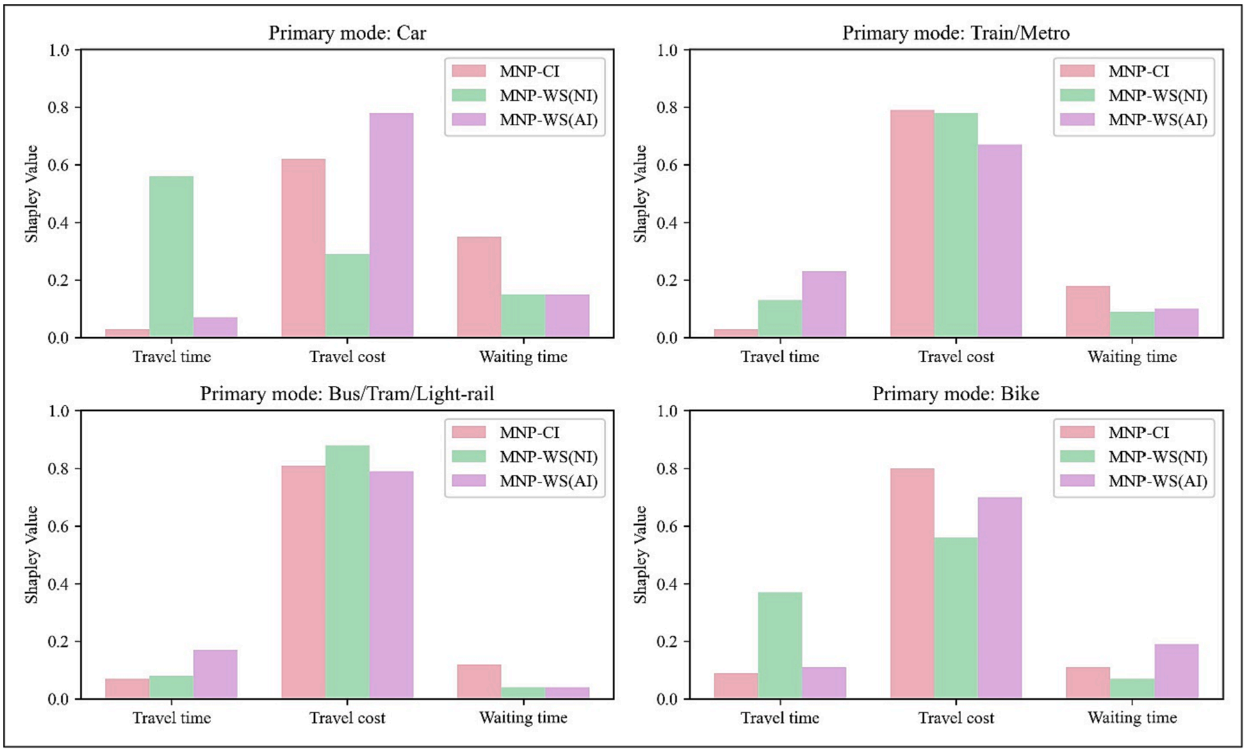


**Fig. 11.** Feature importance (Shapley value).

expected importance should be low or zero for the travel time as correctly captured by the MNP-CI model. A similar observation can be made for the PT (train/metro or bus/tram/light-rail) users concerning travel and waiting time.

In comparison to the MNP-WS(NI) model, the feature importance value obtained from the MNP-WS(AI) model is relatively close to the MNP-CI based feature estimates for car and bike users. The feature importance values are significantly different for train/metro and bus/tram/light-rail cases, especially for travel and waiting times.

Overall, the feature importance values obtained through CI based model are in line with the observations made earlier (section 5.2.2.1) related to non-compensatory behaviour. Next, we compare the models (CI vs. WS) using data-fit statistics to ensure that behavioural findings are statistically valid.

#### 5.2.2.3. *Aggregate model validation*

Table 4 provides the data-fit statistics for all three models. The lowest Akaike information criterion (AIC) value is highlighted in bold. Based on the data-fit statistics, a CI-based model can be considered superior to a pure WS-based model configuration. Overall, these results are in line with the observations made earlier based on both fuzzy measures and feature importance values.

**Table 4**
Data-fit statistics for CI and WS models

| Model | CML value (# of parameters) | AIC |
|---|---|---|
| MNP-CI | −24807.36 (257) | **50,129** |
| MNP-WS(NI) | −26380.98 (237) | 53,236 |
| MNP-WS(AI) | −25355.02 (253) | 51,216 |

*AIC: Akaike information criterion, CML: Composite marginal log-likelihood.

*5.2.2.4. Disaggregate model validation*

The three criteria (fuzzy measure values, feature importance and AIC criterion) used to compare CI and WS-based models are aggregate measures. They do not provide however a direct insight into the performance of the models at an individual level. Hence, we calculate class-specific accuracy (highest probability alternative *equals* chosen option) to highlight the differences at an individual level. Since the distribution of chosen options is skewed towards non-MOD options for all four primary modes, we derive weighted accuracy to ensure overall accuracy is not dominated by alternative(s) with higher shares.

$$\text{Weighted Accuracy (WA)} = \frac{\sum_{i=1}^{I=5} \frac{i_{accuracy}}{i_{share}}}{\sum_{i=1}^{5} \frac{1}{i_{share}}}$$

$$i_{accuracy} = \frac{\#\text{of observations where } p(i) > p(j, j \in A(1,2,..,I)/i)\, and \text{ chosen option} \;==\; i}{\#\text{of observations where chosen option} \;==\; i}$$

where $i_{accuracy}$ is the accuracy of option $i$ and $i_{share}$ is the observed share of option $i$ in the sample

and $0 \leqslant \text{WA} \leqslant 1$.

Fig. 12 shows the weighted accuracy value for all models. For brevity, we only report the aggregate values here. The weighted accuracy is calculated based on the marginalisation of SP options depending on the reported primary mode. A disaggregate description is available in the supplementary sheet (see section S.5). The CI-based model consistently has a higher weighted accuracy value across all primary modes in both estimation and validation samples.[15] This demonstrates that the CI model can reduce the divergence between modelled and true behaviour and hence able to provide improved individual-level predictions.

*5.2.2.5. Regret due to difference in stated vs. actual information or reliability effect*

Table 3.3 provides the estimates of regret-related components. Readers will note that regret components are only applicable to MOD options. During model estimation, we could not empirically identify the regret aversion ($\rho$) parameter (see section 4.2) and hence tried both linear difference and ratio. The ratio approach was found to provide the best results. In particular, we used $\ln\left(Expected\ Value/_{Actual\ value}\right)$. Readers will note that the reliability band is set in such a way that the ratio is always greater than 1. The use of a ratio is also advantageous as it allows us to directly compare the effect of travel and waiting time regrets.

In the case of car users, increased waiting time leads to a higher disutility as compared to travel time. For train/metro users, increased travel time leads to a higher disutility as compared to the waiting time. The behaviour of car users aligns with our expectations. Car users have an option of achieving zero waiting time and hence they are highly sensitive to waiting time fluctuations. On the other hand, train/metro users' greater sensitivity towards travel time than toward wait time requires further investigation. Bus/tram/light-rail and bike users are not sensitive to differences in stated vs. actual information.

*5.2.2.6. Effect of past choices on current decision and inertia effect*

To capture the effect of past choices and regret on the current decision, we begin by applying the auto-regressive structure of order 1 (AR-1) as discussed in section 4.2. While the AR-1 structure is sufficient to capture the effect of past choices and regret, we also include a cumulative count of choices (for each of the alternatives) to assess any alternative-specific inertia. In particular, we use the following power form: $\beta_{CC}(\#\ of\ times\ chosen\ until\ t-1)^{\frac{1}{\alpha}}$, where $\alpha > 0$. A positive $\beta_{CC}$ implies a higher likelihood of choosing an alternative, ceteris paribus. The curvature parameter ($\alpha$) captures the degree of inertia for a mode. A value of $\alpha < 1$ indicates higher inertia towards an alternative. Similarly, a value of $\alpha > 1$ suggests low inertia and $\alpha = 1$ implies indifference. A value of $\alpha \geqslant 5$ indicates the absence of any inertia at all. For all the primary mode and MOD combinations, the value of $\beta_{CC}$ is positive. Table 3.3 provides the estimates related to past choices based on the MNP-CI(2) model.

In the case of car users, the value of $\alpha$ is 1.46 for the car mode and more than 2 for the four MOD options. It implies that for car users to shift towards the MOD service requires overcoming a certain amount of inertia. Nevertheless, the inertia associated with the car is highest compared to MOD alternatives for car users indicating higher stability of transport behaviour (Thøgersen, 2006). In the case of train/metro users, the value of $\alpha$ is 1.85 for the train/metro mode and 1.0 for the remaining four MOD options.[16] This suggests that train/metro users can shift to MOD options if attractive feature (cost and waiting time) values are provided (Thøgersen, 2006). Similar observations can be observed for bus/tram/light-rail and bike users. In this analysis, we did not parametrize the $\alpha$ coefficient and only estimated an intercept. One can parametrize the $\alpha$ parameter as a function of task-specific completion time to control for task fatigue which may prompt individuals to revert to their primary mode option during the SP choice task. Unfortunately, we only recorded the total survey time, thereby prohibiting such an analysis.

[15] We also report the un-weighted accuracy and average implied shares for all the models in the supplementary sheet (see section S.5 & S.6).

[16] All the curvature parameters with value mentioned as 1.0 (fixed) imply that we could not differentiate the value from 1 based on a significance level of 0.20 or less.

Further, the AR coefficient ($\pi$, see Eq.16) turned insignificant (for all the SP stage dependent variables) upon the inclusion of the cumulative count choice parameter. An insignificant AR coefficient highlights two points. First, unobserved factors are IID across time periods (choice tasks). Second, the regret due to the difference in stated vs. actual travel and waiting time is not accumulated and only the latest regret $(t-1)$ is considered during the next choice $(t)$. One possible reason for such behaviour can be attributed to the moderately large choice set (five alternatives). A smaller choice set (primary mode + 2 MOD options) may have allowed respondents to focus better on reliability values and subsequently use them for decision-making in multiple periods. In light of an insignificant AR, the panel effect is only captured through a deterministic inertia function.

#### *5.2.2.7. Temporal mode shift*

To capture the temporal mode shift effect, we added the time of day as a dummy variable (see Fig. 5e). The estimates are provided in Table 3.1. While it is common to observe extensive usage of MOD services in the evening (7–11 pm) and night times (11–5 pm) (Young and Farber, 2019), we find that both car and train/metro users demonstrate some potential for temporal shifts during the morning peak (8–10 am) and midday (10–4 pm). The motives behind such temporal shifts by users are difficult to explain in the absence of trip flexibility information and household schedules. Further, similar to the regret observation, bus/tram/light-rail and bike users exhibit no propensity for temporal mode shift towards MOD service. Such insignificant temporal effect for bus/tram/light-rail can be attributed to the small sample size as discussed earlier.

#### *5.2.2.8. Effect of access and egress mode*

In the case of train/metro users, we observe a positive propensity towards train/metro if accessed through public transport modes and negative if accessed using a car (Table 3.3). It suggests that a seamless public transport connection to the station encourages individuals towards using the train/metro and the hassle of finding parking near the station discourages the use of the train/metro. On the other hand, access to the bus/tram/light-rail stop by bike is preferred possibly due to the ease of bicycle parking in the vicinity of the stop. Jonkeren et al. (2021) report similar statistics at the population level in the Netherlands. They report that 83 % of all train journeys in the Netherlands are multimodal trips with 43 % and 14 % bike share at the home end and activity end, respectively.

#### *5.2.2.9. Effect of trip purpose and sharing/private option*

The trip purpose (see Fig. 5d) and whether the MOD ride is private or shared not only affects the propensity to use MOD service but also the likelihood of changing the departure time. In the case of car users, non-commute trip purposes decrease the likelihood of using MOD service. It suggests that car users may only substitute driving for commute trips (Lavieri and Bhat, 2019). A positive observation from the environmental point of view is that car users exhibit propensity towards shared rides as compared to private MOD rides. Train/metro users also exhibit propensity towards shared rides as compared to private MOD rides for early departure and mode substitution in the usual departure window. The effect of trip purpose and shared/private option is non-significant for users of all other modes.

#### *5.2.2.10. Effect of demographic characteristics*

Young (18–34) and middle (35–54) age car and train/metro users exhibit a higher propensity towards the consideration of a MOD service as compared to older individuals (55 or more). This can be attributed to factors such as the digital divide and openness to new experiences (Lavieri and Bhat, 2019; Young and Farber, 2019). In addition, female train/metro users are more likely to experiment with MOD services than male train/metro users. Highly educated car users also exhibit a higher propensity towards the usage of MOD services, possibly due to greater awareness of urban and environmental issues (Sun et al., 2020).

#### *5.2.2.11. Value of time*

The value of time (VOT) cannot be directly inferred from a CI-based model. Therefore, we report the VOT based on MNP-WS(NI) estimates (see Table S.3.1in the supplementary sheet). The implied VOT for car, train/metro, and bus/tram/light-rail users are 10.51€/h, 7.74€/h, and 5.38€/h, respectively. The implied VOT for the bike based on parameter estimates is 1.62€/h.

#### *5.2.2.12. Error-covariance structure and endogeneity correction*

The use of a probit kernel allows for estimating flexible substitution patterns across alternatives. In our analysis, we obtain a non-independent and identically distributed (IID) error structure (see Table 3.5). In a probit-kernel based model, only a differenced error-covariance matrix can be identified. Since many un-differenced error matrices can lead to the same differenced error matrix, the differenced error-covariance matrix does not have a meaningful interpretation Therefore, we can only conclude on the IID nature of the error structure and not on the exact distribution.

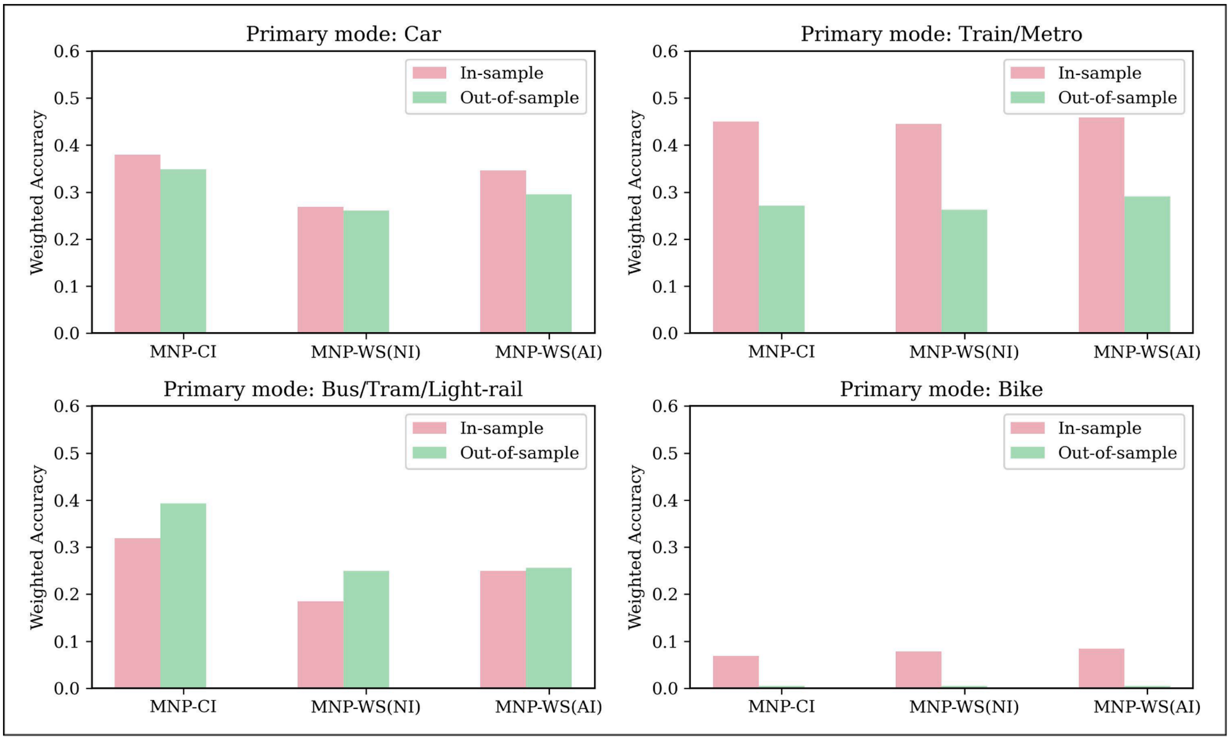


**Fig. 12.** Weighted accuracy value.

Based on estimates provided in Table 3.5, two observations can be made. First, for all the RP and SP stage choices, we observe a non-IID error-covariance structure. Second, the off-diagonal blocks capturing correlation between RP and SP stage have several significant elements suggesting the presence of common unobserved factors.[17] This corrects for endogeneity. The effect of neglecting endogeneity is substantial. CI model without endogeneity correction provides inflated cost importance (Shapley) values of 0.63, 0.88, 0.95, and 1.00 for car, train/metro, bus/tram/light-rail and bike users, respectively.

*5.2.2.13. Tipping point analysis or critical MaaS (Mobility-as-a-service)*

From an operator's point of view, cost is the most important variable among the MOD attributes. An increase/decrease in cost may lead to a change in the market share, ceteris paribus. Therefore, we perform a critical mass analysis to derive the optimal pricing range. In particular, we calculate the MOD share for a range of per km price by keeping other attributes unchanged.[18] Fig. 13 shows the aggregate MOD market share for each of the primary travel modes and MOD combinations.[19] The results show that the tipping point (in terms of cost) varies depending on the primary mode. A per km cost of 0.6€ or less may be required to attract a substantial share of car users towards the MOD service (Fig. 13 top graph). Interestingly, the MOD ridership does not change below a price tag of 0.5€ per km which is also the average per km car operating cost in the sample. Next, the per km cost is 0.3€ and 0.4€ for train/metro and bus/tram/light-rail, respectively. Similar to the car users, the MOD ridership does not change above 0.3€ and 0.4€ for train/metro and bus/tram/light-rail. This highlights that CI based model can capture the non-compensatory effect of the price attribute. However, the pure WS models fail to do so as observed by an increasing slop of the market share line. Both MNP (NI) and MNP-WS(AI) models suggest a continuous decrease in market share due to the underlying assumption of attribute trade-offs. Finally, since the bike user does not incur any cost for their trip, the CI or WS model is unable to provide tipping point cost value for these users. The model only provides the sample average of the MOD option. Future studies may record bike users' cost cut-offs (possibly the upper limit) to derive a tipping point price. The results advocate a differential pricing strategy depending on the primary mode of travel. While such a strategy may not be suitable from an equity perspective, it may help attain a critical mass.

[17] Note that the off-diagonal blocks between various SP choices may have non-zero but relatively small numerical value due to estimation of Cholesky matrix during model estimation.

[18] The assumption to keep travel and waiting time unchanged is innocuous due to the use of Google APIs to extract travel times.

[19] We derive the aggregate share of MOD by adding the share of the four MOD options. The disaggregate values are available for all models in the supplementary sheet (see section S.7).

**Table 3.5**
Choquet-Integral based MNP model differenced error-covariance matrix estimates (t-statistics in brackets)

| | ***Primary mode*** | | | ***Car users*** | | | | ***Train or Metro users*** | | | | ***Tram or Bus or Light-rail users*** | | | | ***Bike users*** | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| ***Primary mode*** | 1.000 | | | | | | | | | | | | | | | | | | |
| | (fixed) | | | | | | | | | | | | | | | | | | |
| | 0.630 | 0.999 | | | | | | | | | | | | | | | | | |
| | (18.35) | (24.37) | | | | | | | | | | | | | | | | | |
| | 0.748 | 0.696 | 0.962 | | | | | | | | | | | | | | | | |
| | (49.30) | (1.67) | (28.42) | | | | | | | | | | | | | | | | |
| ***Car users*** | −0.045 | −0.015 | 0.197 | 1.000 | | | | | | | | | | | | | | | |
| | (-0.30) | (-0.04) | (1.38) | (fixed) | | | | | | | | | | | | | | | |
| | 0.005 | 0.040 | 0.038 | −0.254 | 0.345 | | | | | | | | | | | | | | |
| | (0.06) | (0.22) | (0.27) | (-3.00) | (5.60) | | | | | | | | | | | | | | |
| | −0.001 | −0.002 | 0.146 | −0.050 | −0.059 | 0.295 | | | | | | | | | | | | | |
| | (-0.02) | (-0.01) | (2.29) | (-1.46) | (-2.49) | (3.57) | | | | | | | | | | | | | |
| | −0.025 | 0.123 | 0.189 | −0.118 | −0.052 | 0.088 | 0.329 | | | | | | | | | | | | |
| | (-0.37) | (1.35) | (3.15) | (-2.27) | (-3.19) | (2.16) | (0.54) | | | | | | | | | | | | |
| ***Train or Metro users*** | 0.109 | 0.142 | −0.148 | −0.189* | −0.016* | −0.123* | −0.108* | 1.000 | | | | | | | | | | | |
| | (0.95) | (0.22) | (-0.67) | | | | | (fixed) | | | | | | | | | | | |
| | 0.150 | 0.236 | −0.065 | −0.173* | −0.014* | −0.115* | −0.077* | 0.840 | 0.882 | | | | | | | | | | |
| | (1.50) | (0.65) | (-1.27) | | | | | (2.22) | (1.38) | | | | | | | | | | |
| | 0.227 | 0.289 | −0.123 | −0.260* | −0.021* | −0.170* | −0.136* | 0.900 | 0.834 | 1.002 | | | | | | | | | |
| | (1.43) | (0.66) | (-1.47) | | | | | (3.22) | (0.23) | (0.71) | | | | | | | | | |
| | 0.138 | 0.257 | −0.129 | −0.218* | −0.016* | −0.145* | −0.103* | 0.888 | 0.848 | 0.917 | 0.952 | | | | | | | | |
| | (1.43) | (1.00) | (-1.42) | | | | | (4.11) | (0.46) | (0.31) | (2.04) | | | | | | | | |
| ***Tram or Bus or Light-Rail users*** | −0.104 | 0.124 | 0.308 | 0.233* | 0.032* | 0.146* | 0.201* | −0.243* | −0.199* | −0.322* | −0.254* | 1.000 | | | | | | | |
| | (-0.140) | (0.36) | (0.64) | | | | | | | | | (fixed) | | | | | | | |
| | 0.189 | 0.020 | 0.200 | 0.056* | 0.001* | 0.044* | 0.019* | −0.067* | −0.063* | −0.084* | −0.090* | −0.180 | 0.191 | | | | | | |
| | (0.74) | (0.50) | (0.42) | | | | | | | | | (-0.31) | (0.18) | | | | | | |
| | −0.004 | 0.020 | 0.187 | 0.129* | 0.013* | 0.084* | 0.095* | −0.144* | −0.126* | −0.193* | −0.162* | 0.051 | 0.093 | 0.196 | | | | | |
| | (-0.01) | (0.12) | (0.68) | | | | | | | | | (0.32) | (0.06) | (0.50) | | | | | |
| | 0.228 | −0.011 | 0.228 | 0.068* | −0.001* | 0.054* | 0.015* | −0.087* | −0.086* | −0.112* | −0.119* | −0.055 | 0.096 | 0.061 | 0.219 | | | | |
| | (0.71) | (-0.61) | (0.54) | | | | | | | | | (-0.17) | (0.48) | (0.29) | (1.23) | | | | |
| ***Bike users*** | 0.011 | −0.183 | 0.038 | 0.066* | −0.005* | 0.047* | 0.005* | −0.103* | −0.116* | −0.153* | −0.146* | 0.039* | 0.063* | 0.051* | 0.087* | 1.000 | | | |
| | (0.02) | (-0.14) | (0.17) | | | | | | | | | | | | | (fixed) | | | |
| | −0.080 | −0.126 | −0.035 | 0.039* | −0.002* | 0.025* | 0.011* | −0.060* | −0.068* | −0.094* | −0.081* | 0.037* | 0.013* | 0.028* | 0.020* | −0.179 | 0.29 | | |
| | (-0.24) | (-0.14) | (-0.28) | | | | | | | | | | | | | (-0.34) | (1.23) | | |
| | −0.096 | −0.056 | −0.046 | 0.022* | 0.001* | 0.011* | 0.016* | −0.030* | −0.031* | −0.047* | −0.034* | 0.036* | −0.012* | 0.014* | −0.014* | −0.176 | −0.068 | 0.235 | |
| | (-0.29) | (0.01) | (-0.16) | | | | | | | | | | | | | (-0.46) | (-0.70) | (1.05) | |
| | 0.000 | 0.000 | 0.000 | 0.000* | 0.000* | 0.000* | 0.000* | 0.000* | 0.000* | 0.000* | 0.000* | 0.000* | 0.000* | 0.000* | 0.000* | −0.265 | −0.144 | −0.022 | 0.602 |
| | | | | | | | | | | | | | | | | (-1.3) | (-1.27) | (-1.28) | (1.31) |

Note: All the elements with a superscript (*) were not estimated.

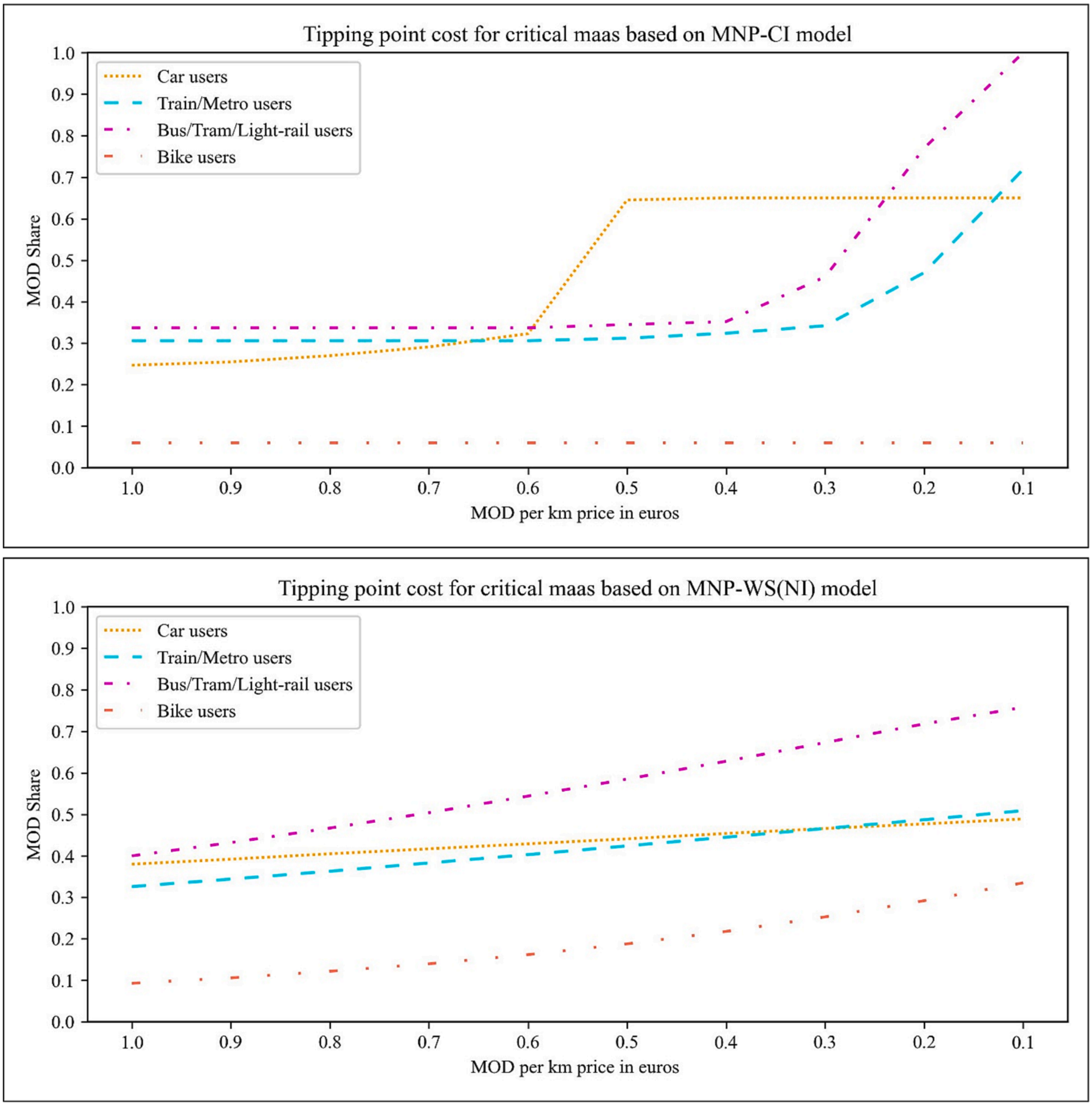


**Fig. 13.** MOD share as a function of price.

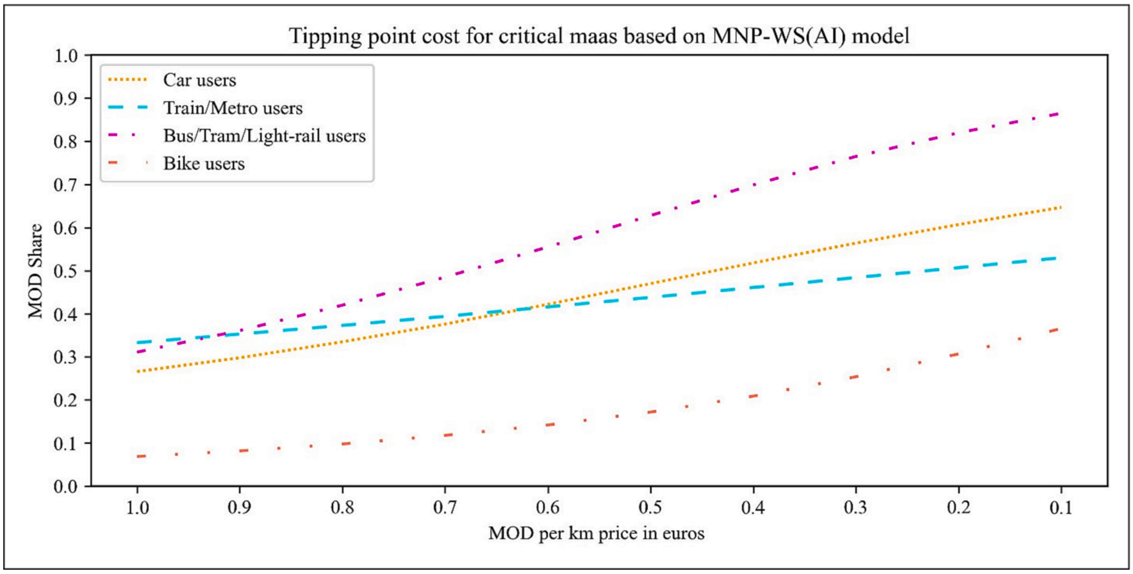


**Fig. 13.** (*continued*).

## 6. Conclusion and future work

We present a framework to capture and understand non-compensatory behaviour in the choice of mobility-on-demand (MOD) services for regular trips. We borrow the findings from the literature on repeated choice behaviour to construct individual specific stated preference (SP) choice sets to alleviate the effect of irrelevant alternatives. It enables us to include temporally distributed MOD options in the choice set without increasing the task complexity due to an increase in the choice set size. Further, we also include reliability effects in the SP design for MOD services to understand its impact on various mode users due to perceived differences in travel and waiting time by car and public transport (PT) users. To increase the realism and enhance the empirical validity of our findings, we designed an SP survey that makes use of Google Map API to obtain true trip attributes (travel, access, egress, and waiting time depending on the mode and departure window). In addition, we allow for capturing a non-compensatory behaviour by estimating a Choquet-Integral (CI) based choice model.

The current study makes several substantial contributions. First, we approximated mode-specific (car, train/metro, bus/tram/light-rail, and bike users) non-compensatory behaviour in the choice of MOD services. Results indicate varying preferences based on primary mode. Car users only consider waiting time and travel cost in their decision of MOD choice. PT (train/metro, bus/tram/light-rail) users are found to be highly selective in their evaluation of MOD modes. While both may utilize waiting time information, bus/tram/light-rail users are more likely to utilize travel time information in their decision-making as compared to train/metro users. Bike users exhibited similar behaviour as that of public transport users. Based on attribute importance (Shapley) value, travel cost is found to be the most important feature with an attribute importance value of 0.62, 0.79, 0.81, and 0.80 for car, train/metro, bus/tram/light-rail and bike users, respectively. Waiting time is the second most key feature with an attribute importance value of 0.35, 0.18, 0.12, and 0.11 for car, train/metro, bus/tram/light-rail and bike users, respectively. Travel time is found to be the least important feature amongst those included with a relatively negligible impact on the choice outcome. It was also noted that the conventional compensatory behaviour framework (additive utility/weighted sum) failed to identify such insightful observations. Our findings can be used by travel journey planners, MOD providers and MaaS applications in customizing information and tailored offerings for specific user profiles.

Second, the likelihood of a temporal shift, i.e. departure time choice, in the mode choice is evaluated. Both car and train/metro users exhibit potential for temporal shifts in the morning peak (8–10 am) and midday (10–4 pm). However, bus/tram/light-rail and bike users exhibit no propensity towards temporal MOD mode shifts. Reliability is also found to play an important role for car and train/metro users. Car users associate high regret with the waiting time difference (actual vs. reported) as compared to the travel time difference. The trend is the opposite for train/metro users. Bus/tram/light-rail and bike users seem insensitive to such differences. These findings offer insights for devising time-dependent pricing instruments that are aimed to stimulate behavioural shifts.

Third, a non-linear inertia effect is captured for various mode users. Car users exhibit high inertia towards their current mode compared to MOD options. Conversely, non-car (train/metro, bus/tram/light-rail and bike) users are indifferent towards MOD options, i.e. past usage does not affect current usage. Overall, car, train/metro, and bike users (to a certain extent) constitute the primary pool of potential MOD riders. Bus/tram/light-rail users can only be brought to the pool of potential riders by substantially reducing the price of the MOD trip.

Fourth, the results of a tipping point analysis indicate a potential for introducing a differential pricing strategy that is based on the current travel behaviour. A per km cost of 0.6€ or less may be required to attract a substantial share (65 %) of car users towards the MOD service. Similarly, a per km cost of 0.3€ and 0.4€ for train/metro (34 %) and bus/tram/light-rail (35 %), respectively, will be needed to attract a significant proportion of their current users towards the MOD service. Hence, the notion of adverse impact on public transport due to the introduction of MOD services at least in the Netherlands is likely to be limited. The current per km cost of Uber in Amsterdam and New York is 1.10€ and 1.26€, respectively, almost twice as much as the critical mass price value identified in our analysis. Since bike users do not incur any cost for their trip, a tipping point cost calculation for this user group is not possible. While the general direction of the effects of all parameters is the same irrespective of underlying behavioural assumption (compensatory vs. non-compensatory), the MOD market share trajectory (as a function of cost) based on the compensatory model is continuous (strictly monotonic in both magnitude and slope) as compared to a relatively discontinuous functional form obtained through the non-compensatory model. This further highlights the need for an integrated context-aware survey and flexible modelling approach to obtain meaningful policy recommendations.

Finally, a significant correlation is observed between the RP and SP stage choices suggesting the presence of endogeneity. A failure to correct for endogeneity may lead to inflated feature importance. A CI model without endogeneity correction provides the cost importance (Shapley) values of 0.63, 0.88, 0.95, and 1.00 for car, train/metro, bus/tram/light-rail and bike users, respectively. These feature importance values for non-car users are substantially higher than the values reported earlier based on the endogeneity corrected model. However, endogeneity corrections require high computational efforts Furthermore, one may not be able to empirically identify all the elements of a joint RP-SP error-covariance matrix. Even though we adopted the Cholesky parametrization, we encountered singularity issues. Overall, depending on the choice set and survey set-up, the computational time required for endogeneity correction can become prohibitive.

The current study is not without limitations. First, reliability is only considered for MOD options in the SP design. Neglecting the reliability, especially for PT modes can introduce bias in the preference estimates of public transport users. Next, in the RP mode choice model, we included aggregate land-use variables as a proxy for socio-economic variables. The inclusion of such variables introduces additional challenges due to the unobserved correlation between land-use variables and the mode choice dimension. Accounting for such correlation requires adding fixed effects and joint modelling of land use and the mode choice dimension known as a self-selection effect. Including them is beyond the scope of the current study. Finally, we only derive the mean non-compensatory behaviour. It is plausible that behaviour (magnitude of fuzzy measures) may change across choice occasions and also across socio-demographic groups. To capture in-task variations and group-specific decision strategies, the CI parameters need to be parametrized as a function of individual characteristics and task-specific mode attributes. However, such a parametrization will increase the number of constraints required to ensure monotonicity. Future works may explore ways to incorporate such flexibility while keeping the level of complexity to a minimum. In addition, future research may consider the inclusion of non-continuous features in the CI. For instance, the approach proposed by Wang et al. (2006) can be exploited. However, this approach is not parsimonious and hence may not scale for a large number of features. Future works should look into this issue to increase the practical appeal of CI-based models.

## CRediT authorship contribution statement

**Subodh Dubey:** Conceptualization, Formal analysis, Methodology, Software, Writing – original draft. **Oded Cats:** Conceptualization, Writing – review & editing, Supervision, Funding acquisition. **Serge Hoogendoorn:** Writing – review & editing, Supervision.

## Ethics approval

Approval was obtained from the TU Delft Human Research Ethics Committee for fielding the stated preference survey. All the information collected through the survey is confidential. The information will not be shared with third-party and will solely be used for academic purposes

## 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

Data will be made available on request.

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## Appendix A

### A.1 Model formulation matrix notations

$$\boldsymbol{U}_t = (U_{1t}, U_{2t}, \ldots, U_{It})' [(I \times 1) \text{ vector}], \boldsymbol{U} = (\boldsymbol{U}'_1, \boldsymbol{U}'_2, \ldots, \boldsymbol{U}'_T)' [(TI \times 1) \text{ vector}],$$

$$\boldsymbol{\beta}_i = (\boldsymbol{\beta}_{i1}, \boldsymbol{\beta}_{i2}, \ldots, \boldsymbol{\beta}_{iK})' [(K \times 1) \text{ vector}], \boldsymbol{\beta} = (\boldsymbol{\beta}'_1, \boldsymbol{\beta}'_2, \ldots, \boldsymbol{\beta}'_I)' [(IK \times 1) \text{ vector}], \boldsymbol{\beta} = reshape(\boldsymbol{\beta})[(I \times K) \text{ matrix}],$$

$$\boldsymbol{\beta} = [\text{ones}(T,1).^*.\ \boldsymbol{\beta}][(TI \times K) \text{ matrix}], \boldsymbol{x}_{i,t} = \left(x_{i,t,1}, x_{i,t,2}, \ldots, x_{i,t,K}\right)' [(K \times 1) \text{ vector}],$$

$$\boldsymbol{x}_t = (\boldsymbol{x}'_1, \boldsymbol{x}'_2, \ldots, \boldsymbol{x}'_I)' [(IK \times 1) \text{ vector}], \boldsymbol{x}_t = reshape(\boldsymbol{x}_t)[(I \times K) \text{ matrix}], \boldsymbol{X} = \begin{bmatrix} \boldsymbol{x}_1 \\ \boldsymbol{x}_2 \\ \vdots \\ \boldsymbol{x}_T \end{bmatrix} [(TI \times K) \text{ matrix}],$$

$$\boldsymbol{CI}_t = (CI_1, CI_2, \ldots, CI_I)' [(I \times 1) \text{ vector}], \boldsymbol{CI} = (\boldsymbol{CI}'_1, \boldsymbol{CI}'_2, \ldots, \boldsymbol{CI}'_T)' [(TI \times 1) \text{ vector}],$$

$$\widehat{\boldsymbol{X}}_{TE} = \begin{bmatrix} 0 \\ TT(\text{eperienced})_1 \\ \vdots \\ TT(\text{eperienced})_{T-1} \end{bmatrix} [(T \times 1) \text{ vector}], \widehat{\boldsymbol{X}}_{TE} = [\widehat{\boldsymbol{X}}_{TE}.^*.\text{ones}(1,I)][(T \times I) \text{ matrix}],$$

$$\widehat{\boldsymbol{X}}_{TD} = \begin{bmatrix} 0 & \cdots & \cdots & 0 \\ TT(\text{displayed})_{1,1} & & & TT(\text{displayed})_{I,1} \\ \vdots & & & \vdots \\ TT(\text{displayed})_{1,T-1} & \cdots & \cdots & TT(\text{displayed})_{I,T-1} \end{bmatrix} [(T \times I) \text{ matrix}],$$

$$\widehat{\boldsymbol{X}}_{WE} = \begin{bmatrix} 0 \\ WT(\text{eperienced})_1 \\ \vdots \\ WT(\text{eperienced})_{T-1} \end{bmatrix} [(T \times 1) \text{ vector}], \widehat{\boldsymbol{X}}_{WE} = [\widehat{\boldsymbol{X}}_{WE}.^*.\text{ones}(1,I)][(T \times I) \text{ matrix}],$$

$$\widehat{\boldsymbol{X}}_{WD} = \begin{bmatrix} 0 & \cdots & \cdots & 0 \\ WT(\text{displayed})_{1,1} & & & WT(\text{displayed})_{I,1} \\ \vdots & & & \vdots \\ WT(\text{displayed})_{1,T-1} & \cdots & \cdots & WT(\text{displayed})_{I,T-1} \end{bmatrix} [(T \times I) \text{ matrix}],$$

$$\widehat{X}_{Chosen} = \begin{bmatrix} 0 & \cdots & \cdots & 0 \\ d(i_m == 1)_{1,1} & & & d(i_m == I)_{I,1} \\ \vdots & & & \vdots \\ d(i_m == 1)_{1,T-1} & \cdots & \cdots & d(i_m == I)_{I,T-1} \end{bmatrix} [(T \times I) \text{ matrix}],$$

where $d$ () is an indicator function and $i_m$ denotes the chosen alternative

*reshape* () function reshape a vector into a matrix

.*. is the kronecker product

.* is element-by-element multiplication

### A.2 Utility difference matrix pseudocode

$\mathbf{M} = zeros((I_{RP}-1)+T(I_{SP}-1)\times(I_{RP})+T(I_{SP}))$
$Iden\_mat = 1_{I_{RP}-1}$
$O\_neg = -1{*}ones(I_{RP}-1,1)$
$if\left(i_{m,RP} == 1\right)$
$\quad temp\_mat = O\_neg \sim Iden\_mat$
$elseif\left(i_{m,RP} == I_{RP}\right)$
$\quad temp\_mat = Iden\_mat \sim O\_neg$
$else$
$\quad temp\_mat = Iden\_mat\left[,1:i_{m,RP}-1\right] \sim O\_neg \sim Iden\_mat\left[,i_{m,RP}:I_{RP}-1\right]$
$\mathbf{M}[1:I_{RP}-1,1:I_{RP}] = temp\_mat$
$for\ m = 1 to T$
$\qquad Iden\_mat = 1_{I_{SP}-1}$
$\qquad O\_neg = -1{*}ones(I_{SP}-1,1)$
$\qquad if\left(i_{m,SP,t} == 1\right)$
$\qquad\quad temp\_mat = O\_neg \sim Iden\_mat$
$\qquad elseif\left(i_{m,SP,t} == I\right)$
$\qquad\quad temp\_mat = Iden\_mat \sim O\_neg$
$\qquad else$
$\qquad\quad temp\_mat = Iden\_mat\left[,1:i_{m,SP,t}-1\right] \sim O\_neg \sim Iden\_mat\left[,i_{m,SP,t}:I_{SP}-1\right]$
$\qquad end$
$\qquad row\_start = (I_{RP}-1)+(m-1)(I_{SP}-1)+1$
$\qquad row\_end = (I_{RP}-1)+(m)(I_{SP}-1)$
$\qquad col\_start = (I_{RP})+(m-1)(I_{SP})+1$
$\qquad col\_end = (I_{RP})+(m)(I_{SP})$
$\qquad \mathbf{M}[row\_start:row\_end,col\_start:col\_end] = temp\_mat$
$where" \sim " refers to horizontal concatenation and i_{m,SP,t} is the chosen SP alternative at time t$

## Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.trc.2023.104455.

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