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A Flexible Behavioral Framework to Model Mobility-on-Demand Service Choice Preferences

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A Flexible Behavioral Framework to Model Mobility-on-Demand Service Choice Preferences

Dissertation

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by

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Dedicated to
My family and friends

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Subodh
November 2023

Content

Chapter 1 – Introduction

1.1 Background & Motivation

1.1.1 Mobility on-demand

Due to rapid advancements in internet technology and computing capabilities in the last decade, Mobility-on-demand (MOD)/ride-hailing services (Uber, Lyft, Ola, DiDi, etc.) have emerged as a strong competitor to taxi services (Brown and LaValle, 2021), carpooling (de Souza Silva et al., 2018) and public transit (Clewlow and Mishra, 2017). MOD services offer higher reliability, lower cost, and better accountability (towards customers) as compared to taxi services. Unsurprisingly, this has led to an increase in MOD market share accompanied by falling taxi shares (Schaller, 2017; Sam Achwartz Engineering, 2019; Brown, 2018). MOD services can potentially yield immense societal and economic benefits. They can potentially transport more people using fewer cars (thereby reducing the number of taxis and private vehicle mileage) and therefore can substantially reduce congestion, greenhouse gas emissions and the requirement for parking space (Agatz et al., 2012; Teubner and Flath, 2015). These services could potentially change the way humans live and travel. In the short term, we can expect changes in mode share and vehicle miles travelled (VMT). In the medium term, there could be changes in vehicle ownership levels and residential location, which may lead to long-term changes in land-use patterns.

The last decade has seen a plethora of research work on both the demand and supply side of the MOD service. On the demand side, research has examined prospective user groups (Frei et al., 2017; Dias et al., Wang et al., 2018; 2017; Lavieri et al., 2018; Yan et al., 2019; Lavieri and Bhat, 2019), features of MOD trips in terms of the time of day, trip characteristics, etc., (Tirachini and del Río, 2019; Acheampong et al., 2020; Suatmadi and Creutzig, 2019; Adam et al., 2020), behavioural intentions behind the usage of MOD services (Lavieri and Bhat, 2019; Acheampong et al., 2020; Nguyen-Phuoc et al., 2022), substitution or complementarity to public transport and other modes (Jin et al., 2019; Young et al., 2020; Cats et al., 2022; Qiao and Yeh, 2023). Similarly, on the supply side, research has been focused on the development of efficient online (Ma et al., 2013; Alonso-Mora et al., 2017) and offline (Kucharski and Cats, 2020) request-to-vehicle matching algorithms, vehicle re-positioning (Ma et al., 2013; Ma et al., 2019; Yu and Hu, 2021, Jiao et al., 2021), generation of feasible ride options given the trip constraints (Atasoy et al., 2015; Song et al., 2018), and driver’s ride acceptance and relocation behaviour (Ashkrof et al., 2020; Ashkrof et al., 2022; Ashkrof et al., 2023; de Ruijter et al., 2022). Since MOD services operate in two-sided markets, several studies have focused on demand and supply interaction in a single framework to investigate user equilibrium (Fielbaum et al., 2022; Ma et al., 2022) and pricing strategy (Wang et al., 2016).

Fig. 1.1 provides a high-level MOD system representation. The user makes a request defined as origin, destination, and ride type (private or shared). The platform/operator performs matching between the request and available vehicles/drivers based on certain criteria (maximum waiting time, maximum detour or maximum profit within a time window) and returns an option(s) to the user(s) depending on the driver's acceptance. Upon receiving the option(s), the user either selects an option or rejects it altogether. A lot of attention has been paid to developing efficient matching algorithms, vehicle re-positioning strategies and driver acceptance/rejection behaviour.

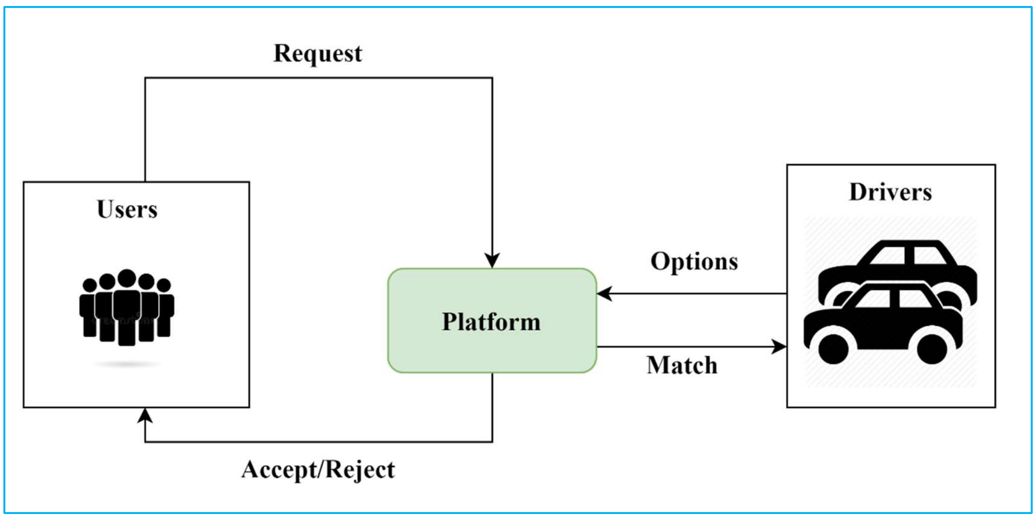

Figure 1.1: Mobility-on-demand system representation

1.1.2 Users Preferences

User preference is commonly represented using a well-known compensatory behaviour strategy. Hence, individuals have been assumed to consider information for each option and perform a cost-benefit analysis to make the choice/decision in a new or relatively unfamiliar/difficult context (Wright, 1975; Swait and Adamowicz, 2001). However, empirical evidence points to the usage of simple heuristics by decision makers (representing some variation of non-compensatory decision strategy) has been well documented in familiar repeated choices such as grocery shopping, mode choice, etc., (Foerster, 1979; Hoyer, 1984; Hoyer and Brown, 1990; Aarts et al., 1997; Innocenti et al., 2013; Rashedi and Nurul Habib, 2020).

Despite such evidence, the majority of the literature on MOD and discrete choice theory continues to utilize compensatory behaviour strategy, arguably due to ease of data collection and computational challenges. For example: the early fully non-compensatory lexicographic (Fishburn, 1974), and disjunctive/conjunctive (Coombs, 1951) were not probabilistic. The probabilistic elimination-by-aspect model (Tversky, 1972; Batsell et al., 2003) has complex attribute selection rules. In the domain of semi-compensatory models, the attribute cut-off approach (Swait, 2001) requires directly asking for the cut-offs from the respondents. Martinez et al., (2009) model of endogenous cut-offs requires solving a complex fixed-point problem.

Similarly, Elord et al., (2004) introduce several trigonometric functions to introduce spikes/drops in the utility function which can induce numerical instability during optimization. Researchers do not face such issues when applying discrete choice models relying on the random utility maximization (RUM) framework with additive systematic utility and stochastic unobserved term. Hence, increasing the practical appeal of non-compensatory models requires modifying the systematic utility aggregation function in the RUM framework with an alternative parsimonious function with minimal to no a-priori assumptions.

Studies often have to resort to a stated preference (SP) survey approach for data collection due to the scarcity of publicly available detailed individual-level trip data. While the SP approach is appealing, 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 faced by an individual through API (application programming interface) and GPS (global positioning system) systems. Using the pivot approach is appealing as it enables the generation of other option attributes based on the reported option leading to a reduction in risk of alternatives that lack meaning and are not engaging (Rose at. Al., 2008; Cherchi and Hensher, 2015). However, it may not enable a true representation of real-world decision strategy due to the high discrepancy between stated and true value. For example: generating a bus travel time based on car travel time with a multiplier. Further, such an approach induces endogeneity (Train and Wilson, 2008; Guevara and Hess, 2019). The use of API and GPS systems can help construct fully context-aware surveys with engaging choice sets (Frei et al., 2017; Song et al., 2018; Danaf et al., 2019) as evident by the high hit rate in personalized menu provider (Song et al., 2018). While the context-aware surveys developed in earlier studies help reduce the divergence between true and modelled decision strategies, their focus has been understanding competition between existing travel options (car and public transport) and new MOD services (on-demand or fully flexible). Such studies include all existing options and the proposed MOD option in the SP choice set Therefore, such studies provide an aggregate representation of competition. However, such studies can introduce bias in parameters due to the inclusion of irrelevant alternatives (Ng'ombe and Brorsen, 2021) in the absence of an individual-level choice set construction mechanism. Since a significant proportion of trips made on weekdays involves mandatory trips such as commute, grocery shopping, school/college trips, etc., and therefore can be categorized as repeated trips, understanding the competition between existing travel options and MOD services for such trips requires a change in the construction of consideration set For example, consider an individual who uses his/her car for the commute trip. If the individual is asked to choose between an existing travel option and a new MOD service then the individual is likely to compare the new MOD service with the currently used mode (car). Brown (2019) reported that most individuals use ride-hailing to fill an occasional rather than regular travel need. Therefore, evaluating medium-to-long-term competition of MOD services requires calibration of the mode choice model on travel preference data based on a modified choice set Restricting the choice set to include relevant alternatives can further reduce the divergence between true and modelled decision strategies. Such preference data can also shed light on departure from widely used compensatory strategy.

1.1.3 The Role of Social Influence

So far, the discussion on the user's preference is assumed to be independent of the preferences of others around him/her (social influence based on spatial proximity or interpersonal network). It is well established that social influence plays an important role in shaping an individual's preferences (Katz and Shapiro, 1985) from purchase of ice cream (Richards et al., 2014), electronic equipment (Narayan et al., 2011), smartphone use and purchase (Park and Chen, 2007), purchase of organic food items (Chen, 2007), recycling behaviour (Laroche et al., 2001) to automobile purchase (Grinblatt et al., 2008). Needless to say, preference towards MOD services may also be shaped by social network influence.

The literature classifies social influence into four categories: conformity, compliance, obedience, and persuasion (Eagly, 1983). Please note that these categories are the outcome and not the mechanism. That is, there are different underlying processes which may lead to different types of outcomes.

Conformity occurs when an individual changes his/her behaviour or belief to mimic or align with the behaviour/norm/standard of the group. It is driven by the desire to be liked and accepted by the group (Kelman 1958) also known as majority influence. The change in behaviour as a result of conformity tends to be long-term behavioural change. A few examples of conformity may include purchasing a popular brand of shoes as it may be worn by friends and peers or changing your music preference to better align with the group's taste.

Compliance refers to a change in behaviour as a result of a direct request from another person or group in public but may disagree with the group's viewpoint in private. Compliance is generally exercised by individuals to avoid conflicts or maintain social relationships. The change in behaviour as a result of compliance tends to be temporary. A few examples of compliance may include agreeing to donate a small amount to the charity or laughing at a joke in public even when you do not find the joke funny.

Obedience is a strict form of compliance as failure to change the behaviour may result in punishment or a fine. In this situation, behaviour change is commanded by authorities such as police officers, government or tax personnel. A few examples of obedience may include paying taxes, following traffic rules and adhering to school administration rules.

Persuasion is the act of influencing others through the art of rhetoric. It generally involves interpersonal conversation but can also be exerted using one-way communication such as advertisement. A few examples of persuasion-related behavioural change may include purchasing a product after watching a commercial or aggregating to subscribe to a new service due to a convincing pitch from a salesperson. Figure 1.2 shows the various categories of social influence based on the level of interpersonal communication and temporal duration of effect.

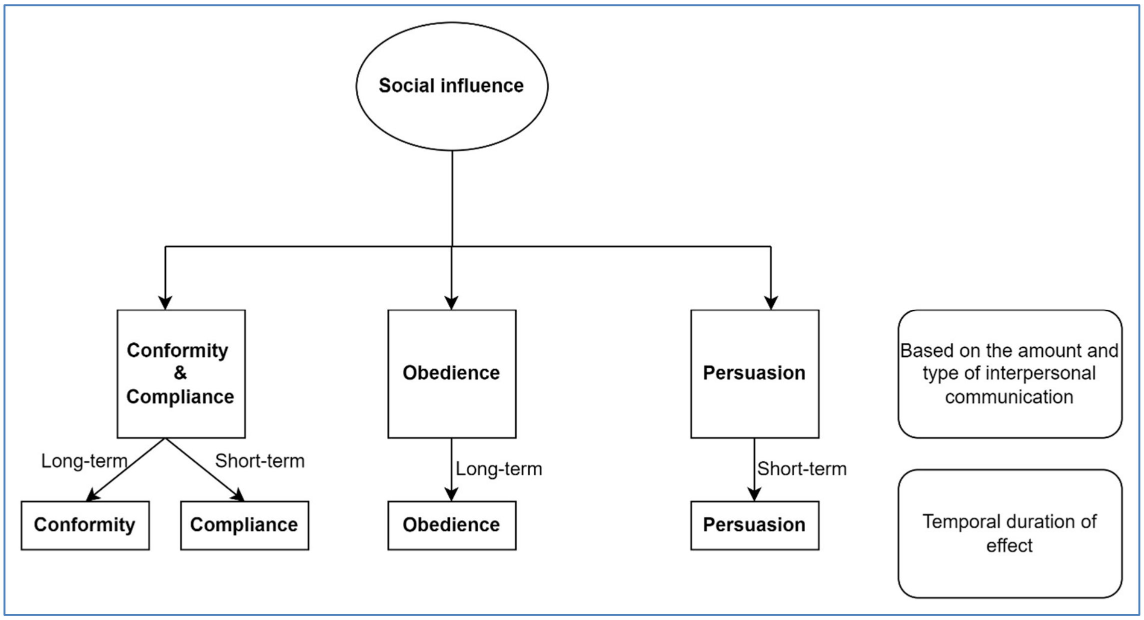

Figure 1.2: Categories of social influence

Based on the above discussion, conformity and compliance are the most plausible forms of social influence in the context of MOD services. Conformity has been the primary social influence mechanism modelled in the transportation literature (see Table 1 in Maness et al., 2015). Between conformity and compliance, conformity is a more plausible social mechanism in the context of MOD choices due to the fact compliance requires explicit influence points such as the group head or supervisor and does not merely happen due to observing others' behaviour. The studies on ride-sharing have also found conformity as a mechanism of social influence operating through both normative and informational conformity. Informational conformity arises when individual(s) align their behaviour with that of the group in the event of risk/uncertainty or are unsure about the final choice. Normative conformity arises when individual(s) align their behaviour with that of the group to be socially accepted or liked. For example, Elnadi and Gheith (2022) found normative conformity to be the mechanism of social influence for the choice (reuse) of ride-hailing services in Egypt. Li et al., (2002) found informational conformity to be more pronounced as compared to normative conformity in the choice of shared electric vehicle in China. Further, switching to MOD is likely to incur additional travel costs (as compared to the base scenario) and hence mere compliance in the absence of monetary support may not be a motivating factor.

In conformity, the individual observes the behaviour of others directly or indirectly and takes action. Conformity may occur in two situations. First, an individual may conform to the behaviour of others for group/social status (Cowan et al., 1997). For example, an individual may simply start to use a MOD service in response to his colleague's usage as it may elevate his/her status in the group as an environmentally conscious person. This is the case of normative conformity. Second, people may conform to the behaviour of others in situations with high risk/uncertainty as guidance (Jager and Janssen, 2002), a case of informational conformity. There are four possible ways in which conformity can be operationalized.

The first approach states that the behaviour of others does not affect the individual valuation of a product, but provides an additional additive component in the utility. This is similar to the "neighbor effect", in which the likelihood of purchase increases with an increase in the number of neighbors with the same or similar product. The underlying behavioural assumption in this approach is that an individual may only observe the final behaviour of others in his/her interpersonal network and accordingly modify his/her behaviour. This resembles threshold models (Granovetter, 1978) used in social science, epidemiology, and diffusion literature, in which the appeal or perceived risk (Dholakia, 2001) associated with the product increases/decreases with the number of people adopting the product or behaviour in one's interpersonal network. This approach has been widely used in the discrete choice literature to account for the effect of social influence either by directly including the utility equation or through an ICLV structure (Kamargianni et al., 2014; Bansal et al., 2016; Ghasri and Vij, 2021). From a mathematical perspective, this approach assumes no correlation between the behaviour of others and unobservable factors leading to a non-endogenous formulation of the discrete choice model.

The second approach considers that the exact nature of social influence is unknown and it is assumed that an individual's utility is affected by the utility of others around him. Hence, the total utility of the product is comprised of an individual's utility plus a weighted sum of others' utility. This approach is useful in the absence of detailed interpersonal network data and is used considerably in spatial econometrics (Anselin, 2013) and transportation (Bhat, 2014).

The third approach states that individuals revise their importance weight for an attribute as a function of his/her initial beliefs and others' preferences (Narayan et al., 2011). Others' preferences are weighted where the weights could be a function of the credibility of the individual as a source of information. This conceptualization of how social influence works captures the underlying notion that the beliefs of others affect the beliefs of an individual. However, unlike the second mechanism, the exact nature of social influence is known to operate through the individual's assigned attribute weights.

The fourth and final approach emphasizes the attribute value rather than attribute weight in a utility measure (Autant-Bernard and LeSage, 2011; Bhat et al., 2014). It is more appropriate in cases where there is high uncertainty surrounding the product features. It represents the phenomenon where individuals learn from their interpersonal network to reduce uncertainty. Hence, an individual revises his/her perception of the values of attributes based on his/her own perceived attribute value and that of others. Here the social influence operates through an individual's perceived attribute value.

The second, third and fourth approaches are endogenous as they account for the correlation between the behaviour of others and unobservable factors. From a data collection approach, the first and second mechanisms require minimal additions/changes in the SP design approach. The third and fourth mechanisms require the development of a highly specialized SP framework with explicit communication links between participants. From a modelling perspective, the first mechanism does not provide any mechanism for information flow and hence is limited in application. On the other hand, the remaining (second to fourth) mechanisms provide an explicit channel for information flow inside the framework and hence can be used to derive policy scenarios. To the best of our knowledge, only Bhat et al., (2016) provide an explicit mechanism for information exchange in a mathematical model. Bhat et al., (2016) approach also improves the interpretation by regulating the change in utility of a product as a function of latent constructs which can be used to represent carriers of social influence such as word-of-mouth, perceived risk, etc.

1.2 Research Objective and Questions

Mathematical modelling and empirical validation of user's MOD services preferences require access to a flexible model and individual-level choice data preferably collected through a SP survey. Therefore, the overarching research objective considered in this work is as follows:

"*Develop and validate a comprehensive user preference module in the context of mobility-on-demand (MOD) services*."

To fulfil this objective, we formulate the following three research questions:

1. Formulate and validate a flexible discrete choice model within a random utility framework (RUM) to model various decision strategies with minimal to no a-priori assumptions
2. Evaluate medium-to-long-term competition of MOD services through a context-aware survey and obtain pricing estimates necessary for achieving a critical mass
3. Develop a framework to explicitly incorporate interpersonal network effects in the preference modelling framework to understand the effect of various policies

1.3 Research Context

This work is part of the CriticalMaaS (2019-2023) project which consists of several work packages intended to investigate the interaction of demand and supply in a Mobility-as-a-Service market In particular, the project develops a suit of modules which can be used inside an agent-based simulation framework to study various scenarios. On the supply side, driver's ride acceptance and relocation behavioural models have been estimated, and the impact of such behaviour models on supply-side evolution has been modelled. On the demand side, the prospective MOD users and the potential of MOD services for access/egress purposes have been investigated. Finally, agent-based simulation software has been developed where various modules are brought together to model the two-sided Mobility-as-a-Service market (Kucharski and Cats, 2022).

1.4 Research Contributions

This section summarizes the main contribution of the thesis, distinguishing scientific and societal contributions.

1.4.1 Scientific Contributions

In this work, we make three contributions towards the development of a comprehensive understanding of user preferences in the context of MOD services and discrete choice theory in general.

C1. *Formulate a flexible discrete choice model within a random utility framework (RUM) to approximate various decision strategies with minimal to no a-priori assumptions (Chapter 2)*
We formulate a flexible discrete choice model which can extract the underlying decision strategy (compensatory or non-compensatory) without imposing any a-priori assumption(s). In particular, we replace the weighted sum aggregation function with a generalized function called Choquet-Integral to represent systematic utility and incorporate endogenous attribute cut-off functions. We evaluate the finite sample property (parameter recoverability and asymptotic standard error) and generalization (ability to extract various data-generating processes) of the proposed model with the help of a simulation study. The model is further empirically validated using a MOD choice experiment conducted by Liu et al., (2019) in October-November 2017 in New York.

C2. *Evaluate medium-to-long-term competition of MOD services through a context-aware survey and obtain pricing estimates necessary for achieving critical mass (Chapter 3)*
We design an SP survey using APIs to understand individuals' preferences towards MOD. In line with existing API-based surveys (Frei et al., 2017; Song et al., 2018; Danaf et al., 2019), we utilize Google Map APIs to obtain trip characteristics (access and egress modes, primary mode, travel time and cost of various legs depending on the mode). Through the use of the model developed in C1, we highlight the evidence of non-compensatory behaviour in the choice of MOD services. We quantify the importance of mode attributes (in-vehicle travel time, out-of-vehicle travel time, and travel cost) for various primary mode users (car, train/metro, bus/light-rail and bike users) and derive mode-specific pricing strategy to maximize the overall market share of MOD service. Further, we also add to the growing literature on reliability and temporal mode-shift patterns due to the emergence of MOD services. In particular, we quantify the reliability effect for all four primary mode users along with the propensity for early or late departure (*Chapter 3*).

C3. *Explicitly account for interpersonal network effect in the preference modelling framework to understand the effect of various policy levers (Chapter 4)*
The third contribution relates to the development of a framework to model user preference in the presence of social influence. In particular, we consider the first two mechanisms (neighbor effect and interpersonal network weighted utility approach) of conformity (see section 1.1.3) in building this framework. The framework is based on an Integrated choice and latent variable approach (Bhat et al., 2016). In this framework, we present two ways of constructing an interpersonal network for readily available SP/revealed preference (RP) data with no explicit communication links between survey respondents. The framework is empirically validated using an automated vehicle (AV) purchase SP data in the absence of suitable MOD preference data. The policy implications are highlighted through an agent-based simulation by deriving AV adoption trajectories under various market conditions.

1.4.2 Societal Contributions

This thesis develops user preference modelling capabilities. A more accurate representation of decision strategy allows the policy-makers/government/ operators to make impactful interventions/changes to achieve near system- or individual-optimal results. For example, the empirical results reported in Chapter 3 (made possible by the methodology developed in Chapter 2) provide the relative importance of travel attributes (in-vehicle time, out-of-vehicle time and cost) for various primary mode users along with critical mass prices. Such information can be used by the operators to introduce differential pricing (pricing based on willingness to pay and not through price coupons) which may lead to an increase in overall MOD market share as compared to a uniform pricing strategy (Kamble, 2019). Furthermore, the same information can be used by the government to establish minimum fares to prevent a decline in the utility of public transport. Depending on the objective, such information can be used to increase/decrease the appeal of MOD services. On a similar note, results from Chapter 4 can be used to understand the impact of various factors such as the number of crashes, reduction in CO_2, unclear liability issues, etc., on automated vehicle purchases propagated through interpersonal networks. Such information can help inform both government and vehicle manufacturers on customers' priorities such that legislation and customer awareness campaigns can be designed around such issues to mitigate negative perceptions.

1.5 Thesis Outline

The outline of the thesis is shown in Fig. 1.3. The thesis consists of five chapters.

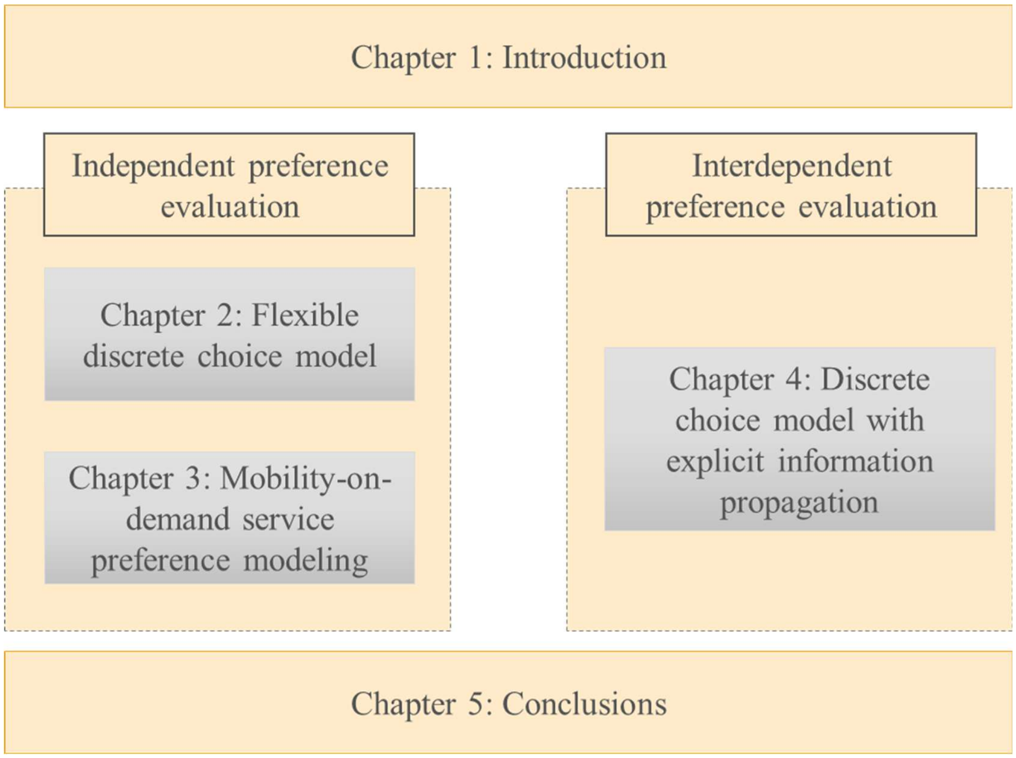

Figure 1.3: Thesis outline

Chapter 2 presents the formulation and validation of a flexible discrete choice model within a random utility framework (RUM) capable of approximating various decision strategies. to model various decision strategies with minimal to no a-priori assumptions. In Chapter 3, we present the design of the SP survey and evaluate the medium-to-long-term competition of MOD services through a context-aware survey and obtain pricing estimates necessary for achieving critical mass. In addition, we also quantify the reliability effect for all various mode users (car, train/metro, bus/light-rail and bike users) along with the propensity for early or late departure. We refer to the models and data used in Chapters 2 and 3 as independent preference evaluations since these models assume independence between individuals. Next, in Chapter 4 we present the framework for modeling the effect of interpersonal network effect which is broadly termed as interdependent preference evaluation. We demonstrate the application of the framework to analyze the purchase of automated vehicles. Finally, Chapter 5 summarizes the main conclusion and limitation of our work and its implications.

Chapter 2 - A Multinomial Probit Model with Choquet Integral and Attribute Cut-offs

Several non-linear functions and machine learning methods have been developed for flexible specification of the systematic utility in discrete choice models (DCMs) to capture various decision strategies (compensatory to non-compensatory). However, the existing models either require additional data (attribute cut-off approaches), testing multiple functions (utility drops and spikes) or are computationally challenging. They also lack interpretability, do not ensure monotonicity conditions, and restrict substitution patterns. This chapter contributes to the growing literature on flexible DCMs by formulating an a-priori assumption-free discrete choice model.

We address the host of issues (a-priori behavioural assumption on information/attribute usage, lack of interpretation, and monotonicity conditions) by modelling the systematic utility using the Choquet Integral (CI) function and embedding the CI into a multinomial probit (MNP) choice probability kernel to handle restriction-free substitution patterns. We also extend the MNP-CI model to account for attribute cut-offs (endogenously) to further mimic the semi-compensatory behaviour using the traditional choice experiment data. The MNP-CI model is estimated using a constrained maximum likelihood approach, and its statistical properties are validated through a comprehensive Monte Carlo study. The CI-based choice model is empirically advantageous as it captures interaction effects while maintaining monotonicity. It also provides information on the complementarity between pairs of attributes coupled with their importance ranking as a by-product of the estimation. These insights could potentially assist policymakers in making policies to improve the preference level for an alternative.

This chapter is based on the following article:

Dubey, S., Cats, O., Hoogendoorn, S., & Bansal, P. (2022). A multinomial probit model with Choquet integral and attribute cut-offs. *Transportation Research Part B: Methodological*, *158*, 140-163.

2.1 Introduction

Eliciting individual-level decisions is of interest in multiple disciplines, such as transportation, economics, environment, ecology, and health, among others. Discrete choice models relying on random utility maximisation (RUM) theory are still workhorse models in these disciplines (McFadden, 1973; Train, 2009). RUM-based models represent the preferences of decision-makers through latent stochastic utility. Most applications assume that the indirect utility consists of a linear-in-parameters systematic utility and additive stochastic unobserved term, with a few instances of the multiplicative stochastic term (Fosgerau and Bierlaire, 2009). Several recent studies have adopted machine learning techniques for flexible representation and data-driven learning of the systematic utility (see Aboutaleb et al. 2021; Hillel et al. 2021; Van Cranenburgh et al., 2021 for literature review). These techniques include kernel smoothing (Bansal et al., 2019), deep learning architectures (Ortelli et al., 2021; Sifringer et al., 2020; Wang et al., 2021; and Wong and Farooq, 2021), and automatic relevance determination (Rodrigues et al., 2020). We identify three main shortcomings of the existing studies. First, the flexible specifications do not ensure the monotonicity of the utility function relative to attributes like cost, which is a necessary condition for a demand function to be valid[1]. Second, most theory-driven machine learning studies claim that they do not compromise interpretability, but their notion of interpretability is no longer associated with the behavioural or physical interpretation of model parameters. For instance, Wang et al. (2021) define interpretation quality metrics based on the learned choice probability function, which can only be measured in simulation studies. Third, previous studies with flexible systematic utility capture restrictive substitution effects among alternatives because they rely on multinomial or nested logit choice probability kernels.

This study addresses the first two limitations by specifying the systematic utility using the Choquet Integral (CI) function and the last one by embedding it into the multinomial probit (MNP) choice probability kernel (i.e., MNP-CI model henceforth). The CI function nests different aggregation functions – weighted means (i.e., linear-in-parameters), ordered weighted averaging functions, minimum, maximum, and order statistics (Grabisch and Labreuche, 2010), offers a systematic way to capture all possible interactions between attributes, and ensures monotonicity in terms of the number of attributes[2] and attribute values. Additionally, the MNP kernel can represent flexible substitution patterns with relatively less computational complexity than a logit kernel. The MNP kernel is also computationally feasible for joint modelling of several choice dimensions and social effects due to the elegant properties of the Gaussian distribution (Astroza et al., 2018; Vinayak et al., 2018). Therefore, demonstrating the application of the CI function embedded into the MNP kernel is practically more relevant.

CI has been a popular aggregation operator in multi-attribute decision-making and preference-learning literature (Alfonso, 2013; Grabisch, 1996). Most studies are concerned with improving the prediction performance (Tehrani et al., 2012; Sobrie et al., 2015; Cano et al., 2019). We identify two main limitations of the literature on CI applications and address them in this study. First, many studies have explored the application of CI in RUM-based logit models (Aggarwal, 2018; Aggarwal, 2019; Aggarwal, 2020; Büyüközkan et al., 2018; Demirel et al., 2017), but fail to develop econometrically-sound estimators and restrict substitution effects. In contrast,

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[1] The specifications similar to Sifringer et al. (2020) could ensure monotonicity by decomposing the utility into flexible and linear-in-parameter components, and including the attributes with directional effect in the latter component. However, since most attributes have a directional effect on choices in stated preference studies, the resulting utility would be driven by the linear-in-parameters part.

[2] Monotonicity in the number of attributes implies that the attribute addition should always increase the informational power (e.g., R-square).

accommodating unrestrictive substitution effects is straightforward in the MNP-CI model. We also estimate the MNP-CI model using a constrained maximum likelihood estimator and establish its statistical properties (e.g., bias and coverage probability) in a Monte Carlo study. Second, the normalisation of attributes across alternatives in traditional CI-based choice models is not feasible in the case of unbalanced attribute configuration (i.e., when different subsets of the attributes are applicable for different alternatives). We resolve this limitation by extending the MNP-CI model to an alternative-specific MNP-CI specification (i.e., analogous to the MNP specification with alternative-specific marginal utilities).

We advance the alternative-specific MNP-CI specification to account for the attribute-level cut-offs or constraints. The MNP-CI model with attribute cut-offs is closely related to one-stage semi-compensatory models (Ding et al., 2012; Elrod et al., 2004; Martínez et al., 2009; Swait 2001; Truong et al., 2015). Swait (2001) formulated the first one-stage semi-compensatory model as the reduced form approximation of Manski (1977) two-stage model – choice set formation based on non-compensatory screening process (e.g., elimination-by-aspects and conjunctive rules) in the first stage, followed by evaluation of the remaining alternatives based on the compensatory decision rule in the second stage (Gilbride and Allenby, 2004; Cantillo and de Dios Ortúzar, 2005; Kaplan et al., 2012). Instead of posing *hard constraints* on the elimination of alternatives in the first stage of Manski's approach, Swait's one-stage model puts *soft constraints* by allowing the decision-maker to violate cut-off rules at the cost of utility penalisation, hence allowing to choose the alternative with attribute cut-off violation if it still has the highest utility even after penalisation (Rashedi and Nurul Habib, 2020). Such one-stage models are empirically attractive because they could approximately mimic the semi-compensatory behaviour by adjusting the systematic utility specification within the traditional RUM framework[3].

We highlight some key differences between the MNP-CI model and the existing one-stage semi-compensatory models. The existing models rely on adding a penalty function in the utility to regulate the overall utility level based on attribute cut-off violations. However, the use of fuzzy membership functions to model attribute cut-offs in MNP-CI obviates the need for penalty functions. Directly specifying cut-offs on attributes could be possible due to the normalisation of attributes and monotonicity constraints in the estimation of MNP-CI. In contrast, such direct attribute-cut-off specifications in the traditional MNP with linear-in-parameters utility often lead to numerical issues due to the unconstrained nature of the likelihood maximisation problem.

The existing semi-compensatory models are also subject to a few shortcomings. Swait (2001) directly asked for attribute cut-offs from the respondents, which could be susceptible to self-reporting bias. Martínez et al. (2009) addressed this limitation by endogenously estimating attribute cut-offs (known as the constrained multinomial logit (CMNL) model)[4], but their estimator relies on solving a rather complex fixed-point problem with little evidence regarding its finite sample properties (see Section 2.5 for details). Moreover, existing one-stage semi-compensatory models consider logit kernel. We address these limitations in this study. Whereas the MNP kernel in the proposed model leads to unrestricted substitution effects, the constrained maximum likelihood estimator of MNP-CI can endogenously estimate attribute cut-offs and has valid statistical properties.

[3] Elrod et al. (2004) illustrated how various non-compensatory rules can be modelled within the RUM framework by specifying the systematic utility using a general nonrectangular hyperbola.

[4] Bierlaire et al. (2010) demonstrated that the CMNL model should be considered as a semi-compensatory model on its own because it poorly approximates Manski's two-stage framework.

The contribution of this study is thus three-fold. First, a nonlinear additive functional form of systematic utility is specified using the CI function to capture interaction effects between attributes with strict monotonicity. Second, the CI-based choice model is extended to capture alternative-specific attribute importance and complementarity. The semi-compensatory behaviour is accounted for through endogenous attribute cut-offs. Third, the CI-based systematic utility is embedded in the MNP choice probability kernel to capture unconstrained substitution patterns. A constrained maximum likelihood estimator is developed for the proposed model, which incorporates constraints to maintain monotonicity requirements arising from the CI function. In addition to a Monte Carlo study, the practical relevance of the model is demonstrated in an empirical study to understand the preferences of New Yorkers for mobility-on-demand services. This work thus makes advancements in three strands of the literature: 1) flexible specification of the systematic utility; 2) multi-attribute decision-making and preference learning using the CI function; and 3) One-stage semi-compensatory behaviour modelling.

The remainder of the chapter is structured as follows. Section 2.2 provides a detailed discussion of the properties of the CI function, our modelling extensions, the estimation procedure, and the advantages of the proposed model. Section 2.3 details the simulation set-up, evaluates the statistical properties of the estimator and demonstrates the superiority of the proposed model over the traditional MNP model with linear-in-parameter systematic utility. Section 2.4 uses an empirical example to illustrate how the proposed model can offer interesting insights into the behaviour of a decision-maker. Conclusions and future work are summarised in Section 2.5.

2.2 Choquet Integral-based Random Utility Choice Model

2.2.1 Properties of Choquet Integral

CI is a fuzzy integral based on fuzzy measures, which provides an elegant way to capture all possible interactions between attributes. For instance, CI allows the analyst to explicitly capture complementarity between attributes which may help explain the outcome (choices) more accurately. In mathematical terms, if the fuzzy measure $\mu(k)$ represents the informational power of attribute k, then the complementarity of two attributes implies that $\left(\mu(1,2) > \mu(1) + \mu(2)\right)$. The CI function also ensures monotonicity while allowing for flexible interactions between attributes. This characteristic of the CI function is critical because arbitrary flexible interactions between attributes generally lead to a non-monotonic utility function (Elrod et al., 2004).

CI ensures monotonicity while capturing attribute interactions through fuzzy measures. A discrete fuzzy measure allows one to assign importance to all possible combinations of attributes. In mathematical terms, one can define discrete fuzzy measures as follows:

$$\mu(\phi) = 0 \quad \mu(\boldsymbol{X}) = 1 \quad \mu(\boldsymbol{A}) \leq \mu(\boldsymbol{B}); \boldsymbol{A} \subseteq \boldsymbol{B} \subseteq \boldsymbol{X} \quad 0 \leq \mu(.) \leq 1$$

where $\boldsymbol{A}$ and $\boldsymbol{B}$ are sets of attributes, ϕ represents the null set, and $\boldsymbol{X}$ is the set of all attributes. The fuzzy measures are monotonic in the number of attributes by definition because adding an attribute to an existing set does not decrease the importance of the new coalition. Normalisation of attributes before passing through fuzzy measures ensures monotonicity in attribute values (see Section 2.2.2 for details). We can write the CI with respect to a discrete fuzzy measure as follows:

$$CI = \sum_{g=1}^{G} h\left(x_{\pi_g}\right)\left(\mu\left(A_g\right) - \mu\left(A_{g-1}\right)\right)$$

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

$$h\left(x_{\pi_g}\right) \rightarrow h\left(x_{\pi_1}\right) \geq h\left(x_{\pi_2}\right) \geq ... \geq h\left(x_{\pi_G}\right) \geq 0$$

$$A_G = \{x_1, x_2, ..., x_G\}$$

The function $h(.)$ represents the numerical value of attributes (x) in descending order. An example of the CI computation is provided in Appendix A.2.1. There are two important points to observe. First, the number of fuzzy measures is a function of the number of attributes, i.e. the number of fuzzy measures is 2^G, two of which are the null set and the complete set. Second, the term $\left(\mu\left(A_g\right) - \mu\left(A_{g-1}\right)\right)$ can be interpreted as the additional information that attribute x_g offers in decision-making. This information can be used to interpret CI as a representation of an information processing strategy adopted by the decision-maker. One way to interpret the CI-based decision-making process could be that individuals first pick the attribute that provides the maximum amount of information ($h\left(x_{\pi_g}\right) \rightarrow h\left(x_{\pi_1}\right) \geq h\left(x_{\pi_2}\right) \geq ... \geq h\left(x_{\pi_G}\right) \geq 0$) while making the choice and assess its value by multiplying it with the corresponding fuzzy measure. Subsequently, the next attribute (in decreasing order of the amount of information offered) is selected and its additional contribution is assessed with ($\left(\mu\left(A_g\right) - \mu\left(A_{g-1}\right)\right) * x_g$). This procedure is followed until all attributes are parsed through. Of course, this is a mathematical interpretation of CI and may not correspond exactly to the underlying decision-behaviour mechanism.

With the use of examples in Appendix A.2.2, we illustrate how CI can approximate various aggregation functions ranging from weighted sum, ordered sum, and minimum or maximum of attributes. With these examples, we aim to convincingly argue for the candidacy of CI as a flexible and monotonic aggregation function in the RUM framework. For a detailed discussion on CI, readers are referred to Tehrani et. al. (2012). In the next subsection, we illustrate how linear additive utility specification can be replaced with CI in the MNP model.

2.2.2 Multinomial Probit Choice Model with Choquet Integral (MNP-CI)

Traditional RUM-based discrete choice models use a weighted sum (WS) aggregation function to represent the systematic part of the indirect utility. In this section, we replace the WS with CI while retaining the stochastic part of the indirect utility function as the normally distributed random variable. For brevity, we refer to the MNP model with the CI function as MNP-CI and to the MNP model with the WS function as MNP-WS.

In MNP-WS, the indirect utility of an individual (n) from choosing an alternative $i \in \{1,2,...,I\}$ as a function of attributes $g \in \{1,2,...,G\}$ is defined in Eq. 2.1 (suppressing individual-level subscript for notational simplicity):

$$U_i = v_i + \varepsilon_i = \boldsymbol{\beta}' \boldsymbol{x}_i + \varepsilon_i \quad (2.1)$$

where $\boldsymbol{x}_i$ is a $(G \times 1)$ vector of exogenous variables, $\boldsymbol{\beta}$ is the corresponding $(G \times 1)$ vector of marginal utilities, and ε_i is a normally distributed idiosyncratic error term. We replace the observed part of the utility (v_i) in the MNP-WS with CI and rewrite Eq. 2.1 as follows:

$$U_i = CI_i + \varepsilon_i$$

where

$$CI_i = \sum_{g=1}^{G} h\left(x^i_{\pi_{N_g}}\right)\left(\mu\left(A^i_g\right) - \mu\left(A^i_{g-1}\right)\right)$$

where A_k is the set of cardinality k formed using permutation of x

$$h\left(x^i_{\pi_{N_g}}\right) \rightarrow 0 \leq \left[h\left(x^i_{\pi_{N_1}}\right) \geq h\left(x^i_{\pi_{N_2}}\right) \geq \ldots \geq h\left(x^i_{\pi_{N_G}}\right)\right] \leq 1 \tag{2.2}$$

$$A^i_G = \left\{x^i_{N_1}, x^i_{N_2}, \ldots, x^i_{N_G}\right\}$$

In Eq. 2.2, the function $h(.)$ is applied to the normalised attribute values. Note that $x^i_{N_g}$ and x^i_g are normalised and un-normalised attribute values of an attribute g for an alternative i. Further, readers will note that the calculation of CI involves the same set of fuzzy measures (μ) for all the alternatives, and therefore, does not have any alternative-specific subscript. This specification is similar to the choice models with generic marginal utilities across alternatives. We extend the MNP-CI to accommodate alternative-specific fuzzy measures (by replacing μ with μ_i) in Section 2.4.1. At this point, two additional conditions need to be ensured in MNP-CI.

First, the attribute values are normalised between 0 and 1 in CI computation with 0 and 1 indicating the lowest and the highest amount of information provided by an attribute, respectively. Such rescaling ensures monotonicity in terms of attribute values. Rescaling the attribute values between 0 and 1 also offers additional stability during numerical optimisation because both parameters (fuzzy measures) and explanatory variables are on the same numerical scale.

The normalisation is performed by using the range of attributes across all available alternatives as illustrated below. Let $\psi\left(x_g\right) = \left\{x^1_g, x^2_g, \ldots, x^I_g\right\}$ be the collection of g^{th} attribute values across all alternatives. For attributes with a positive effect on utility and choice probability (higher the value, better the attribute), the corresponding normalised value can be obtained as follows:

$$x^i_{N_g} = \frac{x^i_g - \min\left(\psi\left(x_g\right)\right)}{\max\left(\psi\left(x_g\right)\right) - \min\left(\psi\left(x_g\right)\right)} \tag{2.3}$$

Similarly, for attributes with a negative effect on utility (the lower the value, the better the attribute), the corresponding normalised value can be obtained as follows:

$$x^i_{N_g} = \frac{\max\left(\psi\left(x_g\right)\right) - x^i_g}{\max\left(\psi\left(x_g\right)\right) - \min\left(\psi\left(x_g\right)\right)} \tag{2.4}$$

Such normalisations ensure that the rescaled values are always a function of available alternatives. It can to some extent help avoid the independence of irrelevant alternatives (IIA) issue in the absence of a non-IID error structure.

Second, to ensure that $\mu(\boldsymbol{X})=1 \quad \mu(\boldsymbol{A}) \leq \mu(\boldsymbol{B}); \boldsymbol{A} \subseteq \boldsymbol{B} \subseteq \boldsymbol{X} \quad 0 \leq \mu(.) \leq 1$, we write constraints using Möbius transformation as the transformed space has a one-to-one mapping with fuzzy measures:

$$\sum_{H \subseteq A_G} m(H) = 1; \quad \text{where } A_G = \{x_1, x_2, ..., x_G\}$$

$$\sum_{H \subseteq A_G \setminus g} m(H \cup k) \geq 0 \ \forall g \subseteq A_G, \forall k \subseteq A_G;$$

where $A_G \setminus g$ represents the collection of all attributes except the g^{th} attribute (2.5)

$\cup$ represents the union of two sets

$m(.)$ is the Möbius representation of $\mu(.)$ and one-to-one mapping between them is as follows:

$$m(H) = \sum_{F \subseteq H} (-1)^{|H \setminus F|} \mu(F)$$

$$\mu(F) = \sum_{H \subseteq F} m(H)$$

Thus, after the estimation of Möbius parameters, one can derive the fuzzy measure $\mu(.)$ from the estimated Möbius parameters $m(.)$ using the above equation. While the fuzzy measures are constrained between 0 and 1, Möbius parameters, except singleton elements, are unconstrained. An example in Appendix A.2.3 illustrates a mapping between Möbius parameters and fuzzy measures.

We also emphasize that the number of CI-specific parameters in the generic CI function depends on the number of attributes (rather than the number of alternatives). In other words, the computational challenges associated with the large choice sets in the MNP-CI model would be the same as those in the MNP model with linear-in-parameter utility. Specifically, the dimensionality of the integrals (i.e., multivariate normal cumulative density function) in the MNP choice probability kernel is one less than the number of alternatives. Nevertheless, advancements in quasi-Monte-Carlo, quadrature, and other analytical approximation methods have enabled efficient computations of high-dimensional integrals in the case of large choice sets (Bansal et al., 2021; Bhat, 2018).

In sum, unlike the MNP-WS model, the estimation of MNP-CI requires solving a constrained optimisation problem with a set of equality and inequality constraints. The addition of constraints means that the typically used Broyden–Fletcher–Goldfarb–Shanno (BFGS) algorithm (Fletcher, 2013) can no longer be used for the loglikelihood maximisation. Therefore, we use the sequential least-square programming (SLSQP) algorithm to solve the constrained loglikelihood maximisation problem of MNP-CI. Readers are referred to Nocedal et al. (2006, pages 529-562) for a detailed discussion of the SLSQP algorithm. We use the SLSQP algorithm's off-the-shelf implementation in Python's Scipy package. A detailed description of the MNP-CI formulation and estimation is provided in Appendix A.2.4. This section illustrates the changes due to the replacement of the WS with CI, the normalisation of attributes, and the constrained likelihood maximisation problem.

2.2.3 Inferences from a Choice Model with Choquet Integral

Whereas Möbius parameters are direct outputs of the estimation, several important metrics can be derived after transforming them into fuzzy measures. We discuss two such metrics – Shapley value and interaction indices, which provide further insights into the decision-making process. Readers are referred to Beliakov et al. (2016, chapter 4) for a detailed discussion on such metrics.

The Shapley value of an attribute is expressed as follows:

$$S(g)=\sum_{A\subset G\backslash g}\frac{Fact\left(|\boldsymbol{X}|-|A|-1\right)Fact\left(|A|\right)}{Fact\left(|\boldsymbol{X}|\right)}\left[\mu\left(A\cup\{g\}\right)-\mu\left(A\right)\right]\quad 0\leq S(g)\leq 1, \tag{2.6}$$

where $Fact(.)$ represents the factorial, $|.|$ indicates the cardinality of the set and $\boldsymbol{X}=\{x_1,x_2,...,x_G\}$ is the set of all attributes. The Shapley value is interpreted as the average marginal contribution of an attribute g in all coalitions. Intuitively, Eq. 2.6 provides the sum of scaled (multiplication by a factor) difference between fuzzy measures of sets with and without attribute g. In other words, the Shapley value aggregates all additional worth of attribute g as represented by $\left[\mu\left(A\cup\{g\}\right)-\mu\left(A\right)\right]$.

While the Shapley value is informative, it is not sufficient to describe the entire effect of an attribute on the choice outcome because it does not capture the importance of the attribute's interaction with other attributes in explaining the choice outcome. However, interaction indices can address this limitation of the Shapley value.

The interaction index – a pair-wise value (which represents if two attributes are complementary or not) can be obtained as follows:

$$I(qw)=\sum_{A\subset G\backslash\{q,w\}}\frac{Fact\left(|\boldsymbol{X}|-|A|-2\right)Fact\left(|A|\right)}{Fact\left(|\boldsymbol{X}|-1\right)}\left[\mu\left(A\cup\{q,w\}\right)-\mu\left(A\cup\{q\}\right)-\mu\left(A\cup\{w\}\right)+\mu\left(A\right)\right],$$
$$-1\leq I(qw)\leq 1 \tag{2.7}$$

Similar to Eq. 2.6, Eq. 2.7 essentially provides the sum of scaled differences between fuzzy measures of sets with and without the pair of attributes. A positive value of the interaction index indicates a complementary relation (positive interaction) between two attributes and a negative value suggests otherwise.

The interaction index can also be obtained for a group of more than two attributes (set *B*) with the help of Eq. 2.8:

$$I(B)=\sum_{A\subset G\backslash\{B\}}\frac{Fact\left(|\boldsymbol{X}|-|A|-|B|\right)Fact\left(|A|\right)}{Fact\left(|\boldsymbol{X}|-|B|+1\right)}\sum_{C\subseteq B}(-1)^{|B\backslash C|}\mu\left(A\cup C\right) \tag{2.8}$$

Grabisch and Roubens (2000) provide a policy-relevant interpretation of both Shapley value and interaction index in quantifying the effect of an attribute on the overall choice process – "*A positive value of interaction index implies a conjunctive behaviour between the pair of attributes. This means that the simultaneous satisfaction of both attributes is significant for the final choice. On the other hand, a negative value implies a disjunctive behaviour, which means that the satisfaction based on either of the attributes has a substantial impact on the final* *choice. Finally, the Shapley value acts as a weight vector in a weighted arithmetic mean, i.e. it represents the linear part of the Choquet integral.*"

We illustrate the interpretation of both metrics in a mode choice context. Let us consider a travel mode choice scenario with three attributes namely price, comfort, and out-of-vehicle travel time (OVTT). Further, we assume that the Shapley value and interaction indices for the attribute pairs are as follows:

$$S(\text{Price}) = 0.45 \qquad , S(\text{Comfort}) = 0.25 \quad , \text{and } S(\text{OVTT}) = 0.30$$
$$I(\text{Price,Comfort}) = -0.25, I(\text{Price,OVTT}) = 0.15, \text{ and } I(\text{Comfort,OVTT}) = 0.12$$

If we only consider Shapley values in isolation, then one may conclude that price is the most important attribute for the traveller when making a travel mode choice, followed by OVTT and comfort. In other words, if one wishes to improve the share of a travel mode, then lowering the price followed by improving OVTT and comfort is likely to yield the best results. However, when we analyse interaction indices along with Shapley values, we observe that price and OVTT exhibit a complementary behaviour, i.e. the travel mode needs to score lower on both of these attributes (as they cause disutility) to be chosen. However, if a decision-maker chooses a travel mode based on price and comfort, the travel mode needs to score lower on price or substantially higher on comfort (due to a low Shapley value) to be chosen. This example demonstrates that Shapley values alone (individual ranking of attributes) are informative but not adequate, and interaction indices play an imperative role in making policy-relevant recommendations.

The above discussion suggests that there could be a structured way to identify important attributes (to increase the market share of an alternative) based on Shapley values and interaction indices. The analyst can focus on the attribute with the highest Shapley value and can find the corresponding complementary pair with the highest interaction index value. Any improvement in both attributes simultaneously is likely to improve the share of an alternative substantially. This process can be viewed as equivalent to a strategy where one may evaluate the elasticity value of both attributes individually and simultaneously to identify which yields maximum improvement in the market share of an alternative.

2.2.4 Extensions of the Choice Model with Choquet Integral

In addition to operationalising CI in the MNP framework, we propose two extensions of MNP-CI. Readers are referred to appendix A.2.4.1 for a generalised formulation of MNP-CI with these extensions.

2.2.4.1 Alternative-specific Choquet Integral

Analogous to the MNP specification with alternative-specific marginal utilities, we extend the MNP-CI to an alternative-specific MNP-CI specification where different subsets of the attributes could be used for different alternatives. It is worth noting that the alternative-specific MNP-CI obviates several behavioural constraints such as the same ranking of attribute importance for all alternatives. For instance, there is no reason to assume that individuals attach the same importance to the price across all alternatives in the presence of brand loyalty. Thus, relaxing this assumption in alternative-specific MNP-CI allows the analyst to uncover important alternative-specific attribute ranking and complementary pairs of attributes. Unbalance datasets (i.e., when different subsets of the attributes are applicable for different alternatives) can also be easily handled using this specification.

2.2.4.2 Choquet Integral with Attribute Cut-offs

We explicitly incorporate and endogenously estimate attribute cut-offs to account for the semi-compensatory behaviour of decision-makers. We parametrise attribute cut-offs with socio-demographic characteristics of decision-makers to inherently capture heterogeneity in preferences due to the adoption of different attribute cut-offs.

Since CI requires the analyst to rescale attribute values between 0 and 1, we can directly use fuzzy membership functions (e.g., triangular, sinusoidal, and trapezoidal) to specify attribute cut-offs. The selection of a membership function depends on the perception of the attribute. For instance, the cut-off for attributes with a negative marginal utility such as travel time and cost in travel model choice can be represented by the following half-triangular membership function:

$$x_N = \begin{cases} 1 & x \le a \\ \dfrac{b-x}{b-a} & a < x \le b \\ 0 & x > b \end{cases} \tag{2.9}$$

To illustrate the above equation, Figure 2.1 shows an example of how the membership function value changes with the change in actual travel time in a mode choice scenario. Figure 2.1 shows that the disutility of travel time remains constant below 10 minutes. The upper limit of 25 minutes indicates that all travel time values above 25 minutes offer a similar level of disutility to the traveller as of 25 minutes. The linear change is similar to a regular MNP-CI normalisation with a minimum of 10 minutes and a maximum of 25 minutes, as illustrated in Eq. 2.4.

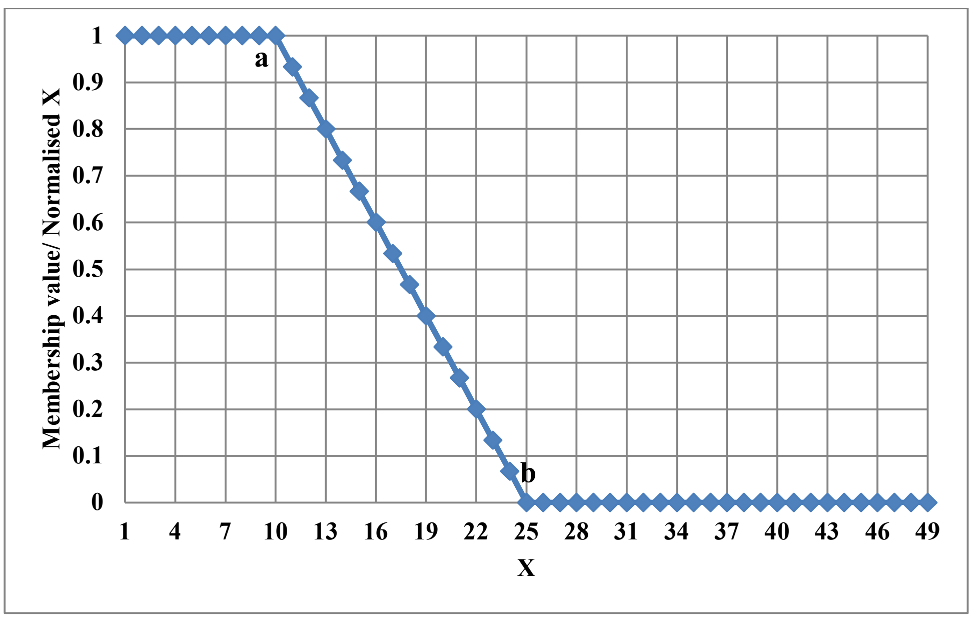

Figure 2.1: Two-point cut-off graph for attributes with negative marginal utility (Half-triangular function)

The application of these membership functions allows us to endogenously determine preference ranges for an attribute independently for each alternative and variation across different groups can be captured by parameterising kink points as a function of demographic characteristics. The kink point parameters are estimated during the estimation (loglikelihood maximisation) process.

In this attribute cut-off framework, behaviour remains compensatory in a certain range of attributes, but it becomes semi-compensatory outside the attribute ranges. Consider a mode choice example, where the decision-maker chooses travel mode based on travel time and cost within the ranges [10, 25] and [2, 4], respectively (omitted units for simplicity). Both attributes follow the half-triangular fuzzy membership function, as illustrated in Figure 1. Since the systematic utility for any travel time value above 25 units would remain the same as the one obtained at 25, we can say that the decision-maker is not making any trade-off between travel time and cost outside the ranges of attributes. Section A.2.5 in the appendix discusses other fuzzy membership functions, and the operationalisation of attribute cut-offs in CI is illustrated through an example in Section A.2.6.

2.2.5 Discussion on the Advantages of MNP-CI with Attribute Cut-offs and Computational Challenges

In summary, "MNP-CI with attribute cut-offs" is a flexible specification at several levels. The importance attached to the "individual attribute" based on its range is captured by the fuzzy membership function in the normalisation step, flexible interactions between attributes are incorporated by the CI function in the aggregation step, and unrestricted substitution effects are specified using the MNP kernel. The operationalization of attribute cut-offs through the fuzzy membership function makes the MNP-CI model superior to the existing penalty-based semi-compensatory approaches (Swait, 2001; Martínez et al., 2009). For instance, the binomial function in Martínez et al. (2009) induces a non-zero penalty even if the attribute's value is within a certain range. Moreover, this function has an additional parameter (cut-off tolerance to define choice probability at the boundary) to bound the penalty term, but this parameter is assumed fixed to make the estimation stable (Rashedi and Nurul Habib, 2020). In sum, modelling and estimation of one-stage semi-compensatory models with endogenous attribute cut-offs have several challenges, which can be addressed by directly specifying attribute cut-offs through fuzzy membership function in MNP-CI and estimating it through a constrained maximum likelihood estimator.

It is worth noting that irrespective of the type of aggregation function, the attribute cut-off approach can be applied as part of the MNP-WS framework to model the semi-compensatory choice behaviour. However, the incorporation of attribute cut-offs in the weighted sum utility specification leads to numerical issues. Unlike fuzzy measures in CI, the magnitude of parameters in the weighted sum approach could explode because they are unconstrained. The problem is particularly acute in the case of a mix of explanatory variables of different natures (continuous, ordinal, and count). These issues are not directly related to the cut-off approach but are a limitation of numerical optimization. Thus, from a practical standpoint, we recommend using the attribute cut-off approach with a fuzzy-measure-based aggregation function instead of the weighted sum function.

Figure 2.2 summarizes the trade-off between model complexity and interpretability in MNP-WS, Generalized MNP-CI (alternative-specific Choquet integral and attribute cut-off) and popular machine learning/data-driven/non-parametric algorithms. In particular, by complexity, we refer to the number of parameters in the model. The CI-based indirect utility function specification with attribute cut-offs offers greater interpretability but requires the estimation of more parameters as compared to a traditional MNP-WS model. Conversely, the number of parameters in the MNP-WS model can increased to match the complexity of the Generalized MNP-CI model by including higher-order interaction terms. However, adding higher-order interaction terms requires introducing sign constraints on the parameters. A mere increase in the number of parameters in the MNP-WS model does not guarantee a better approximation of the Generalized MNP-CI model as we show below through both simulation and empirical examples. Next, the Generalized MNP-CI may have lower or higher complexity depending on the choice of machine-learning (ML) algorithm. For example, the Generalized MNP-CI model is certainly more complex than a decision tree and clustering methods but less complex than ensemble methods (random forest) and boosting methods (gradient-boosted trees). However, the Generalized MNP-CI model or MNP-WS model (a parametric theory-based model) cannot be directly compared with ML algorithms as they are specifically designed for prediction and do not capture the process. Therefore, their behavioural interpretability remains very low. The same reasoning applies to deep-learning ML models based on neural networks which have higher complexity than the Generalized MNP-CI model.

Next, in terms of estimation, the Generalized MNP-CI model is a constrained optimization problem due to the presence of monotonicity constraints. Further, the number of constraints (inequality) increases non-linearly with the number of attributes. As discussed earlier, we use the sequential least-square quadratic programming (SLSQP) algorithm to estimate the Generalized MNP-CI model. The SLSQP algorithm is very similar to un-constrained algorithms such as BFGS. The SLSQP iteratively solves the Lagrangian function associated with the original constrained problem. In each iteration, constraints are divided into sets of active and non-active constraints which determine the feasibility region of parameter space. It has many similarities to the Quasi-Newton methods in the sense that Hessian is approximated using the BFGS update of B-matrix. Hence, the similarity to Quasi-Newton methods (in particular BFGS algorithm widely used for the estimation of traditional discrete choice models) makes the SLSQP algorithm robust at solving constrained optimization problems. In our simulation evaluation (see section 2.3), we did not encounter any major issues during estimation such as a large number of sample failures. In our experience, the scaling of attribute values (between 0 and 1) and fuzzy measures (constrained between 0 and 1) may add to the stability of the Generalized MNP-CI model. This is similar to rescaling continuous attribute values in a range of 0 to 5 in un-constrained discrete choice models to improve the stability of numerical optimization. Further, since the starting value of the parameter plays an important role in the convergence of non-linear models. We experimented with different configurations of fuzzy measures and found constructing the fuzzy measure values using small but non-zero singleton fuzzy measure coefficients speeds up the estimation. That being said, we only tested the Generalized MNP-CI model for up to six attribute cases (see section 2.3) and convergence issues may prop up for a higher number of attributes.

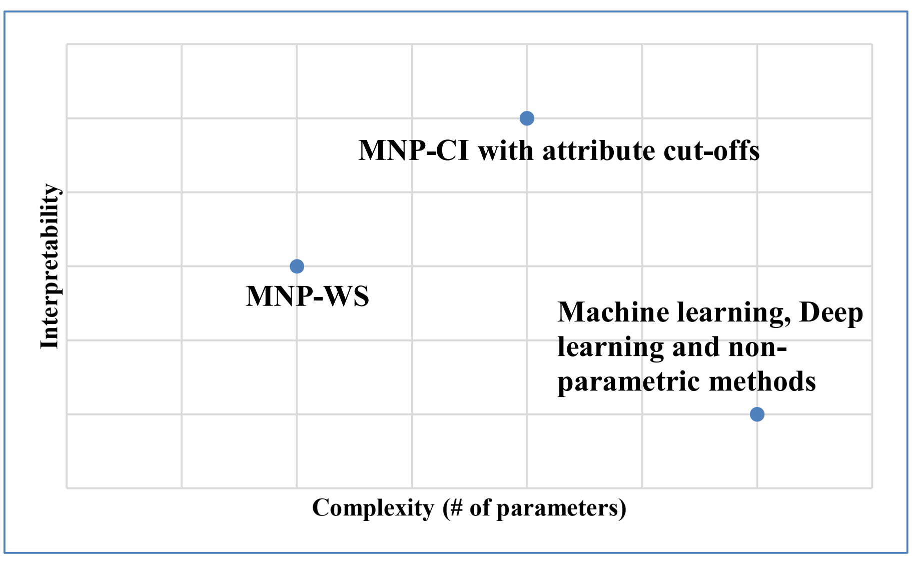

Figure 2.2: Trade-off between complexity and interpretability in different models

2.2.6 Generalized MNP-CI vs Explicit and Implicit Semi-compensatory Choice Models

The Generalized MNP-CI model can be classified as a one-stage semi-compensatory modelling framework. As discussed earlier in section 2.1, one-stage semi-compensatory models (also known as reduced form models) were developed in response to reduce the computational complexity of the explicit two-stage choice model. The rationale for a reduced form model was given by Swait (2001) as follows: "I*t is behaviorally equivalent whether the decision-maker simply chooses the best good that satisfies the constraints, or alternatively, first screens based on constraints, then chooses the best alternative*". Based on this, one may be able to observe the one-to-one correspondence between a reduced-form model and a two-stage model if the constraints are specified correctly (i.e., parameters recovered from two models are unbiased and equal). However, Bierlaire et al., (2010) found that a reduced-form model tends to provide biased estimates in the interior region of alternative availability (away from 0 or 1). They conclude that reduced-form models are a good approximator of a two-stage model only in extreme cases (an alternative is either available or not available with a probability equal to 1). Recently, Paleti (2015) used higher-order approximations in the reduced-form modelling framework (also known as implicit choice set generation) to obtain a better approximation of Manski's explicit two-stage choice model.

In light of the above discussion, probably, the Generalized MNP-CI model may exhibit the same limitations as other reduced-form models. However, a thorough comparison requires changing the weighted sum function in a two-stage model with CI. Such a detailed comparison is beyond the scope of this work.

Nevertheless, the Generalized MNP-CI introduces an attribute processing strategy different from the existing explicit two-stage model and one-stage semi-compensatory models with the foundation in bounded rationality. The majority of economic choice models (especially within RUM) assume a rational choice behaviour (McFadden, 1977; McFadden and Train, 2000). Under the rational choice behaviour paradigm, the individual is assumed to utilize full information while making the choice. However, empirical behavioural evidence points consistently to the contrary. Simon's (1955, 1956, 1966) bounded rationality model already acknowledged the impact of problem difficulty, cognitive capability and time constraints on choice behaviour. Owing to such constraints, a full cost-benefit analysis utilizing full information to determine the choice outcome may be challenging. A substantive amount of literature in diverse fields, most notably psychology and marketing, has documented deviations from the rational choice behaviour (Fishburn, 1974; Conlisk, 1996; Gabaix and Laibson, 2000; DeShazo and Fermo, 2002; DeShazo and Fermo, 2004; Jedidi and Kohli, 2005; Gilbride and Allenby, 2006; DellaVigna, 2009; Cameron and DeShazo, 2010; Gigerenzer and Gaissmaier, 2011; Swait et al., 2016). Within the confines of bounded rationality, the limitations (problem difficulty, cognitive capability and time constraint, among others) may manifest in the form of information usage (Payne, 1982). Decision-makers may resort to strategies which involve processing only a subset of information or paying attention to only a few pieces of information. In the section below, we provide a review of the literature on information-processing strategies to highlight how the Generalized MNP-CI model fits into the realm of bounded rationality.

2.2.7 Generalized MNP-CI as an Information Processing Strategy Approach

The information processing strategy may result in a decision behaviour where decision-makers may (1) utilize only a subset of information and behave as utility-maximizers (Swait et al., 2016), (2) process full or subset of information in a particular order to arrive at the final choice-outcome based on hard-cutoffs (Tversky, 1972; Campbell et al., 2006) and (3) both where information is processed fully or partially in a particular order and behave as utility-maximizers (DeShazo and Fermo, 2004). While the second strategy (notably operationalized using the method of 'elimination by aspect') was introduced 50 years ago, it has undergone substantial refinements, most notably the treatment of attribute constraints (lower and upper limits) from "hard" to "soft" (Swait, 2001; Martínez et al., 2009). Notwithstanding, several notable renewed efforts to develop models with explicit information-processing strategies have taken place in the last two decades (DeShazo and Fermo, 2004; Cameron and DeShazo, 2010; Swait et al., 2016).

DeShazo and Fermo (2004) argue that "*individuals may sequentially evaluate the information up to the point where the marginal benefits and marginal costs of further information evaluation are equal (thus maximizing the net benefits of the information to the choice process) in a rationally adaptive process*" (Lew and Whitehead, 2020). While the actual attribute ordering is difficult to determine, DeShazo and Fermo (2004) hypothesize that attributes with greater variability across alternatives are likely to be systematically attended more than others. The authors define variability based on range and standard deviation of values. A significant coefficient corresponding to such range and standard deviation provides evidence for greater attendance.

Cameron and DeShazo (2010) extend the concept of DeShazo and Fermo (2004) by providing an approach to systematically allocate attention/attendance to an attribute based on its marginal contribution to the optimal choice. The marginal contribution is captured by evaluating the probability of making the optimal choice as a function of utility achieved by ignoring an attribute and the full-information utility. In simple terms, if the utility difference in the absence of an attribute is close to zero then the probability of attending that attribute increases to better distinguish between choice options. While the model offers a concrete information processing strategy grounded in cost-benefit analysis, the model estimation is rather cumbersome. It involves an iterative procedure alternating between estimating a full-information model and correcting those weights based on the similarity of alternatives in the absence of an attribute until the convergence (change in parameter values is below a threshold).

The rationally adaptive rational choice model (DeShazo and Fermo, 2004) and differential attention attribute model (Cameron and DeShazo, 2010) infer the propensity to attendance through a range of attributes. This approach can be classified as an inferred attribute non-attendance (ANA) approach. Another modelling approach that has gained considerable traction in the realm of the inferred ANA approach is the equality-constrained latent class (ECLC) model (Scarpa et al., 2009). The ECLC model uses a latent class approach where classes are a function of attributes. In this model, $2^K + 1$ classes (K : number of attributes) are estimated (every attribute combination) with generic attribute coefficients across classes (a total of K parameters). The classes are differentiated by which attribute(s) are ignored by fixing the corresponding parameter(s) value to zero. Even though the ECLC model is parsimonious, estimating a large latent class model could be challenging (Hole, 2011). Hole (2011) proposes a two-step process (endogenous attribute attendance (EAA)) for attribute attendance similar to the approach used by Swait and Ben-Akiva (1987) for choice set formation. In the first step, the probability of attribute attendance is modelled under the IID assumption followed by an evaluation of choice probability conditional on attribute attendance. Both the ECLC and EAA approaches assume zero marginal utility for ignored attributes. Hess and Hensher (2010) note that it is possible that individuals stating ANA (i.e., ignoring certain attributes altogether) may have just placed less importance on it and therefore its marginal utility really should be non-zero. Balcombe et al. (2015) also note that stated attendance diverges from visual attendance (as observed through eye-tracking data) of attributes. Respondents have lower but non-zero, marginal utility for those attributes that they state they have not attended. Thus, respondents use the stated attribute non-attendance question as an opportunity to signal that something was of 'low value', but not that it played no role in their choices.

In the inferred, stated ANA approach, and eye-tracking studies, attribute attendance/non-attendance is modelled using the shrinkage factor approach. Essentially, the weight of coefficients is scaled up or down by utilizing information on the range of attributes, stated ANA information, and eye-tracking data. Swait et al. (2016) note that "*such approaches are not process oriented beyond its basic reliance on self-reported or inferred differential attention levels to account for information usage*". They propose a model for endogenous clustering of attributes based on psychological underpinnings. In their work, the authors propose a cost-benefit analysis for endogenous clustering of attributes based on information provided by the attributes to arrive at optimal choice (i.e., benefit) and the mental cost to process such attributes (i.e., cost). The benefit offered by an attribute is quantified as a function of the range of the attribute's range across all alternatives. The cost is defined as a function of the number of attributes, the number of attribute levels and the range of the attribute itself. Compared to Cameron and DeShazo's (2010) model, the endogenous clustering model is easy to formulate and estimate. However, the model is still not parsimonious and the specification of cost function requires more psychological underpinnings.

Hence, we may argue that the Generalized MNP-CI model offers a parsimonious and more importantly a process-oriented way to account for processing of attributes based on marginal benefit as compared to existing models.

2.3 Simulation Study

2.3.1 Simulation Set-up

2.3.1.1 Statistical Measures and Model Specifications

Before adopting MNP-CI models in empirical applications, their statistical properties need to be studied. In this section, we analyse the parameter recovery measured by the standard deviation normalized mean absolute error (SDMAE) in a comprehensive Monte Carlo study. SDMAE for a parameter is obtained by dividing the mean of absolute error (mean of the absolute difference between true and estimated value across samples) with the standard deviation of true values of all parameters. SDMAE is more appropriate than absolute percentage bias (APB) because APB for low values (i.e. between 0 and 1) of CI parameters tends to exaggerate the bias. Other statistics such as symmetric mean absolute percentage error (SMAPE) and root mean square error (RMSE) also suffer from similar issues and lack interpretation (Goodwin and Lawton, 1999; Hyndman and Koehler, 2006; and Armstrong and Collopy, 1992). Further, we also statistically compare the marginal effects based on the true and estimated parameters. For inference evaluation, we compute coverage probability (CP). CP is defined as the proportion of time the confidence interval (95%) contains the true value of the parameter. It can be calculated using the following expression (Koehler, et. al., 2009):

$$\text{CP} = \frac{1}{R}\sum_{r=1}^{R} I\left[\beta_{est} - 1.96 * \text{std.err}(\beta_{est}) \le \beta_{true} \le \beta_{est} + 1.96 * \text{std.err}(\beta_{est})\right]$$

where β_{true} is the true value of the parameter, β_{est} is the estimated value of the parameter, R is the number of samples and the term $\text{std.err}(.)$ indicates the asymptotic standard error (ASE) of the estimated parameter. A CP value close to 0.95 suggests that the estimator is overall reliable in terms of parameter recovery and inference.

We consider four specifications of the MNP-CI model in increasing order of complexity:

1. CI and identical and independent (IID) error structure (CI-IID)
2. CI with cut-off on attributes, and (IID) error structure (CIC-IID)
3. CI with cut-off on attributes, and diagonal error structure (CIC-DE)
4. CI with cut-off on attributes, and full-covariance error structure (CIC-FE)

A comparison of the results of CI-IID and CIC-IID specifications will show the effect of adding attribute cut-offs on the statistical properties of model parameters. Step-by-step increment in error complexity from CIC-IID to CIC-FE allows us to comprehend how statistical properties of CI and attribute cut-off parameters are affected due to the complexity of the error-covariance structure. We also benchmark the performance of each MNP-CI specification against the corresponding MNP-WS specification.

Since the number of CI parameters and constraints quickly increases with the number of attributes due to an increase in interaction effects, we analyse the statistical properties of the above-discussed specifications for both four and six attributes. This exercise is imperative to ensure that the performance of the model does not deteriorate due to an increase in the number of parameters. Table 2.1 provides the total number of parameters estimated for each of the four model configurations for both attribute cases.

In all four specifications and both attribute configurations, we consider the data-generating process (DGP) with five alternatives and a sample size of 3000 respondents. For each specification-attribute configuration, MNP-CI and MNP-WS are estimated for 50 datasets. In MNP-WS specifications, interactions are ignored and only the mean effect (β) parameters are considered. We set the fuzzy-measure value $\mu(.)$ of an attribute in MNP-CI's DGP as its true marginal utility in MNP-WS's DGP while keeping covariate values the same as that of MNP-CI. Although incorporating cut-offs in the MNP-WS model is challenging from the numerical optimization perspective, we did not encounter parameter explosion issues in the Monte Carlo study because all the mean effect parameters in the DGP are between 0 and 1. Further, all attribute values are drawn from a uniform distribution with a lower and upper limit of 1 and 10 respectively. We restrict the simulation study to MNP-CI with generic fuzzy measures and illustrate the application of alternative-specific MNP-CI in the empirical study. We employ generic CI configuration for two reasons. First, it helps us understand the effect of added complexity (cut-off parameters and error covariance structure) on the recoverability of CI parameters. Second, it allows us to test various MNP-CI specifications within a reasonable computational budget.

Table 2.1: Number of parameters and constraints in MNP-CI in the Monte Carlo Study

# of attributes	Specification	# of CI Parameters	# of Cut-off Parameters	# of Error Parameters	Total # of parameters	# of constraints
4	CI-IID	14	0	0	18	32
	CIC-IID	14	12	0	30	
	CIC-DE	14	12	3	33	
	CIC-FE	14	12	9	39	
6	CI-IID	62	0	0	66	192
	CIC-IID	62	18	0	84	
	CIC-DE	62	18	3	87	
	CIC-FE	62	18	9	93	

Note: Total # of parameters includes alternative-specific constants

2.3.1.2 Data Generating Process

Appendix A.2.7 provides the data-generating process for both four and six-attribute cases. We first discuss the details of the simulation configuration for the four-attribute scenario. Since we have five alternatives, we include four alternative-specific intercepts/constants (ASCs) while normalising the first ASC to zero for identification. The four attributes are included in the utility equation through CI in the MNP-CI specification. The attribute cut-offs do not appear in the DGP and estimation of CI-IID specification. In the CIC-DE specification, we only estimate the diagonal elements of the error matrix while fixing non-diagonal elements to 0.5. For the CIC-FE specification, all the elements of the error matrix are estimated. Note that the first diagonal element of the error-covariance matrix is normalised to unity to set the scale of utility in all specifications. For the CI-IID model, the normalisation of attributes is performed using Eq. 2.3 and for the remaining models, a fuzzy membership function (i.e., half-triangular or trapezoidal) is used depending on the number of cut-off points and the possible sign of the marginal utility of the attribute. In the Monte Carlo study, we also calculate the implied Shapley values and interaction indices using the estimated CI parameters for each dataset to ensure that we do not just assess the statistical properties of the CI parameters but also establish the recovery of underlying attribute ranking and complementary effects for pairs of attributes. This exercise is particularly important because the recovery of CI parameters may be relatively poor due to the high number of parameters, but the statistical properties of MNP-CI will be acceptable for empirical applications if the resulting attribute rankings and complementarity of attribute pairs are recovered well. True Shapley values and interaction indices are also presented along with the DGP in Appendix A.2.7.

Next, we provide the details of the simulation configuration for the six-attribute scenario. While the number of alternatives, normalisation strategies and sample size remain the same in both attribute configurations, details about attribute cut-offs are required due to the addition of two attributes the in six-attribute scenario. For the first four attributes, we use the same membership function as the ones we have for the four-attribute case. For the fifth and sixth attributes, we use half-triangular and trapezoidal membership functions, respectively.

2.3.2 Simulation Results and Discussion

2.3.2.1 Recoverability of Model Parameters

Since the considered MNP-CI specifications involve a large number of parameters, we aggregate statistical measures across a group of parameters. Figure 2.3 reports SDMAE for four groups of parameters for each specification – CI parameters, Shapley value and interaction indices, attribute cut-offs, and error-covariance matrix. A similar plot of APB values is also presented in Figure S.2.1 of the supplement-2 (at the end of this chapter after the appendix). The findings from APB and SDMAE are fairly consistent, but we discuss the latter because the former provides exaggerated values when true parameter values are small (e.g., interaction indices in our case study).

SDMAE for CI parameters (Figure 2.3a) does not increase substantially with the model complexity for the four-attribute scenario, but the recovery of CI parameters for the six-attribute case is affected substantially in the case of non-IID error covariance structure. As expected, the SDMAE of CI parameters is higher for the six-attribute scenario as compared to that for the four-attribute scenario, simply due to an increase in the number of parameters from 14 to 62. Specifically, the SDMAE of CI parameters for the six-attribute scenario is almost four times higher than that for the four-attribute scenario in the case of non-IID error structure (i.e., CIC-DE and CIC-FE configurations). There is no specific pattern in SDMAE of MNP-

WS and MNP-CI, but we can see that the former has a much lower value of SDMAE in the most complex error structure (i.e. CIC-FE configuration) for both attribute scenarios.

On the other hand, the recoverability of the Shapley values and interaction indices (Figure 2.3b) are excellent with an SDMAE below 0.1 for all configurations, except for MNP-CI in the CIC-FE configuration. SDMAE is not very sensitive to model complexity and the number of attributes. This result indicates that despite the slightly poor recovery of CI parameters for complex error structures and a higher number of attributes, the underlying attribute ranking and complementarity of attribute pairs are recovered equally well in the considered scenarios. Such a characteristic is critical to enable the analyst to build a comprehensive MNP-CI model without worrying too much about the deterioration in the recovery of Shapley values and interaction indices. It is worth re-emphasizing that CI parameters do not have much behavioural meaning (except the knowledge about the importance of attribute pairs), rather measures like Shapley values and interaction indices are critical from the perspective of policy recommendations.

SDMAE for the attribute cut-off parameters is presented in Figure 2.3c. First, the recovery of cut-offs for the four-attribute scenario is slightly better than that for the six-attribute scenario across model configurations for the CI-based MNP model. On the other hand, the difference is negligible for the MNP-WS model (both across model configurations and the number of attributes). Overall, the recovery of cut-off parameters is excellent irrespective of model complexity. This is a highly encouraging result as it suggests that semi-compensatory behaviour can be recovered in MNP-CI as well as MNP-WS while considering a flexible substitution pattern across alternatives. This result is even more important for the wider applicability of MNP-CI because MNP-WS with attribute cut-offs might encounter numerical issues in the estimation due to the differences in the scale of model parameters.

SDMAE values of error-covariance parameters (Figure 2.3d) are similar for MNP-WS and MNP-CI in the case of a diagonal error covariance matrix (i.e., CIC-DE configuration); however, the former outperforms the latter in case of full error covariance matrix (i.e., CIC-FE configuration). The recovery of error-covariance parameters in MNP-CI for the most complex configuration is twice as bad as that of MNP-WS, suggesting that recovery of full error-covariance matrix is slightly challenging in MNP-CI model.

We also evaluate the difference between true and the estimated marginal effect values for CIC-FE specification and plot them for four- and six-attribute scenarios in Figures 2.4a and 2.4b, respectively. In both scenarios, we change specific attributes by a certain percentage (indicated on the horizontal axis of plots) and evaluate the change in the probability of choosing all five alternatives. This process was repeated for all 50 datasets and the difference between true (computed using true parameter values) and the estimated marginal effect value was evaluated using a t-test for each dataset. To perform the t-test, for every dataset, the average and standard deviation of the marginal effect values (for both true and estimated) are used as the point estimate (β_{ME}) and corresponding standard error (σ_{ME}). Then the t-test to check if two estimates are statistically indifferent can be performed using the following expression:

$$\text{t-value} = \frac{abs\left(\beta_{\text{true ME}} - \beta_{\text{estimated ME}}\right)}{\left(\sigma^2_{\text{true ME}} + \sigma^2_{\text{estimated ME}}\right)^{0.5}}$$

If the calculated t-value is smaller than 1.96, we do not have enough statistical evidence to reject the null hypothesis at a 0.05 significance level that true and estimated marginal effect values are equal. The t-value was obtained for each alternative with respect to each attribute for 50 samples. The t-value is converted into a binary indicator (with 1 representing the inability to reject the null hypothesis and 0 otherwise) and the overall proportion for each case is subsequently obtained. In the case of four attributes, the overall proportion is 0.79 (across all alternatives and attributes), but it is 0.65 for the six-attribute case. This result suggests that the MNP-CI model does a good job for the four-attribute case, but the performance slightly deteriorates for the higher number of attributes.

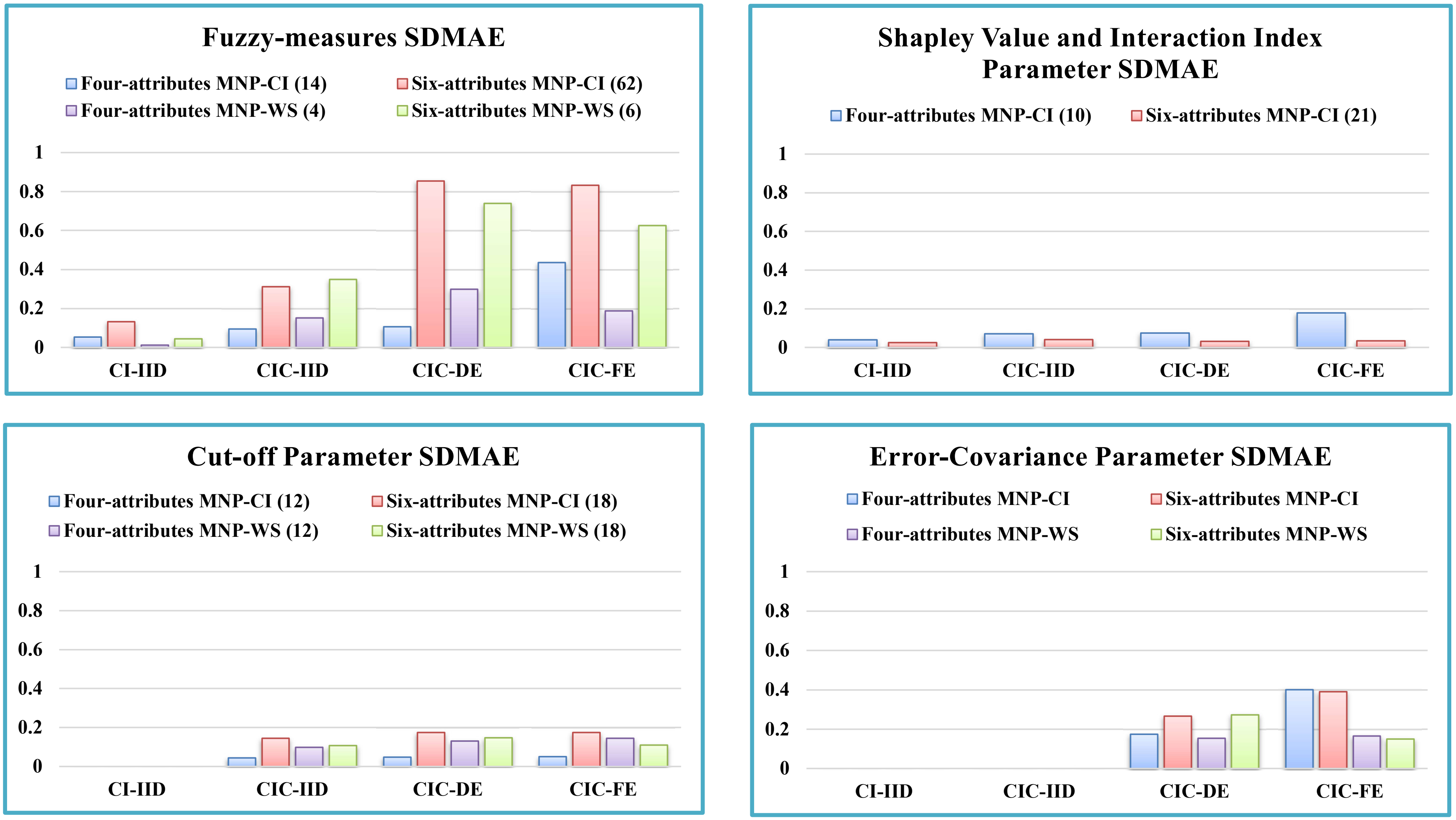

Figure 2.3: Standard deviation normalized mean absolute error (SDMAE) for various parameter groups (the number of parameters in parenthesis)

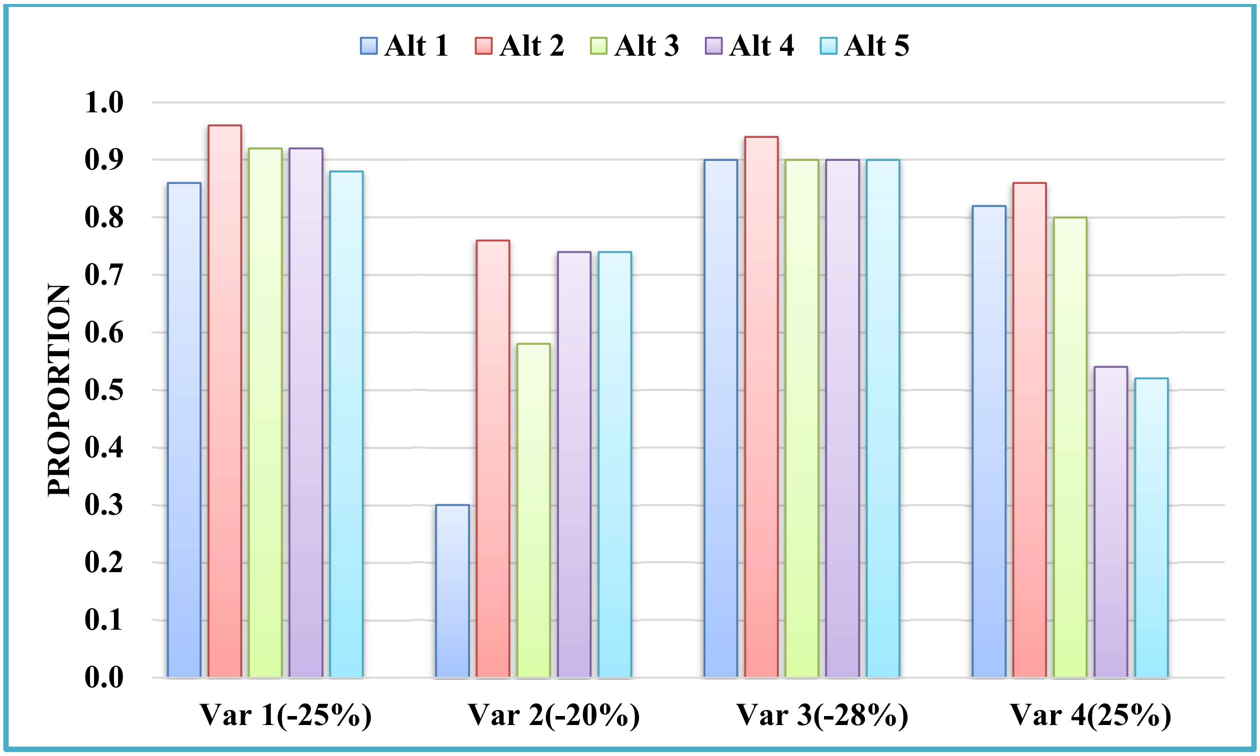

Figure 2.4a: Proportion of samples with statistically insignificant difference between marginal effect values based on true and estimated parameters (four-attribute scenario)

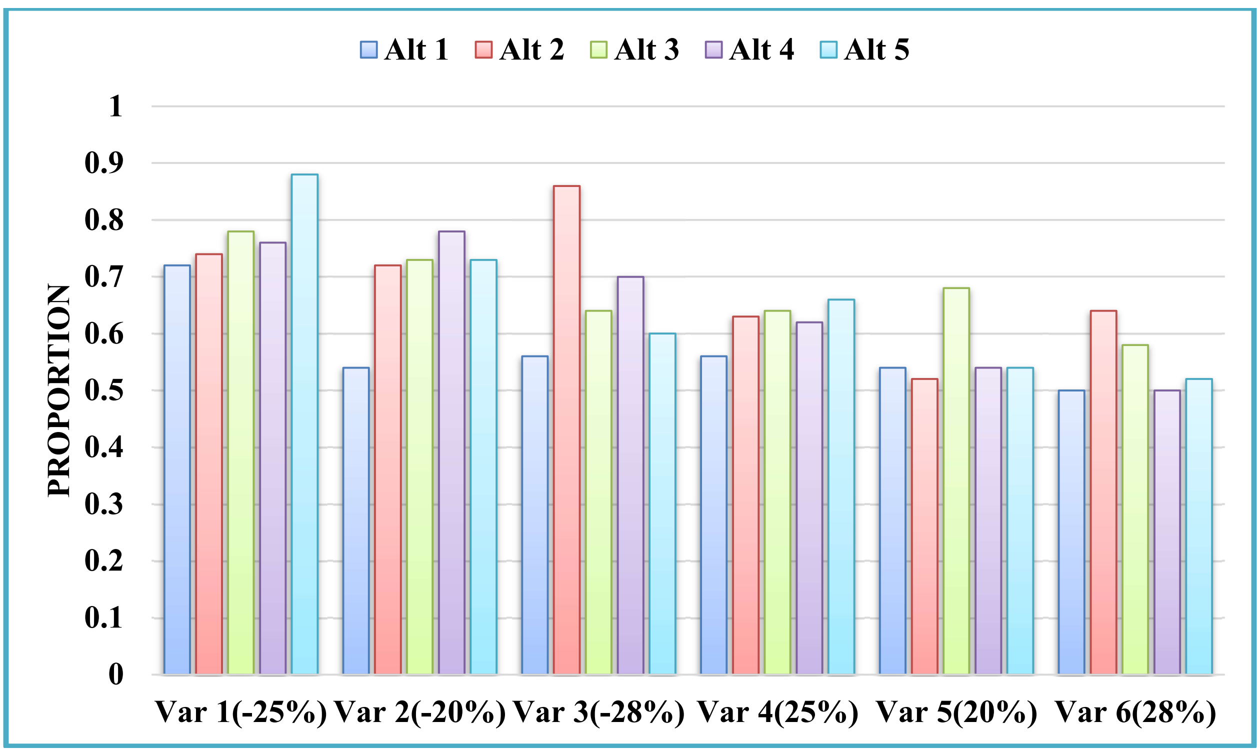

Figure 2.4b: Proportion of samples with statistically insignificant difference between marginal effect values based on true and estimated parameters (six attribute scenario)

2.3.2.2 Coverage Probability and Estimation Time

Figures 2.5a to 2.5c show CP for CI parameters, cut-off parameters and error-covariance parameters. Figure 2.5a shows that CP values for CI parameters across all specifications of MNP-CI are excellent with a minimum value of more than 0.9. This result reduces worry associated with slightly poor SDMAE values in a few instances. In fact, MNP-CI has better CP values for CI parameters than those of corresponding MNP-WS model specifications. CP values for cut-off parameters in MNP-CI are slightly lower than those of CI parameters – around 0.89 for the four-attribute and 0.77 for the six-attribute scenario (see Figure 2.5b). Whereas these CP values are marginally higher for the MNP-CI model as compared to the MNP-WS model for the four-attribute scenario, MNP-WS marginally outperforms MNP-CI for the six-attribute scenario (around 0.77 vs. 0.84). This trend can be attributed to more complex interaction effects in the six-attribute scenario. Finally, Figure 2.5c shows that CP for error-covariance parameters is excellent for both MNP-CI and MNP-WS with an average CP of 0.98 and 0.90, respectively. This result suggests that relatively larger SDMAE values of MNP-CI for error-covariance parameters in CIC-FE configuration are not concerning. Overall, the Monte Carlo simulation suggests that the statistical properties of the MNP-CI estimator are comparable to that of MNP-WS.

Figure 2.5d shows the estimation time for all four model configurations (IID: model with no attribute cut-off and IID error structure, C-IID: model with attribute cut-off and IID error structure, C-DE: model with attribute cut-off and diagonal error structure, and C-FE: model with attribute cut-off and full error covariance). All the models were estimated on a 16-core machine using a multithreading module using Python language. The estimation time for the WS and CI-based MNP models is comparable. For a 6-attribute configuration, the CI-based model is slightly faster than the corresponding WS model.

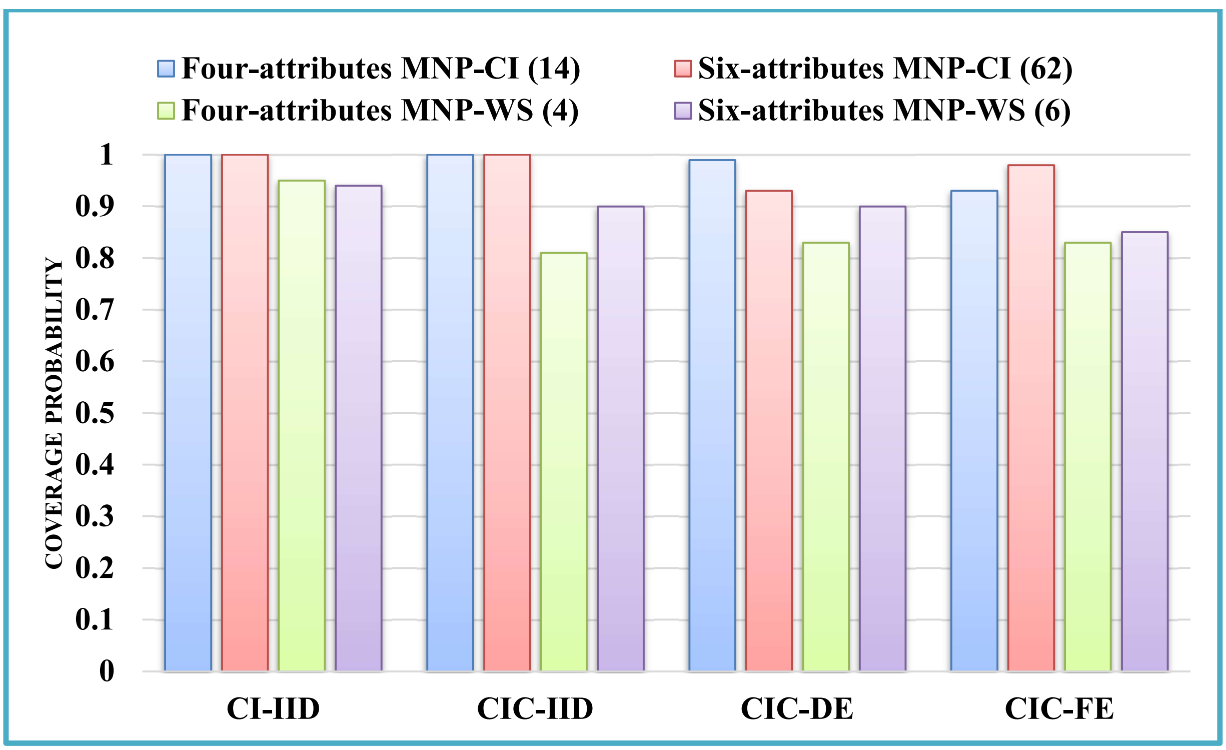

Figure 2.5a: Coverage probability for fuzzy-measures/mean-effect parameters in MNP-CI and MNP-WS models

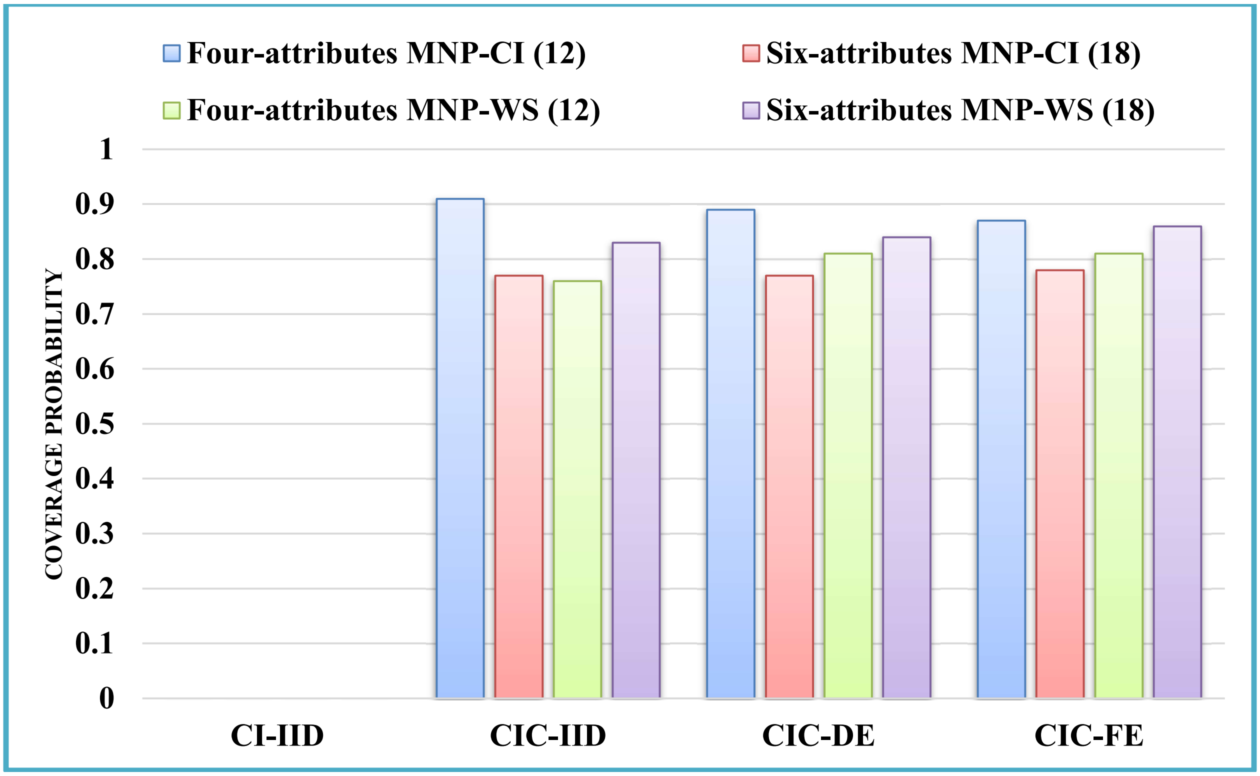

Figure 2.5b: Coverage probability for cut-off parameters in MNP-CI and MNP-WS models

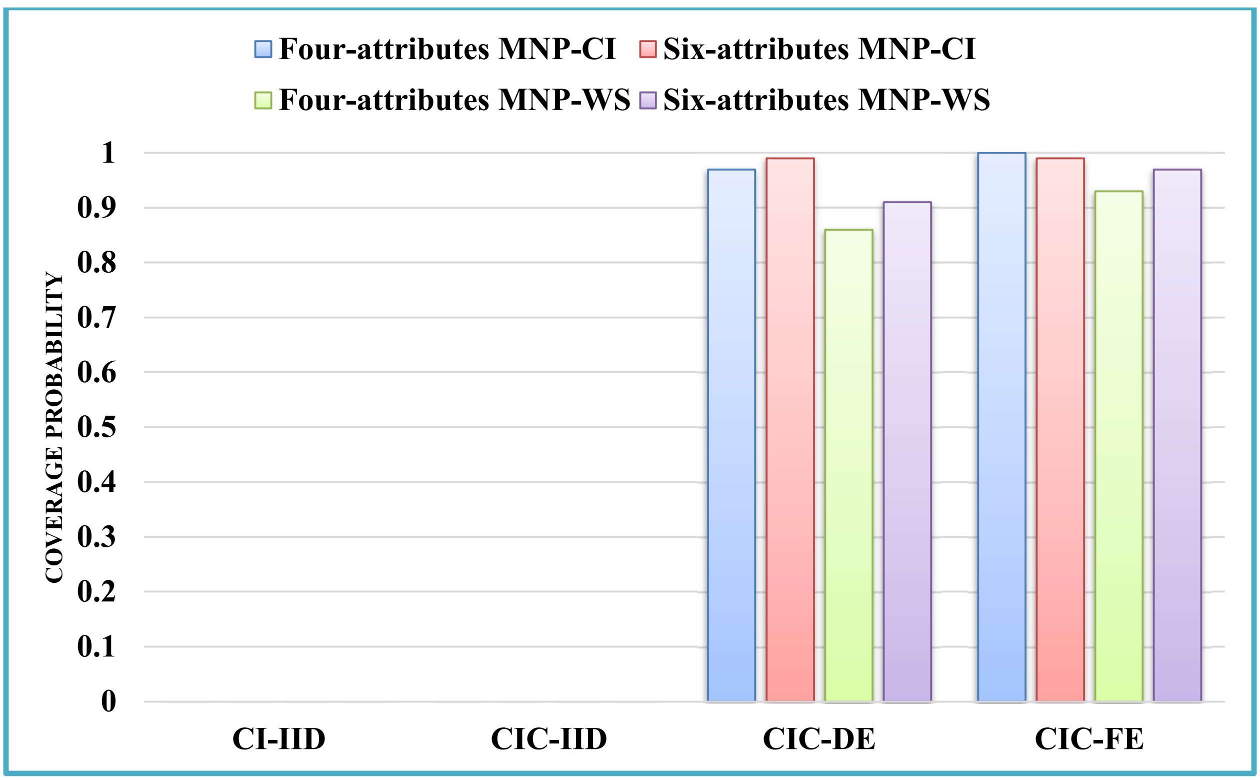

Figure 2.5c: Coverage probability for error-covariance parameters in MNP-CI and MNP-WS models

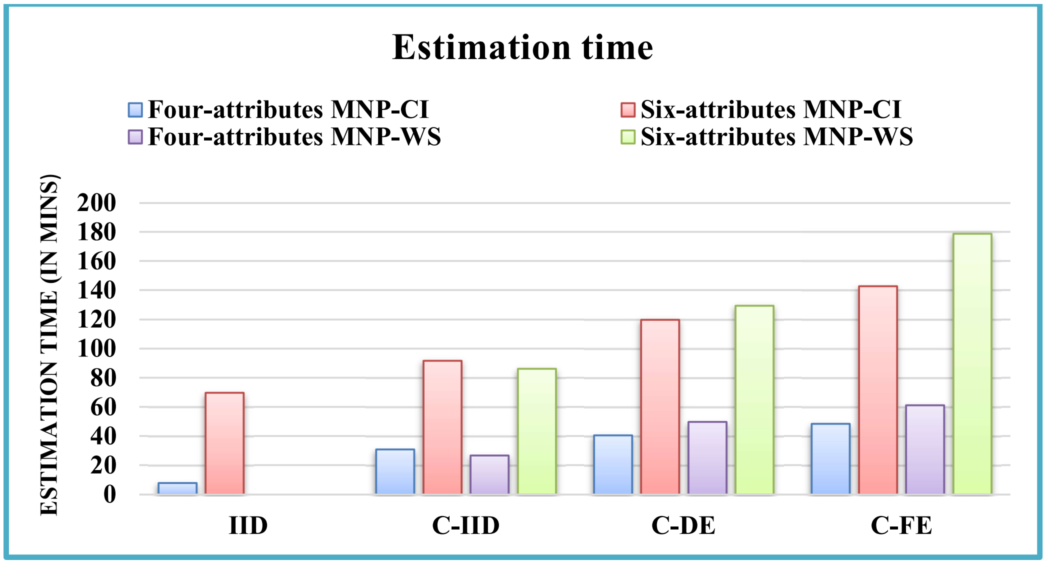

Figure 2.5d: Estimation time for various models

2.3.3 Assessing the Generality of the MNP-CI Model

So far, we have estimated models that are consistent with the DGP. In this section, we assess the ability of MNP-CI to recover the underlying behavioural process when the true DGP follows MNP-WS specification and vice-versa. We expect that MNP-CI should be able to replicate the weighted attribute aggregation behaviour (MNP-WS) because the weighted sum is a special case of CI, but not vice versa. Conditional on the validity of our hypothesis, these simulation results will make a strong case to replace the weighted sum utility function with CI in empirical applications.

We consider two simulation studies. In the first study, we generate data using MNP-CI specification and then estimate both MNP-WS and MNP-CI models. In the second study, the DGP follows the MNP-WS specification, and both models are estimated. Specifically, we use the four-attribute CIC-FE (with cut-offs and full-error structure) specification in both DGPs as well as estimation. MNP-CI and MNP-WS only differ in terms of the aggregation function. We ignore interaction effects in the MNP-WS estimation and the DGP of the second simulation study (i.e., the systematic utility of MNP-WS has four mean effects). Since MNP-WS and MNP-CI cannot be compared in terms of parameters, we evaluate statistical differences in terms of Akaike information criterion (AIC) values at convergence and the marginal effect values. We perform this comparison for 100 datasets. For marginal effect comparison, we obtain the average change in probability of choosing an alternative due to changing the four attributes by -25%, -20%, -28%, and 25% (one attribute at a time), and conduct a t-test to compare marginal effects of MNP-WS and MNP-CI.

Whereas marginal effects of both simulation studies are provided in Tables S.2.2.1 and S.2.2.2 (Section S.2.2) of supplement-2, Table 2.2 presents the t-test results for both simulation studies. Whereas most t-statistic values are above 1.96 in the first simulation study (when the DGP is MNP-CI), they are below 1.96 in the second simulation study. This result implies that MNP-CI can reproduce the marginal effect values of the MNP-WS model when the DGP follows the latter specification. However, MNP-WS fails to do so when the DGP follows the MNP-CI specification.

The average AIC values for MNP-WS and MNP-CI across 50 datasets are 8991.90 and 8778.74 in the first study, and 8727.79 and 8792.83 in the second study. On average, the MNP-CI model outperforms the MNP-WS model when the true DGP is based on the CI function. Conversely, the difference between MNP-WS and MNP-CI is not substantial when the true DGP is based on the WS function. These findings suggest that MNP-WS may not provide acceptable results when the underlying DGP follows MNP-CI specification, but MNP-CI can recover the underlying weighted-sum DGP.

In sum, Monte Carlo studies establish statistical properties of the MNP-CI model. They also illustrate how MNP-CI can nest MNP-WS and recover flexible substitution patterns and semi-compensatory behaviour through attribute cut-offs. MNP-CI thus has all the characteristics to become a workhorse model in discrete choice modelling literature.

Table 2.2: T-statistics for marginal effect difference between MNP-CI and MNP-WS

Variable	Quantile	When DGP follows MNP-CI					When DGP follows MNP-WS				
		Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5
1	0.10	4.21	4.55	3.99	3.96	4.02	0.77	1.09	0.67	0.34	0.60
1	0.20	4.15	4.15	3.82	3.87	3.82	0.62	0.97	0.45	0.20	0.39
1	0.30	3.97	3.95	3.74	3.80	3.91	0.45	0.91	0.27	0.02	0.20
1	0.40	3.78	3.92	3.57	3.59	3.86	0.28	0.90	0.14	0.14	0.08
1	0.50	3.66	3.71	3.47	3.46	3.76	0.15	0.89	0.03	0.19	0.00
1	0.60	3.53	3.59	3.35	3.37	3.58	0.02	0.90	0.02	0.22	0.04
1	0.70	3.47	3.55	3.19	3.25	3.47	0.07	0.88	0.07	0.25	0.09
1	0.80	3.44	3.46	3.09	3.16	3.40	0.09	0.90	0.14	0.29	0.12
1	0.90	3.36	3.41	3.01	3.11	3.33	0.16	0.90	0.15	0.31	0.16
1	0.99	3.28	3.38	2.95	3.07	3.23	0.19	0.90	0.18	0.32	0.18
2	0.10	3.84	4.22	3.37	3.46	3.98	0.18	0.63	0.00	0.04	0.14
2	0.20	3.89	4.18	3.35	3.50	3.95	0.07	0.46	0.12	0.03	0.07
2	0.30	3.98	4.16	3.35	3.56	3.95	0.03	0.41	0.16	0.10	0.02
2	0.40	3.92	4.04	3.37	3.63	3.94	0.12	0.35	0.22	0.18	0.10
2	0.50	3.91	4.03	3.35	3.68	3.92	0.17	0.28	0.24	0.23	0.16
2	0.60	3.94	4.05	3.34	3.75	3.94	0.22	0.25	0.29	0.27	0.21
2	0.70	3.94	4.04	3.38	3.75	3.91	0.25	0.21	0.32	0.32	0.23
2	0.80	3.94	4.02	3.37	3.75	3.90	0.28	0.17	0.35	0.34	0.27
2	0.90	3.95	3.99	3.39	3.74	3.90	0.31	0.13	0.36	0.38	0.30
2	0.99	3.92	3.99	3.41	3.76	3.89	0.35	0.10	0.39	0.39	0.32
3	0.10	5.24	5.14	4.61	4.52	4.67	0.07	0.45	0.26	0.40	0.30
3	0.20	4.91	4.80	4.57	4.35	4.48	0.20	0.46	0.41	0.51	0.42
3	0.30	4.70	4.81	4.23	4.23	4.36	0.36	0.45	0.46	0.56	0.55
3	0.40	4.45	4.74	4.32	4.07	4.19	0.41	0.43	0.49	0.58	0.58
3	0.50	4.39	4.70	4.13	3.95	4.19	0.50	0.44	0.51	0.61	0.62
3	0.60	4.27	4.66	4.00	3.84	4.12	0.54	0.42	0.53	0.64	0.64
3	0.70	4.16	4.53	3.95	3.78	3.99	0.57	0.43	0.55	0.64	0.65
3	0.80	4.10	4.46	3.82	3.80	3.91	0.60	0.42	0.56	0.66	0.68
3	0.90	4.03	4.41	3.79	3.72	3.92	0.61	0.41	0.58	0.66	0.68
3	0.99	3.95	4.36	3.64	3.69	3.87	0.62	0.39	0.58	0.67	0.69
4	0.10	4.86	5.44	4.18	3.99	4.04	0.59	0.77	0.37	0.48	0.54
4	0.20	4.79	5.25	4.14	4.20	3.94	0.40	0.65	0.27	0.31	0.37
4	0.30	4.63	5.22	4.06	4.10	3.98	0.29	0.55	0.19	0.18	0.26
4	0.40	4.47	5.18	3.99	4.09	4.02	0.19	0.50	0.13	0.14	0.17
4	0.50	4.51	5.20	4.10	4.13	4.05	0.14	0.45	0.08	0.11	0.12
4	0.60	4.50	5.17	4.10	4.14	4.07	0.11	0.40	0.06	0.07	0.07
4	0.70	4.49	5.16	4.09	4.12	4.03	0.08	0.38	0.04	0.05	0.05
4	0.80	4.45	5.13	4.08	4.13	4.03	0.07	0.35	0.02	0.03	0.03
4	0.90	4.41	5.05	4.05	4.15	4.08	0.04	0.32	0.00	0.01	0.01
4	0.99	4.41	5.04	4.03	4.15	4.08	0.02	0.31	0.01	0.00	0.00

2.4 Empirical Application

2.4.1 Data Description

For the empirical application, we use data from a travel mode choice experiment conducted by Liu et al. (2019) in October-November 2017. New Yorkers were asked to choose from three travel modes on the most frequent trip in a discrete choice experiment: i) current travel mode (car or public transport), ii) single-occupancy mobility-on-demand (MoD) service (e.g. Uber), and iii) shared MoD service (e.g. Uberpool). Respondents chose an alternative based on six attributes – out-of-vehicle time (OVTT), in-vehicle travel time (IVTT), trip cost, parking cost, powertrain (gas or electric), and automation availability. The final sample included 1507 respondents with each respondent completing seven choice tasks. Readers are referred to Section 2.1 of Liu et al. (2019) for a detailed discussion on attribute level selection and design of the choice experiment.

2.4.2 Results & Discussion

We estimate five MNP-CI specifications with full error-covariance structure – i) generic CI with no attribute cut-offs (CI-NAC), ii) generic CI with constant only attribute cut-offs (CI-CAC), iii) generic CI with parameterised generic attribute cut-offs as a function of respondent's characteristics (CI-GAC), iv) generic CI with parameterised alternative-specific attribute cut-offs as a function of respondent's characteristics (CI-AGAC), and v) alternative-specific CI with parameterised alternative-specific attribute cut-offs as a function of respondent's characteristics (ACI-AGAC). Note that ACI-AGAC is the application of the extended alternative-specific MNP-CI model (as discussed in Section 2.2.4.1). We introduce flexibility in attribute cut-off representation in a sequential manner to disentangle the contribution of pure CI-based specification and a variety of attribute cut-off specifications towards goodness of fit statistics (i.e., loglikelihood at convergence).

The indirect utility of all the estimated models has two components. Whereas the weighted sum component includes alternative-specific constants (ASCs), an electric powertrain dummy, and an automation dummy, the CI component includes in-vehicle travel time per km (IVTT/Km), out-of-vehicle travel time per km (OVTT/Km) and cost per km (Cost/Km). While combining weighted sum and CI components in the systematic utility, an estimable factor is multiplied with the CI component to adjust for scale differences between the two components (Tehrani et al., 2012). The estimated scale factor in our analysis turns out to be statistically indifferent from 1 at a 0.1 significance level, and therefore, set to 1 in all specifications.

The parameter estimates for the weighted sum component are presented in Table 2.3. By considering the current travel mode as the base, ASCs are estimated for both Uber and Uberpool and found to be statistically significant. In all model specifications, the marginal utilities of electric powertrain and automation dummies are negative and statistically significant. Consistent with Liu et al. (2019), these results suggest that New Yorkers have higher preferences for non-electric and non-automated MoD services.

Table 2.3: Parameter estimates in the weighted sum component of the indirect utility (T-statistic in parenthesis)

Travel Mode	Covariates	CI-NAC	CI-CAC	CI-GAC	CI-AGAC	ACI-AGAC
Uber	Constant	-0.381(-5.8)	-0.440(-10.4)	-0.432(-10.5)	-0.404(-8.3)	-0.406(-7.7)
	Electric	-0.045(-1.3)	-0.054(-1.7)	-0.044(-1.4)	-0.063(-2.0)	-0.057(-1.8)
	Automated	-0.117(-3.4)	-0.099(-3.0)	-0.089(-2.7)	-0.113(-3.4)	-0.110(-3.2)
Uberpool	Constant	-0.621(-8.0)	-0.424(-9.9)	-0.572(-11.7)	-0.487(-9.5)	-0.516(-8.9)
	Electric	-0.068(-2.4)	-0.029(-1.7)	-0.042(-1.9)	-0.027(-1.2)	-0.033(-1.5)
	Automated	-0.011(-0.3)	-0.049(-2.6)	-0.064(-2.6)	-0.058(-2.4)	-0.052(-2.2)

Note: current travel model is base.

Further, in all the estimated models, we consider a full error-covariance structure, with a traditional MNP identification strategy – only the difference of error-covariance matrix is estimable, and the top-left element is normalised to 1 (see section A.2.4.2 of Appendix A.2 for a detailed discussion). The estimated differenced (and normalised) error covariance matrices are presented in Table 2.4. The results indicate that errors are correlated[5], and, thus accounting for flexible substitution patterns is crucial to obtain correct elasticity estimates.

Table 2.4: The estimated differenced error-covariance for various models (t-statistics in parenthesis)

Model	Error-covariance
Generic CI with no attribute cut-offs (**CI-NAC**)	$\begin{bmatrix} 1.00\ (\text{fixed}) & \\ -0.041\ (-1.28) & 0.697\ (6.69) \end{bmatrix}$
Generic CI with generic constant only attribute cut-offs (**CI-CAC**)	$\begin{bmatrix} 1.00\ (\text{fixed}) & \\ -0.406\ (-4.50) & 0.284\ (5.40) \end{bmatrix}$
Generic CI with generic demographics-based attribute cut-offs (**CI-GAC**)	$\begin{bmatrix} 1.00\ (\text{fixed}) & \\ -0.602\ (-7.61) & 0.513\ (6.29) \end{bmatrix}$
Generic CI with alternative-specific demographics-based attribute cut-offs (**CI-AGAC**)	$\begin{bmatrix} 1.00\ (\text{fixed}) & \\ -0.572\ (-7.81) & 0.479\ (6.05) \end{bmatrix}$
Alternative-specific CI with alternative-specific demographics-based cut-offs (**ACI-AGAC**)	$\begin{bmatrix} 1.00\ (\text{fixed}) & \\ -0.590\ (-7.40) & 0.489\ (6.01) \end{bmatrix}$

2.4.2.1 Shapley Values and Interaction Indices

We focus on three variables that are included in the CI component of the utility. We do not discuss the estimated fuzzy measures here due to lack of interpretability (but are available in Table S.2.3.1

[5] The diagonal and off-diagonal elements of differenced independent and identically distributed (IID) error-structure covariance are 1 and 0.5, respectively. This matrix is equivalent to an identity matrix in un-differenced form.

in Section S.2.3 of supplement-2). Instead, the resulting Shapley values and interaction indices are presented in Table 2.5 and are discussed in detail. Three interesting trends can be observed in the Shapley values across different model specifications. First, Cost/Km is the most important variable (from the respondent's point of view), followed by OVTT/Km and IVTT/Km. This result is consistent with the literature, as cost and OVTT are reported to be the two main determinants of mode choice (Gang, 2007; Xie et al., 2019; Dong, 2020). Shapley values are empirically advantageous to determine such rankings directly, without having to calculate the marginal effect values. Second, as we start to increase the degrees of freedom in MNP-CI through attribute cut-offs, we observe that the attribute ranking remains the same, but IVTT/Km becomes less important (i.e., lower Shapley value) in explaining an individual's choice. Third, results of the alternative-specific MNP-CI specification (ACI-AGAC) suggest that the distance between OVTT/Km and IVTT/Km is more pronounced for the current travel mode than Uber and Uberpool. Close Shapley values indicate that OVTT and IVTT play a similar role in determining travellers' preferences for MoD services.

The interaction indices also exhibit two interesting trends. First, in the absence of attribute cut-offs, all the pairs have a positive interaction index. Second, as we introduce attribute cut-offs, only OVTT/Km and Cost/Km exhibit a significant complementarity effect. Thus, a comparison of both Shapley values and interaction indices between CI-NAC and specifications with attribute cut-offs highlights the importance of accounting for the semi-compensatory behaviour, taste heterogeneity, and alternative-specific effects to correctly identify the importance attached to attributes by the decision-maker in the decision process.

Table 2.5: Shapley values and interaction indices in the empirical study

Variables	CI-NAC	CI-CAC	CI-GAC	CI-AGAC	ACI-AGAC	
	All modes	All modes	All modes	All modes	Current mode	Uber and Uberpool
	Shapley values					
IVTT/Km	0.207	0.117	0.114	0.125	0.130	0.206
OVTT/Km	0.284	0.319	0.282	0.336	0.347	0.265
Cost/Km	0.509	0.564	0.604	0.539	0.523	0.529
	Interaction Indices					
IVTT/Km, OVTT/Km	0.182	-0.034	-0.029	0.093	0.122	0.046
IVTT/Km, Cost/Km	0.124	0.106	0.045	-0.093	-0.122	0.033
OVTT/Km, Cost/Km	0.068	0.223	0.228	0.328	0.306	0.270

2.4.2.2 Attribute Cut-off Values

Next, we turn our attention to attribute cut-off values. Since all three variables are likely to cause disutility with an increase in their values, we employ two-point half-triangular cut-offs for all three variables (see Figure 2.1 in Section 2.2.4.2). First, in the constant-only attribute cut-off model (i.e. CI-CAC), the lower and upper thresholds for IVTT/Km are 2.17 and 5.75. This result suggests that the lowest and the highest disutility induced by IVTT/km can be computed by plugging 2.17 and 5.75 values for IVTT/km in CI. Specifically, the normalised IVTT/km value becomes zero when the true IVTT/km is 5.75, and thus, its contribution to CI is 0 (i.e., maximum disutility) for all IVTT/km values above 5.75. The thresholds for OVTT/Km [1.29, 5.71] and Cost/Km [0.07, 2.15] can be interpreted in a similar fashion.

When we parameterise the attribute cut-offs as a function of socio-demographic variables in CI-GAC specification, we obtain several interesting findings regarding the heterogeneity in thresholds on Cost/km (see Table 2.6). First, households with annual income below 125 thousand dollars have a smaller upper threshold for Cost/Km as compared to higher-income households, everything else being constant. Second, older males have a lower upper threshold on Cost/Km as compared to younger females, when controlling for income and distance to transit stops. Considering that the lower threshold is the same for both demographic groups, this result implies that the marginal effect of Cost/Km is much higher for older males compared to that for younger females.

Similarly, we observe several interesting relations between socio-demographics and OVTT/Km thresholds. First, households living within a 0.5 km radius of the bus stop or subway have a higher threshold for OVTT/Km. Second, males tend to be slightly less patient than females when it comes to OVTT/Km. This result is consistent with the findings of Dittrich and Leopold (2014). Finally, people tend to get impatient with walking and waiting time as they get older, possibly because younger people can better utilize OVTT via mobile phones and tablets.

Table 2.7 shows the sampling distribution of attribute cut-off values for the CI-GAC specification, which are obtained by transforming the estimates reported in Table 6. It is worth noting that the lower cut-off is always kept constant and the upper cut-off is parameterised by demographics to ensure that the upper cut-off is always greater than the lower cut-off. Since we did not find any statistically significant cut-off heterogeneity for IVTT/Km, its cut-off values are kept constant across respondents. While there is a substantial variation in thresholds for OVTT/Km and Cost/Km in CI-GAC specification, median values are close to the one obtained by CI-CAC specification.

Finally, we allow the attribute cut-off values to be alternative-specific in the CI-AGAC and ACI-AGAC specification and capture heterogeneity in alternative-specific cut-offs across different socio-demographic groups. We do not discuss the heterogeneity results of CI-AGAC and ACI-AGAC in detail here as they are intuitive and are consistent with those of CI-GAC specification (i.e., the one with generic attribute cut-offs). They are available in Table S.2.3.2 to S.2.3.7 in Section S.2.3 of supplement-2. We note that preference ranges for attributes vary substantially across alternatives (see Table S.2.3.8 to S.2.3.13 in Section S.2.3 of supplement-2). For example, in contrast to generic lower and upper thresholds of {1.33, 3.96} for IVTT/Km in CI-GAC specification, these values for current travel mode, Uber and Uberpool are {3.03, 3.53}, {0.85, 5.19}, and {0.52, 8.37} in ACI-AGAC specification, respectively.

Table 2.6: Attribute cut-off heterogeneity in the CI-GAC model (T-statistic in parenthesis)

Explanatory variables		**IVTT/Km**		**OVTT/Km**		**Cost/Km**	
		Lower Cut-off	**Upper Cut-off**	**Lower Cut-off**	**Upper Cut-off**	**Lower Cut-off**	**Upper Cut-off**
	Constant	0.29 (1.0)	0.97 (3.9)	0.44 (10.8)	1.77 (16.5)	-1.73 (-6.1)	1.2 (24)
Household income * travel distance (in USD * km) [Base: >125K]	(<=50K) * distance						-0.28 (-4.9)
	(> 50K & <=125K) * distance						-0.25 (-4.8)
Distance to Bus stop (in km) [Base: ≤ 0.5]	(> 0.5 & ≤ 1)				-1.42 (-5.7)		
	(> 1 & ≤ 2)				-0.35 (-1.5)		
	(> 2)				-0.35 (-1.5)		
Distance to subway (in km) [Base: ≤ 0.5]	(> 0.5 & ≤ 1)				-0.3 (-2.1)		
	(> 1 & ≤ 2)				-1.97 (-5.2)		
	(> 2)				-1.17 (-5.3)		
Male					-0.23 (-1.9)		-0.16 (-2.5)
Years since owing a driver's license					0.01 (1.5)		
Age (in years) [Base: 23 – 38]	Age (7 - 22)				1.09 (5.4)		
	Age (39 - 54)						-0.56 (-8.2)
	Age (55 - 73)				-0.6 (-2.0)		-0.98 (-9.6)

Table 2.7: Distribution of attribute cut-off for generic CI with demographics-based attribute cut-offs (CI-GAC model)

Percentile	IVTT/Km		OVTT/Km		Cost/Km	
	Lower Cut-off	Upper Cut-off	Lower Cut-off	Upper Cut-off	Lower Cut-off	Upper Cut-off
10	1.33	3.96	1.55	2.44	0.18	1.24
20	1.33	3.96	1.55	2.94	0.18	1.57
30	1.33	3.96	1.55	4.07	0.18	1.80
40	1.33	3.96	1.55	5.68	0.18	2.08
50	1.33	3.96	1.55	6.31	0.18	2.51
60	1.33	3.96	1.55	7.13	0.18	2.77
70	1.33	3.96	1.55	7.44	0.18	2.99
80	1.33	3.96	1.55	8.10	0.18	3.11
90	1.33	3.96	1.55	9.06	0.18	3.34
95	1.33	3.96	1.55	11.44	0.18	3.50
99	1.33	3.96	1.55	11.85	0.18	3.50
100	1.33	3.96	1.55	12.47	0.18	3.50

2.4.2.3 Marginal Effects

We compare the marginal effects (change of probability) obtained by the CI-NAC and the ACI-AGAC specifications for scenarios where one aspect of the MoD service quality is improved at a time. Table 2.8 provides the sampling distribution of change in the probability of choosing all three options when the IVTT/Km is reduced by 10% for both Uber and Uberpool. The change in probability implied by the CI-NAC specification is higher in magnitude as compared to the ACI-AGAC model at almost every percentile point. This trend is in line with expectations because attribute cut-offs moderate the change in the value of the variable through preference ranges depending upon the demographics. Thus, the difference between the policy implications of CI-NAC and ACI-AGAC specifications is considerable.

Table 2.8: Change in probability due to a 10% decrease in IVTT/Km of Uber and Uberpool

Percentile	Current Mode		Uber		Uberpool	
	CI-NAC	ACI-AGAC	CI-NAC	ACI-AGAC	CI-NAC	ACI-AGAC
10	-0.0141	-0.0119	0	0	0	0
20	-0.0103	-0.0064	0	0	0	0
30	-0.0084	-0.0011	0	0	0	0
40	-0.0073	0	0	0	0	0
50	-0.0052	0	0	0	0	0
60	-0.0035	0	0	0	0	0
70	0	0	0.0042	0	0.0041	0
80	0	0	0.0095	0	0.0075	0.0049
90	0	0	0.0131	0	0.0143	0.0089
95	0	0	0.0193	0.0137	0.0183	0.0123
99	0	0	0.0318	0.0362	0.0380	0.0197
100	0	0	0.0608	0.1675	0.0656	0.0636

2.4.2.4 Goodness-of-fit Statistics

We also evaluate whether increasing the flexibility in attribute cut-off specification translates into better goodness of fit by providing the log-likelihood and Akaike information criterion (AIC) values for all models in Table 2.9. The results show that the ACI-AGAC specification has the lowest AIC value, demonstrating the significance of considering alternative-specific preference heterogeneity (parameterised attribute cut-offs) and alternative-specific importance of attributes (Choquet parameters). However, the difference between CI-AGAC and ACI-AGAC models is marginal (3-point difference in AIC statistics). It suggests that for the current dataset, alternative-specific preference heterogeneity (i.e., attribute cut-offs) is much more dominant in explaining the choices than alternative-specific attribute ranking (i.e., CI). Another interesting observation is that the AIC value of the CI-CAC model is substantially higher than that of the CI-NAC model (a difference of 44 points). It indicates that imposing a constant preference range for all respondents leads to worse goodness-of-fit than the one with no attribute cut-offs. Further, to benchmark the MNP-CI model against the traditional MNP-WS model, we also estimate two MNP-WS specifications with and without interactions between attributes (see Table S.2.3.14 in Section S.2.3 of the supplement-2 for the results of MNP-WS). Both MNP-WS specifications have lower loglikelihood and higher AIC values than all considered MNP-CI specifications. It is worth acknowledging that the MNP-WS model with attribute cut-offs is not presented because its estimation encountered numerical issues.

Table 2.9: Comparison of goodness-of-fit statistics across the model

Model	Log-likelihood at convergence	Number of parameters	AIC
Generic CI with no attribute cut-offs (**CI-NAC**)	-8736.36	15	17502.72
Generic CI with generic constant only attribute cut-offs (**CI-CAC**)	-8752.09	21	17546.18
Generic CI with generic demographics-based attribute cut-offs (**CI-GAC**)	-8662.06	34	17392.12
Generic CI with alternative-specific demographics-based attribute cut-offs (**CI-AGAC**)	-8521.05	49	17140.10
Alternative-specific CI with an alternative- specific demographics-based cut-offs (**ACI-AGAC**)	-8511.71	57	17137.42
MNP-WS model with **no interactions**, non-IID error structure and no cut-offs	-8995.90	11	18013.80
MNP-WS model with **all interactions**, non-IID error structure and no cut-offs	-8812.60	15	17655.20

2.5 Conclusion and Future Works

We present an extension of the multinomial probit (MNP) model where the systematic part of the indirect utility is modelled using the Choquet integral (CI). CI is an appropriate aggregation function as it can flexibly capture attribute interactions while ensuring monotonicity in attribute values and the number of attributes. We further advance the MNP-CI model to account for semi-compensatory behaviour by specifying individual-specific attribute cut-offs through fuzzy membership functions parameterised by demographics. Thus, the proposed MNP-CI model with attribute cut-offs can simultaneously capture: (i) attribute-level evaluation by the decision-maker and heterogeneity in evaluation across socio-demographic groups, (ii) theory-driven flexible aggregation of attributes in the systematic utility, and (iii) unrestricted substitution patterns.

We estimate the proposed model using a constrained maximum likelihood estimator. A comprehensive Monte Carlo study is performed to establish the statistical properties of the estimator. In another simulation study, we demonstrate the generality of the MNP-CI model by showing that it nests the traditional MNP model with weighted-sum utility. The empirical advantages of the proposed model are illustrated in a travel mode choice study that focuses on understanding the preferences of New Yorkers to shift from the current travel model to on-demand mobility.

The MNP-CI model with attribute cut-offs offers several insights. First, the analyst can elicit semi-compensatory choice behaviour using datasets from traditional choice experiments. Second, the estimation of MNP-CI provides the Shapley values of attributes, which translate into attribute importance ranking. Moreover, interaction indices are also a by-product of the MNP-CI estimation that helps in identifying whether simultaneous information on a set of attributes is more meaningful for the decision-maker in making a choice. The complementarity between pairs of attributes coupled with their individual importance ranking can help policymakers make informed decisions to improve the preference level of an alternative. In sum, we make a convincing case for the MNP-CI model with attribute cut-offs to become a workhorse model in the discrete choice analysis. The generality and monotonicity of the CI function make the case stronger. This work will spark the interest of researchers to explore other fuzzy-integral-based aggregation functions, such as CI with bipolar scale (i.e., fuzzy measures range between -1 and 1) (Grabisch and Labreuche, 2005).

We discuss four main limitations or challenges of the proposed MNP-CI model (and the related fuzzy measures), which also open up avenues for future research. First, the traditional CI can only handle continuous attributes, but incorporating other attribute types, such as ordinal, categorical and count, is non-trivial. To address this challenge, we specify the observed part of the utility function as a combination of the weighted sum and CI function in our empirical study, where the continuous attributes are used in the CI function, and other attributes are used in the weighted sum function. Although this approach is practical, advancements in fuzzy integrals can be explored to automatically learn interactions between non-continuous attributes. For instance, Wang et al. (2006) proposed an approach to convert a mix of non-continuous variables (depending upon their observed scale or count value) into a number between 0 and 1 using a fuzzy logic alpha-cut approach. Such advanced methods to directly incorporate non-continuous variables in CI can be explored in future studies.

Second, we could capture systematic heterogeneity in attribute cut-offs and derive behavioural insights by parameterising cut-offs, but capturing unobserved taste heterogeneity through random parameters is not straightforward in MNP-CI. The non-additivity and constrained range (between 0 and 1) of the fuzzy measures make the use of random parameters challenging. Future research may introduce random heterogeneity into the attribute cut-off function, but this additional flexibility comes at the expense of high computation time because the estimation of the extended model will require another layer of simulation.

Third, the analyst needs to pre-determine the sign of the marginal utility of an attribute to apply the fuzzy membership function. This constraint could be challenging for studies with relatively new explanatory variables (e.g., new technologies such as automation). However, we think that CI with a bipolar scale could provide insights into selecting the type of membership function. In particular, the analyst can first estimate the MNP model with bipolar CI and no attribute cut-off to identify the sign of fuzzy measures. Subsequently, attributes can be assigned a fuzzy membership function according to the direction of fuzzy measures in the first step.

Fourth, we have illustrated that the proposed MNP-CI model with attribute cut-offs has good statistical properties for four and six attributes. However, these properties might deteriorate for a large number of attributes due to a steep increase in the number of parameters and constraints. Whereas most empirical studies have six or fewer attributes, and there is a flexibility to include more control variables in the weighted-sum component, future studies need to explore scalable fuzzy measures to ensure their broader and seamless applicability in discrete choice analysis. Readers are referred to recent advancements by Beliakov and Wu (2019) and Beliakov and Divakov (2020), who propose new methods to control the rate of increase in the number of parameters and constraints with the number of attributes.

Appendix-2

A.2.1 Example of CI computation

As an illustration, we show how to calculate CI for a case of three attributes.

Let $\boldsymbol{X} = \{x_1, x_2, x_3\}$.I.e, $G = 3$

Further, discrete fuzzy measures have the following configuration:

$$\mu(\phi)=0;\ \mu(x_1)=0.2;\ \mu(x_2)=0.3;\ \mu(x_3)=0.1;$$
$$\mu(x_1x_2)=0.687;\ \mu(x_1x_3)=0.362;\ \mu(x_2x_3)=0.493;$$
$$\mu(x_1x_2x_3)=1$$

Next, the observed value of three attributes is as follow: $\{x_1 = 0.3, x_2 = 0.1, x_3 = 1\}$.

We observe that $x_3 > x_1 > x_2$

Therefore $h(x_{\pi_1}) = x_3$ $h(x_{\pi_2}) = x_1$ $h(x_{\pi_3}) = x_2$ and

$A_0 = \phi$ $A_1 = \{x_3\}$ $A_2 = \{x_3, x_1\}$ $A_3 = \{x_3, x_1, x_2\}$. Thus,

$$\begin{aligned}CI &= h(x_{\pi_1})(\mu(A_1)-\mu(A_0)) + h(x_{\pi_2})(\mu(A_2)-\mu(A_1)) + h(x_{\pi_3})(\mu(A_3)-\mu(A_2))\\ &= x_3(\mu(x_3)-\mu(\phi)) + x_1(\mu(x_3x_1)-\mu(x_3)) + x_2(\mu(x_3x_1x_2)-\mu(x_3x_1))\\ &= 1(0.1-0)+0.3(0.362-0.1)+0.1(1-0.362)\\ &= 0.242\end{aligned}$$

A.2.2 Functions Nested by Choquet Integral

A.2.2.1 Choquet Integral as Weighted Sum:

Calculation of Choquet Integral when fuzzy measures are additive

Let $\boldsymbol{X} = \{x_1, x_2, x_3\}$ and $\mu(ab) = \mu(a) + \mu(b)$ (i.e, they are additive)

$\mu(\phi)=0;\ \mu(x_1)=0.4;\ \mu(x_2)=0.45;\ \mu(x_3)=0.15;\ \mu(x_1x_2)=0.85;\ \mu(x_1x_3)=0.55;\ \mu(x_2x_3)=0.60$

Observed Value $\{x_1 = 0.3, x_2 = 0.1, x_3 = 1\}$

Here $x_3 > x_1 > x_2$

So, $h(x_{\pi_1}) = x_3; h(x_{\pi_2}) = x_1; h(x_{\pi_3}) = x_2$

$A_0 = \phi$ $A_1 = \{x_3\}$ $A_2 = \{x_3, x_1\}$ $A_3 = \{x_3, x_1, x_2\}$

$$\begin{aligned}CI &= \pi_1(\mu(A_1)-\mu(A_0)) + \pi_2(\mu(A_2)-\mu(A_1)) + \pi_3(\mu(A_3)-\mu(A_2))\\ &= x_3(\mu(x_3)-\mu(\phi)) + x_1(\mu(x_3,x_1)-\mu(x_3)) + x_2(\mu(x_3,x_1,x_2)-\mu(x_3,x_1))\\ &= 1(0.15-0)+0.3(0.55-0.15)+0.1(1-0.55)\\ &= 0.315\end{aligned}$$

Calculation of weighted sum using additive fuzzy measure weights

Let $\boldsymbol{X} = \{x_1, x_2, x_3\}$ and $\mu(ab) = \mu(a) + \mu(b)$ (i.e, they are additive)

$\mu(\phi) = 0;\ \mu(x_1) = 0.4;\ \mu(x_2) = 0.45;\ \mu(x_3) = 0.15;\ \mu(x_1x_2) = 0.85;\ \mu(x_1x_3) = 0.55;\ \mu(x_2x_3) = 0.60$

Observed Value $\{x_1 = 0.3, x_2 = 0.1, x_3 = 1\}$

$$
\begin{aligned}
WS &= x_1\mu(x_1) + x_2\mu(x_2) + x_3\mu(x_3) \\
&= 0.3*0.4 + 0.1*0.45 + 1*0.15 \\
&= 0.315
\end{aligned}
$$

A.2.2.2 Choquet Integral as Ordered Weighted Sum (OWS):

Calculation of Choquet Integral when fuzzy measures are symmetric

Let $\boldsymbol{X} = \{x_1, x_2, x_3\}$ and $\mu(A) = f(|A|)$ (i.e, they are symmetric (function of cardinality of set))

Let's assume $\mu(A) = 0.333*(|A|)$

$\mu(\phi) = 0;\ \mu(x_1), \mu(x_2), \mu(x_3) = 0.333;\ ;\ \mu(x_1x_2), \mu(x_1x_3), \mu(x_2x_3) = 0.666;\ \mu(x_1x_2x_3) = 0.999$

Observed Value $\{x_1 = 0.3, x_2 = 0.1, x_3 = 1\}$

Here $x_3 > x_1 > x_2$

So, $h(x_{\pi_1}) = x_3; h(x_{\pi_2}) = x_1; h(x_{\pi_3}) = x_2$

$A_0 = \phi\ \ A_1 = \{x_3\}\ \ A_2 = \{x_3, x_1\}\ \ A_3 = \{x_3, x_1, x_2\}$

$$
\begin{aligned}
CI &= \pi_1(\mu(A_1) - \mu(A_0)) + \pi_2(\mu(A_2) - \mu(A_1)) + \pi_3(\mu(A_3) - \mu(A_2)) \\
&= x_3(\mu(x_3) - \mu(\phi)) + x_1(\mu(x_3, x_1) - \mu(x_3)) + x_2(\mu(x_3, x_1, x_2) - \mu(x_3, x_1)) \\
&= 1(0.333 - 0) + 0.3(0.666 - 0.333) + 0.1(0.999 - 0.666) \\
&= 0.4662
\end{aligned}
$$

Calculation of ordered weighted sum using symmetric fuzzy measure weights

Let $\boldsymbol{X} = \{x_1, x_2, x_3\}$ and $\mu(A) = f(|A|)$ (i.e, they are symmetric (function of cardinality of set))

Let's assume $\mu(A) = 0.333*(|A|)$

$\mu(\phi) = 0;\ \mu(x_1), \mu(x_2), \mu(x_3) = 0.333;\ ;\ \mu(x_1x_2), \mu(x_1x_3), \mu(x_2x_3) = 0.666;\ \mu(x_1x_2x_3) = 0.999$

Observed Value $\{x_1 = 0.3, x_2 = 0.1, x_3 = 1\}$

Here $x_3 > x_1 > x_2$

$$
\begin{aligned}
OWS &= x_3\mu(x_3) + x_1\mu(x_1) + x_2\mu(x_2) \\
&= 1(0.333) + 0.3(0.333) + 0.1(0.333) \\
&= 0.4662
\end{aligned}
$$

A.2.2.3 Choquet Integral as Minimum or Maximum of Attributes

Let $\boldsymbol{X} = \{x_1, x_2, x_3\}$

$\mu(\phi) = 0;\ \mu(x_1) = 0;\ \mu(x_2) = 0;\ \mu(x_3) = 1;\ \mu(x_1x_2) = 0;\ \mu(x_1x_3) = 1;\ \mu(x_2x_3) = 1; \mu(x_1x_2x_3) = 1$

The above configuration of fuzzy-measures are additive

Observed Value $\{x_1 = 0.3, x_2 = 0.1, x_3 = 1\}$

Here $x_3 > x_1 > x_2$

So, $h(x_{\pi_1}) = x_3; h(x_{\pi_2}) = x_1; h(x_{\pi_3}) = x_2$

$A_0 = \phi\ \ A_1 = \{x_3\}\ \ A_2 = \{x_3, x_1\}\ \ A_3 = \{x_3, x_1, x_2\}$

$$\begin{aligned}
CI &= \pi_1(\mu(A_1) - \mu(A_0)) + \pi_2(\mu(A_2) - \mu(A_1)) + \pi_3(\mu(A_3) - \mu(A_2)) \\
&= x_3(\mu(x_3) - \mu(\phi)) + x_1(\mu(x_3, x_1) - \mu(x_3)) + x_2(\mu(x_3, x_1, x_2) - \mu(x_3, x_1)) \\
&= 1(1-0) + 0.3(1-1) + 0.1(1-1) \\
&= 1\ (\text{Maximum of attributes})
\end{aligned}$$

Similarly,for the following configuration, we can obtain minimum of attributes

$\mu(\phi) = 0;\ \mu(x_1) = 0;\ \mu(x_2) = 1;\ \mu(x_3) = 0;\ \mu(x_1x_2) = 1;\ \mu(x_1x_3) = 0;\ \mu(x_2x_3) = 1; \mu(x_1x_2x_3) = 1$

$$\begin{aligned}
CI &= \pi_1(\mu(A_1) - \mu(A_0)) + \pi_2(\mu(A_2) - \mu(A_1)) + \pi_3(\mu(A_3) - \mu(A_2)) \\
&= x_3(\mu(x_3) - \mu(\phi)) + x_1(\mu(x_3, x_1) - \mu(x_3)) + x_2(\mu(x_3, x_1, x_2) - \mu(x_3, x_1)) \\
&= 1(0-0) + 0.3(0-0) + 0.1(1-0) \\
&= 0.1\ (\text{Minimum of attributes})
\end{aligned}$$

A.2.3 Example of Mapping between Möbius Transform and Fuzzy Measures

Consider there are 4 attributes $g = \{1,2,3,4\}$ and $\mu(.)$ and $m(.)$ represent the fuzzy measure and Möbius parameters, respectively. Then the equality and inequality constraints can be written using Möbius parameters (and their implied fuzzy measures conditions) as follow:

Equality constraint

$$\begin{aligned}
&m(1) + m(2) + m(3) + m(4) + m(12) + m(13) + m(14) + m(23) + m(24) + m(34) \\
&+ m(123) + m(124) + m(134) + m(234) + m(1234) = 1
\end{aligned}$$

This constraint implies that $\mu(1234) = 1$

Inequality constraints

$m(1) \geq 0$	$\mu(1) \geq 0$
$m(2) \geq 0$	$\mu(2) \geq 0$
$m(3) \geq 0$	$\mu(3) \geq 0$
$m(4) \geq 0$	$\mu(4) \geq 0$
$m(1) + m(12) \geq 0$	$\mu(12) - \mu(2) \geq 0$
$m(1) + m(13) \geq 0$	$\mu(13) - \mu(3) \geq 0$
$m(1) + m(14) \geq 0$	$\mu(14) - \mu(4) \geq 0$
$m(2) + m(12) \geq 0$	$\mu(12) - \mu(1) \geq 0$
$m(2) + m(23) \geq 0$	$\mu(23) - \mu(3) \geq 0$
$m(2) + m(24) \geq 0$	$\mu(24) - \mu(4) \geq 0$
$m(3) + m(13) \geq 0$	$\mu(13) - \mu(1) \geq 0$
$m(3) + m(23) \geq 0$	$\mu(23) - \mu(2) \geq 0$
$m(3) + m(34) \geq 0$	$\mu(34) - \mu(4) \geq 0$
$m(4) + m(14) \geq 0$	$\mu(14) - \mu(1) \geq 0$
$m(4) + m(24) \geq 0$	$\mu(24) - \mu(2) \geq 0$
$m(4) + m(34) \geq 0$	$\mu(34) - \mu(3) \geq 0$
$m(1) + m(12) + m(13) + m(123) \geq 0$	$\mu(123) - \mu(23) \geq 0$
$m(1) + m(12) + m(14) + m(124) \geq 0$	$\mu(124) - \mu(24) \geq 0$
$m(1) + m(13) + m(14) + m(134) \geq 0$	$\mu(134) - \mu(34) \geq 0$
$m(2) + m(12) + m(23) + m(123) \geq 0$	$\mu(123) - \mu(13) \geq 0$
$m(2) + m(12) + m(24) + m(124) \geq 0$	$\mu(124) - \mu(14) \geq 0$
$m(2) + m(23) + m(24) + m(234) \geq 0$	$\mu(234) - \mu(34) \geq 0$
$m(3) + m(13) + m(23) + m(123) \geq 0$	$\mu(123) - \mu(12) \geq 0$
$m(3) + m(13) + m(34) + m(134) \geq 0$	$\mu(134) - \mu(14) \geq 0$
$m(3) + m(23) + m(34) + m(234) \geq 0$	$\mu(234) - \mu(24) \geq 0$
$m(4) + m(14) + m(24) + m(124) \geq 0$	$\mu(124) - \mu(12) \geq 0$
$m(4) + m(14) + m(34) + m(134) \geq 0$	$\mu(134) - \mu(13) \geq 0$
$m(4) + m(24) + m(34) + m(234) \geq 0$	$\mu(234) - \mu(23) \geq 0$
$m(1) + m(12) + m(13) + m(123) + m(14) + m(124) + m(134) + m(1234) \geq 0$	$\mu(1234) - \mu(234) \geq 0$
$m(2) + m(12) + m(23) + m(123) + m(24) + m(124) + m(234) + m(1234) \geq 0$	$\mu(1234) - \mu(134) \geq 0$
$m(3) + m(13) + m(23) + m(123) + m(34) + m(134) + m(234) + m(1234) \geq 0$	$\mu(1234) - \mu(124) \geq 0$
$m(4) + m(14) + m(24) + m(124) + m(34) + m(134) + m(234) + m(1234) \geq 0$	$\mu(1234) - \mu(123) \geq 0$

A.2.4 Generalized Multinomial Probit Model with Choquet Integral

A.2.4.1 Model Formulation

If i be the index for alternative $i \in \{1,2,...,I\}$ and g be the index for attributes $g \in \{1,2,...,G\}$, individual $n \in \{1,2,...,N\}$ derives the following indirect utility by choosing i^{th} alternative (suppresed individual-level subscript for notational simplicity):

$$U_i = CI_i + \varepsilon_i \tag{A.2.4.1.1}$$

$$CI_i = \sum_{g=1}^{G} h\left(x^i_{\pi_{N_g}}\right)\left(\mu_i\left(A^i_g\right) - \mu_i\left(A^i_{g-1}\right)\right) \tag{A.2.4.1.2}$$

$$h\left(x^i_{\pi_{N_g}}\right) \rightarrow 0 \leq \left[h\left(x^i_{\pi_{N_1}}\right) \geq h\left(x^i_{\pi_{N_2}}\right) \geq ... \geq h\left(x^i_{\pi_{N_G}}\right)\right] \leq 1$$

$$A^i_G = \left\{x^i_{N_1}, x^i_{N_2}, ..., x^i_{N_G}\right\}$$

where the function $h(.)$ is applied on the normalised attribute values to arrange them in decreasing order, A^i_g is the set of attributes of cardinality g for the i^{th} alternative, $\mu_i\left(A^i_g\right)$ is the corresponding fuzzy measure and ε_i is a normally-distributed error term.

In Eq. A.2.4.1.2, the function $h\left(x^i_{\pi_{N_g}}\right)$ is bounded between 0 and 1. Thus, before calculating the CI value, one needs to rescale the attribute values. Below, we define a set of notations to simultaneously rescale the attribute values using fuzzy membership function and re-write Eq. A.2.4.1.1 in matrix form. We define the following vector/matrix notations:

$\boldsymbol{U} = (U_1, U_2, ..., U_I)$ $\left[(I \times 1) \text{ vector}\right]$,

$\boldsymbol{x}_i = (x^i_1, x^i_2, ..., x^i_G)\left[(1 \times G) \text{ vector}\right]$, $\quad \boldsymbol{x} = (\boldsymbol{x}_1, \boldsymbol{x}_2, ..., \boldsymbol{x}_I)\left[(I \times G) \text{ matrix}\right]$,

$\boldsymbol{\mu}_i = (\mu_1, \mu_2, ..., \mu_{2^G-1})\left[1 \times \left(2^G - 1\right) \text{ vector}\right]$, $\quad \boldsymbol{\mu} = (\boldsymbol{\mu}_1, \boldsymbol{\mu}_2, ..., \boldsymbol{\mu}_I,)\left[I \times \left(2^G - 1\right) \text{ matrix}\right]$,

$\boldsymbol{\varepsilon} = (\varepsilon_1, \varepsilon_2, ..., \varepsilon_I)\left[(I \times 1) \text{ vector}\right]$.

Here for notational simplicity, we assume that all alternatives have G attributes but that can be relaxed in alternative-specific CI. Further, we assume a trapezoidal membership function for all the explanatory variables, i.e. four- thresholds per explanatory variable (g) for alternative i (i.e., $\psi_{g_i,1} \leq \psi_{g_i,2} \leq \psi_{g_i,3} \leq \psi_{g_i,4}$). Now, stack the threshold elements as follow:

$\boldsymbol{\psi}_{g_i} = \left(\psi_{g_i,1}, \psi_{g_i,2}, \psi_{g_i,3}, \psi_{g_i,4}\right)\left[(1 \times 4) \text{ vector}\right], \boldsymbol{\psi}_i = \left(\boldsymbol{\psi}_{1_i}, \boldsymbol{\psi}_{2_i}, ..., \boldsymbol{\psi}_{G_i}\right)\left[(G \times 4) \text{ matrix}\right]$

$\boldsymbol{\psi} = \left(\boldsymbol{\psi}_1, \boldsymbol{\psi}_2, ..., \boldsymbol{\psi}_I\right)\left[(I \times G \times 4) \text{ matrix}\right]$

With this, we can perform the normalisation as follows:

$$\boldsymbol{x}_N = I\left(\boldsymbol{x} .< \boldsymbol{\psi}[.,.,1]\right)*0 + I\left(\boldsymbol{\psi}[.,.,1] .< \boldsymbol{x} .< \boldsymbol{\psi}[.,.,2]\right)*\left(\frac{\boldsymbol{x}-\boldsymbol{\psi}[.,.,1]}{\boldsymbol{\psi}[.,.,2]-\boldsymbol{\psi}[.,.,1]}\right)$$
$$+I\left(\boldsymbol{\psi}[.,.,2] .< \boldsymbol{x} .< \boldsymbol{\psi}[.,.,3]\right)*1 + I\left(\boldsymbol{\psi}[.,.,3] .< \boldsymbol{x} .< \boldsymbol{\psi}[.,.,4]\right)*\left(\frac{\boldsymbol{\psi}[.,.,4]-\boldsymbol{x}}{\boldsymbol{\psi}[.,.,4]-\boldsymbol{\psi}[.,.,3]}\right)$$
$$+I\left(\boldsymbol{\psi}[.,.,4] .< \boldsymbol{x}\right)*0$$

where $\boldsymbol{x}_N$ is the normalised attribute matrix of size $(I \times G)$, $I(.)$ is the indicator function which returns a value of 1 if the condition is true otherwise 0, and $.<$ is an element-by-element comparison operator.

Next, using $\boldsymbol{x}_N$ and $\boldsymbol{\mu}$, we evaluate the CI for each alternative using equation A.2 and write equation A.1 in the matrix for as follows:

$$\boldsymbol{U} = \boldsymbol{CI} + \boldsymbol{\varepsilon} \qquad \text{(A.2.4.1.3)}$$

Where $\boldsymbol{CI} = \left(CI_1, CI_2, \ldots, CI_I\right)\left[(I \times 1) \text{ vector}\right]$. Thus, we can write the distribution of $\boldsymbol{U}$ as $\boldsymbol{U} \sim MVN_{(I\times I)}\left[\boldsymbol{CI}, \boldsymbol{\Lambda}\right]$ where $\boldsymbol{\Lambda}$ is the covariance matrix of $\boldsymbol{\varepsilon}$.

A.2.4.2 Estimation

Since, only the difference in utility matters, we work with utility differences. We specifically subtract the utility of the chosen alternative from utilities of all non-chosen alternatives. Moreover, top left element of the differenced error covariance matrix ($\tilde{\boldsymbol{\Lambda}}$) is fixed to 1 to set the utility scale for identifiability (Train, 2009). Thus, for I alternative, only $\left[I*(I-1)*0.5\right]-1$ covariance elements are identifiable. Further, since all the differenced error covariance matrices must originate from the same undifferenced error covariance matrix ($\boldsymbol{\Lambda}$), we specify matrix $\boldsymbol{\Lambda}$ as follows: $\boldsymbol{\Lambda} = \begin{bmatrix} 0 & 0 \\ 0 & \tilde{\boldsymbol{\Lambda}} \end{bmatrix}$. To perform utility difference, we construct a matrix $\mathbf{M}$ of size $[(I-I)\times I]$ using the following pseudo-code:

Iden_mat = $\mathbf{1}_{I-1}$
O_neg = -1*ones($I-1$,1)
if(i_m == 1)
  M = O_neg~Iden_mat
elseif(i_m == I)
  M = Iden_mat ~ O_neg
else
  M = Iden_mat[.,1:i_m-1] ~ O_neg~Iden_mat[.,i_m:I-1]
end

where " ~ " refers to horizontal concatenation and i_m is the chosen alternative.

Using $\mathbf{M}$, we can write the distribution of utility differences $\bar{\boldsymbol{U}} \sim MVN_{(I-I)}\left(\tilde{\mathbf{B}}, \tilde{\mathbf{\Theta}}\right)$, where $\tilde{\mathbf{B}} = \mathbf{M} * \boldsymbol{CI}$, and $\tilde{\mathbf{\Theta}} = \mathbf{M} * \mathbf{\Lambda} * \mathbf{M}'$. Thus, the likelihood of the decision-maker n can be written as: $L_n(\boldsymbol{\theta}) = \int_{-\infty}^{\tilde{\mathbf{B}}} f_{(I-I)}\left(\boldsymbol{r} \middle| \tilde{\mathbf{B}}\ , \tilde{\mathbf{\Theta}}\right) d\mathbf{r}$. Thus, the constrained likelihood maximization problem becomes:

$$\max_{\boldsymbol{\theta}} \sum_{n=1}^{N} Log\left(L_n(\boldsymbol{\theta})\right) \tag{A.2.4.2.1}$$

Such that for each alternative $\forall i$

$$\sum_{H \subseteq A_G} m\left(H\right) = 1; \quad \text{where } A_G = \left\{x_1, x_2, ..., x_G\right\}$$

$$\sum_{H \subseteq A_G \setminus g} m\left(H \cup k\right) \geq 0 \qquad \forall g \subseteq A_G, \forall k \subseteq A_G; \forall i$$

where $A_G \setminus g$ represents collection of all attributes except the g^{th} attribute (A.2.4.2.2)

$\cup$ represents the union of two sets

$m(.)$ is the Möbius representation of $\mu(.)$

$$m\left(H\right) = \sum_{F \subseteq H} \left(-1\right)^{\left|H \setminus F\right|} \mu\left(F\right)$$

Further, the one-to-one mapping between $\mu(.)$ and $m(.)$ is as follows:

$$\mu\left(F\right) = \sum_{H \subseteq F} m\left(H\right)$$

We convert fuzzy-measures (matrix $\boldsymbol{\mu}$) into their corresponding Möbius parameters (matrix $\boldsymbol{m}$) and solve the above constrained optimization problem. The decision variables in the constrained maximisation problem are $\boldsymbol{\theta} = \left[\mathrm{Vech}\left(\boldsymbol{m}\right), \mathrm{Vech}\left(\boldsymbol{\psi}\right), \mathrm{Vech}(\tilde{\mathbf{\Lambda}})\right]$, where $\mathrm{Vech}(.)$ operator vectorises the unique element of a matrix. Readers will note that the number of constraints does not depend on the number of alternatives in generic CI-based indirect utility specification, but they grow linearly with the number of alternatives in alternative-specific CI.

The likelihood function involves computation of a $(I-1)$ dimensional multivariate normal cumulative density function (MVNCDF) for each decision-maker. One can use Geweke, Hajivassiliou and Keane (GHK) simulator (Geweke, 1991; Hajivassiliou et al., 1992; Keane, 1994; Genz, 1992) or analytical approximation methods (Bhat, 2011; Bhat, 2018) to accurately evaluate the multivariate normal cumulative distribution function (MVNCDF). For approximate computation of the MVNCDF function, we use GHK simulator with Halton Draws (Bhat, 2014; Train, 2009).

A.2.4.3 Positive definiteness of error-differenced covariance matrix:

In order to maintain the positive definiteness of the error covariance matrix, we work with the Cholesky decomposition. Since the first element of error differenced covariance matrix is fixed to 1, we use the following parametrisation on the Cholesky decomposition.

Let $\mathbf{LL}' = \tilde{\mathbf{\Lambda}}$, where $\mathbf{L}$ is the lower traingular Cholesky matrix. To derive $\mathbf{L}_p$ from $\mathbf{L}$, we first compute $a_i = \left[1 + \left(\mathbf{L}[i,1:i-1] \right)^2 \right]^{0.5}$ $\forall i \geq 2$. Then, we parametrize all the non-diagonal elements of the i^{th} row as $\mathbf{L}_p[i,r] = \frac{\mathbf{L}[i,r]}{a_i}$ $\forall r = 1$ to $i-1$ and the diagonal element as $\mathbf{L}_p[i,i] = \frac{1}{a_i}$.

For example: consider a differenced error-covariance matrix of three alternatives as follow: $\tilde{\mathbf{\Lambda}} = \begin{bmatrix} 1.0 & 0.5 \\ 0.5 & 1.2 \end{bmatrix}$. Then, the corresponding lower triangular Cholesky matrix can be written as follow: $\mathbf{L} = \begin{bmatrix} 1.0 & 0 \\ 0.5 & 0.98 \end{bmatrix}$. Then, we obtain $a_2 = \left[1 + (0.5)^2 \right]^{0.5} = 1.12$. Therefore, $\mathbf{L}_p$ can be parameterised as follow: $\mathbf{L}_p = \begin{bmatrix} 1.0 & 0 \\ 0.50/1.12 & 1.00/1.12 \end{bmatrix} = \begin{bmatrix} 1.0 & 0 \\ 0.45 & 0.89 \end{bmatrix}$

A.2.5 Fuzzy Membership Functions for Attribute Cut-offs

Attributes with positive marginal utility such as the number of seats, doors, storage area in a vehicle choice scenario can be represented using the following half triangular function (see Figure A.2.1):

$$x_N = \begin{cases} 0 & x \leq a \\ \dfrac{x-a}{b-a} & a < x \leq b \\ 1 & x > b \end{cases} \tag{A.2.5.1}$$

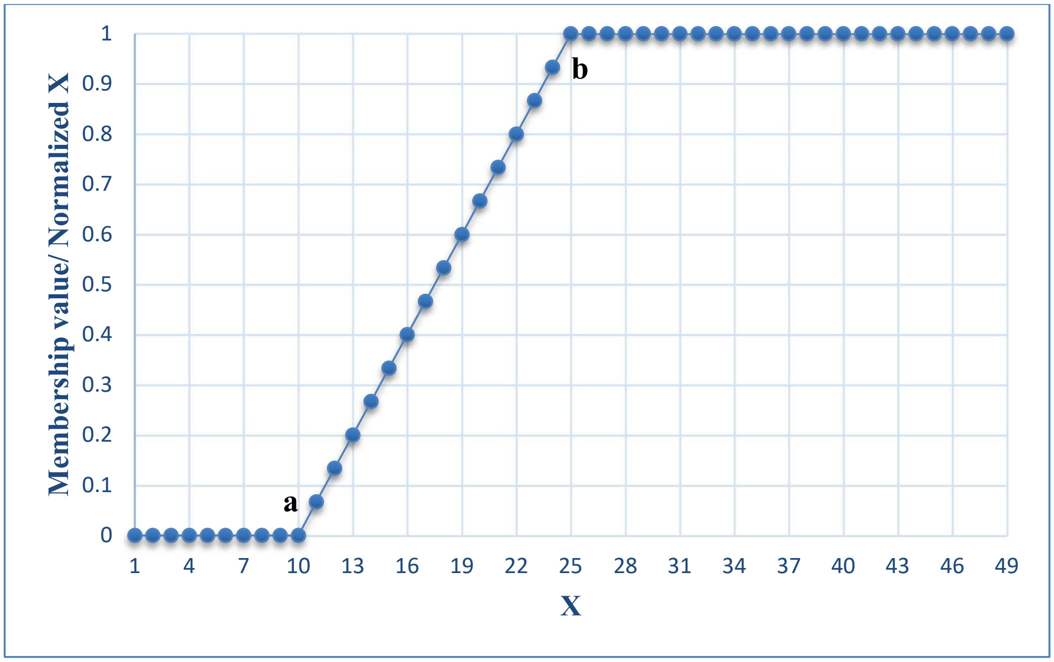

Figure A.2.1: Two-point cut-off graph for attributes with negative marginal utility (i.e., half-triangular function)

Similarly, variables such as driving range in an electric vehicle choice can be represented by the following trapezoidal membership function (see Figure A.2.2):

$$x_N = \begin{cases} 0 & x \le a; x > d \\ \dfrac{x-a}{b-a} & a < x \le b \\ 1 & b < x \le c \\ \dfrac{d-x}{d-c} & c < x \le d \end{cases} \tag{A.2.5.2}$$

It is worth noting that the triangular membership function can easily be represented by using a trapezoidal function after imposing equality constraint on b and c.

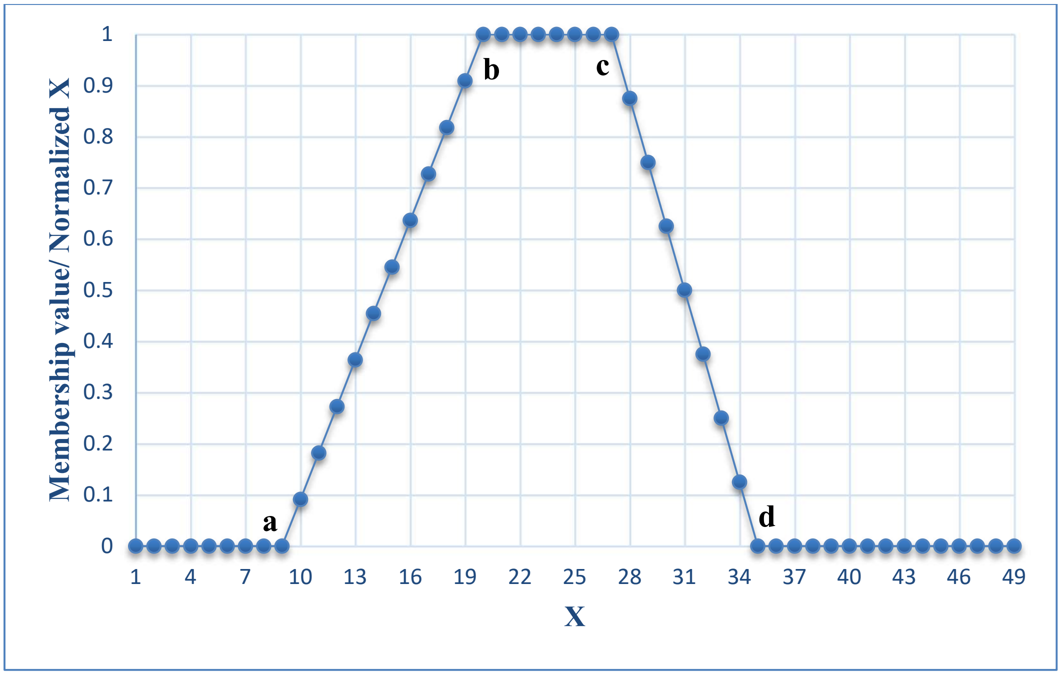

Figure A.2.2: Four-point cut-off graph (i.e., trapezoidal membership function)

A.2.6 Operationalisation and Interpretation of Attribute Cut-offs in CI

Consider that an individual needs to make a binary choice (choose or not choose) for a Mobility-on-Demand (MoD) service in three scenarios, where a scenario is characterised with three attributes in-vehicle travel time per km (IVTT/Km), out-of-vehicle travel time per km (OVTT/Km), and cost per km (Cost/Km)) as shown below in Table A.2.1.

Table A.2.1: MoD choice scenario

Scenario	IVTT/Km	OVTT/Km	Cost/Km
1	5	3	1.6
2	4	4	1.6
3	4	2	2

Further, we assume that the individual considers a half-triangular fuzzy membership function for all three attributes with cut-off points a and b as follow:

$$\text{IVTT/Km}\left[a,b\right]=\left(2.5,4.5\right),\text{OVTT/Km}\left[a,b\right]=\left(1.5,3.5\right),\text{Cost/Km}\left[a,b\right]=\left(1.0,1.9\right)$$

Using the attribute cut-offs, we obtain the normalized value for three attributes in all scenarios, as shown in Table A.2.2.

Table A.2.2: MoD choice scenario normalized value

Scenario	IVTT/Km	OVTT/Km	Cost/Km
1	0	0.25	0.33
2	0.25	0	0.33
3	0.25	0.75	0

Further, we assume the following configuration for fuzzy measures:

$\mu(\phi)=0;\ \mu(\text{IVTT/Km})=0.087;\ \mu(\text{OVTT/Km})=0.21;\ \mu(\text{Cost/Km})=0.443;$
$\mu(\text{IVTT/Km, OVTT/Km})=0.382;\ \mu(\text{IVTT/Km, Cost/Km})=0.595;\ \mu(\text{OVTT/Km,Cost/Km})=0.653;$
$\mu(\text{IVTT/Km, OVTT/Km,Cost/Km})=1.00$

Then, we can calculate the CI value of three scenarios using the normalised value of attributes (Table A.2.2) and the fuzzy measures as follows:

$$\begin{aligned}
CI(1) &= \text{Cost/Km}\big(\mu(\text{Cost/Km})-\mu(\phi)\big)+\text{OVTT/Km}\big(\mu(\text{OVTT/Km,Cost/Km})-\mu(\text{Cost/Km})\big)\\
&\quad +\text{IVTT/Km}\big(\mu(\text{IVTT/Km, OVTT/Km,Cost/Km})-\mu(\text{OVTT/Km,Cost/Km})\big)\\
&= 0.33(0.443-0)+0.25(0.653-0.443)+0(1-0.653) \ =0.1987\\
CI(2) &= \text{Cost/Km}\big(\mu(\text{Cost/Km})-\mu(\phi)\big)+\text{IVTT/Km}\big(\mu(\text{IVTT/Km,Cost/Km})-\mu(\text{Cost/Km})\big)\\
&\quad +\text{OVTT/Km}\big(\mu(\text{IVTT/Km, OVTT/Km,Cost/Km})-\mu(\text{IVTT/Km,Cost/Km})\big)\\
&= 0.33(0.443-0)+0.25(0.595-0.443)+0(1-0.595) \ =0.1842\\
CI(3) &= \text{OVTT/Km}\big(\mu(\text{OVTT/Km})-\mu(\phi)\big)+\text{IVTT/Km}\big(\mu(\text{IVTT/Km, OVTT/Km})-\mu(\text{OVTT/Km})\big)\\
&\quad +\text{Cost/Km}\big(\mu(\text{IVTT/Km, OVTT/Km,Cost/Km})-\mu(\text{IVTT/Km, OVTT/Km})\big)\\
&= 0.75(0.21-0)+0.25(0.382-0.21)+0(1-0.382) \ =0.2005
\end{aligned}$$

Finally, assuming a probit choice probability kernel, we obtain the probability of choosing MoD as shown in Table A.2.3.

Table A.2.3: Utility and corresponding probability of choosing MoD

Scenario	Utility	Probability of choice
1	0.1987	0.336
2	0.1842	0.327
3	0.2005	0.337

It is worth noting that each scenario sets one of the attribute values to be zero after normalization (see Table A.2.2) because the realized value of attribute goes beyond the upper limit. This can be viewed as a situation where the contribution of the attribute to the utility of an alternative beyond a certain attribute threshold does not change. For instance, zero value for IVTT/km in first choice scenario indicates that the value of 5 for IVTT/km cause the same disutility as the value of 4.5.

A.2.7 Data Generating Process

A.2.7.1 Four-attribute configuration

Alternative-specific intercepts: $\begin{bmatrix} ASC_1 \\ ASC_2 \\ ASC_3 \\ ASC_4 \\ ASC_5 \end{bmatrix} = \begin{bmatrix} 0 \\ -0.7 \\ -0.6 \\ -0.5 \\ -0.4 \end{bmatrix}$

Choquet integral parameters for MNP-CI:

$\mu(1) = 0.3, \mu(2) = 0.25, \mu(3) = 0.2, \mu(4) = 0.1,$

$\mu(12) = 0.58, \mu(13) = 0.53, \mu(14) = 0.44, \mu(23) = 0.49, \mu(24) = 0.36, \mu(34) = 0.33,$

$\mu(123) = 0.79, \mu(124) = 0.68, \mu(134) = 0.64, \mu(234) = 0.59, \mu(1234) = 1.0$

Mean effect parameters for MNP-WS: $\beta(1) = 0.3, \beta(2) = 0.25, \beta(3) = 0.2, \beta(4) = 0.1$

Cut-off parameters:

Explanatory variables	**Cut-off type**	**Cut-off points**			
		a	*b*	*c*	*d*
1	Half-triangular	3.0	7.0		
2	Half-triangular	3.5	6.5		
3	Trapezoidal	2.0	4.0	6.0	7.0
4	Trapezoidal	3.5	5.5	7.5	8.5

Shapley values and Interaction indices:

Explanatory variable	**Shapley value**	**Explanatory variable pair**	**Interaction index**
$S(1)$	0.338	$I(12)$	0.035
$S(2)$	0.285	$I(13)$	0.030
$S(3)$	0.242	$I(14)$	0.050
$S(4)$	0.135	$I(23)$	0.045
		$I(24)$	0.025
		$I(34)$	0.040

Error structure: $\begin{bmatrix} 1.0 & & & \\ 0.5 & 1.1 & & \\ 0.5 & 0.5 & 1.2 & \\ 0.5 & 0.5 & 0.5 & 1.3 \end{bmatrix}$

A.2.7.2 Six-attribute configuration

Alternative-specific intercepts: $\begin{bmatrix} ASC_1 \\ ASC_2 \\ ASC_3 \\ ASC_4 \\ ASC_5 \end{bmatrix} = \begin{bmatrix} 0 \\ -0.7 \\ -0.6 \\ -0.5 \\ -0.4 \end{bmatrix}$

Choquet integral parameters for MNP-CI:

$\mu(1)=0.17, \mu(2)=0.18, \mu(3)=0.20, \mu(4)=0.16, \mu(5)=0.19, \mu(6)=0.18,$

$\mu(12)=0.33, \mu(13)=0.35, \mu(14)=0.31, \mu(15)=0.34, \mu(16)=0.33,$

$\mu(23)=0.36, \mu(24)=0.32, \mu(25)=0.35, \mu(26)=0.34,$

$\mu(34)=0.34, \mu(35)=0.37, \mu(36)=0.36,$

$\mu(45)=0.33, \mu(46)=0.32, \mu(56)=0.35,$

$\mu(123)=0.51, \mu(124)=0.47, \mu(125)=0.50, \mu(126)=0.49, \mu(134)=0.49, \mu(135)=0.52,$

$\mu(136)=0.51, \mu(145)=0.48, \mu(146)=0.47, \mu(156)=0.50,$

$\mu(234)=0.50, \mu(235)=0.53, \mu(236)=0.52, \mu(245)=0.49, \mu(246)=0.48, \mu(256)=0.51,$

$\mu(345)=0.51, \mu(346)=0.50, \mu(356)=0.53, \mu(456)=0.49,$

$\mu(1234)=0.65, \mu(1235)=0.68, \mu(1236)=0.67, \mu(1245)=0.64, \mu(1246)=0.63, \mu(1256)=0.66,$

$\mu(1345)=0.66, \mu(1346)=0.65, \mu(1356)=0.68, \mu(1456)=0.64,$

$\mu(2345)=0.67, \mu(2346)=0.66, \mu(2356)=0.69, \mu(2456)=0.65, \mu(3456)=0.67,$

$\mu(12345)=0.82, \mu(12346)=0.81, \mu(12356)=0.84, \mu(12456)=0.80, \mu(13456)=0.82,$

$\mu(23456)=0.83, \mu(123456)=1.00$

Mean effect parameters for MNP-WS:

$\beta(1)=0.17, \beta(2)=0.18, \beta(3)=0.20, \beta(4)=0.16, \beta(5)=0.19, \beta(6)=0.18$

Cut-off parameters:

Explanatory variables	**Cut-off type**	**Cut-off points**			
		a	*b*	*c*	*d*
1	Half-triangular	3.0	7.0		
2	Half-triangular	3.5	6.5		
3	Trapezoidal	2.0	4.0	6.0	7.0
4	Trapezoidal	3.5	5.5	7.5	8.5
5	Half-triangular	3.3	6.8		
6	Trapezoidal	2.5	5.0	6.5	7.5

Shapley values and Interaction indices:

Explanatory variable	Shapley value	Explanatory variable pair	Interaction index
$S(1)$	0.157	$I(12)$	0.00
$S(2)$	0.167	$I(13)$	0.00
$S(3)$	0.187	$I(14)$	0.00
$S(4)$	0.147	$I(15)$	0.00
$S(5)$	0.177	$I(16)$	0.00
$S(6)$	0.167	$I(23)$	0.00
		$I(24)$	0.00
		$I(25)$	0.00
		$I(26)$	0.00
		$I(34)$	0.00
		$I(35)$	0.00
		$I(36)$	0.00
		$I(45)$	0.00
		$I(46)$	0.00
		$I(56)$	0.00

Error structure: $\begin{bmatrix} 1.0 & & & \\ 0.5 & 1.1 & & \\ 0.5 & 0.5 & 1.2 & \\ 0.5 & 0.5 & 0.5 & 1.3 \end{bmatrix}$

Supplement-2

S.2.1 Absolute percentage bias of various parameters

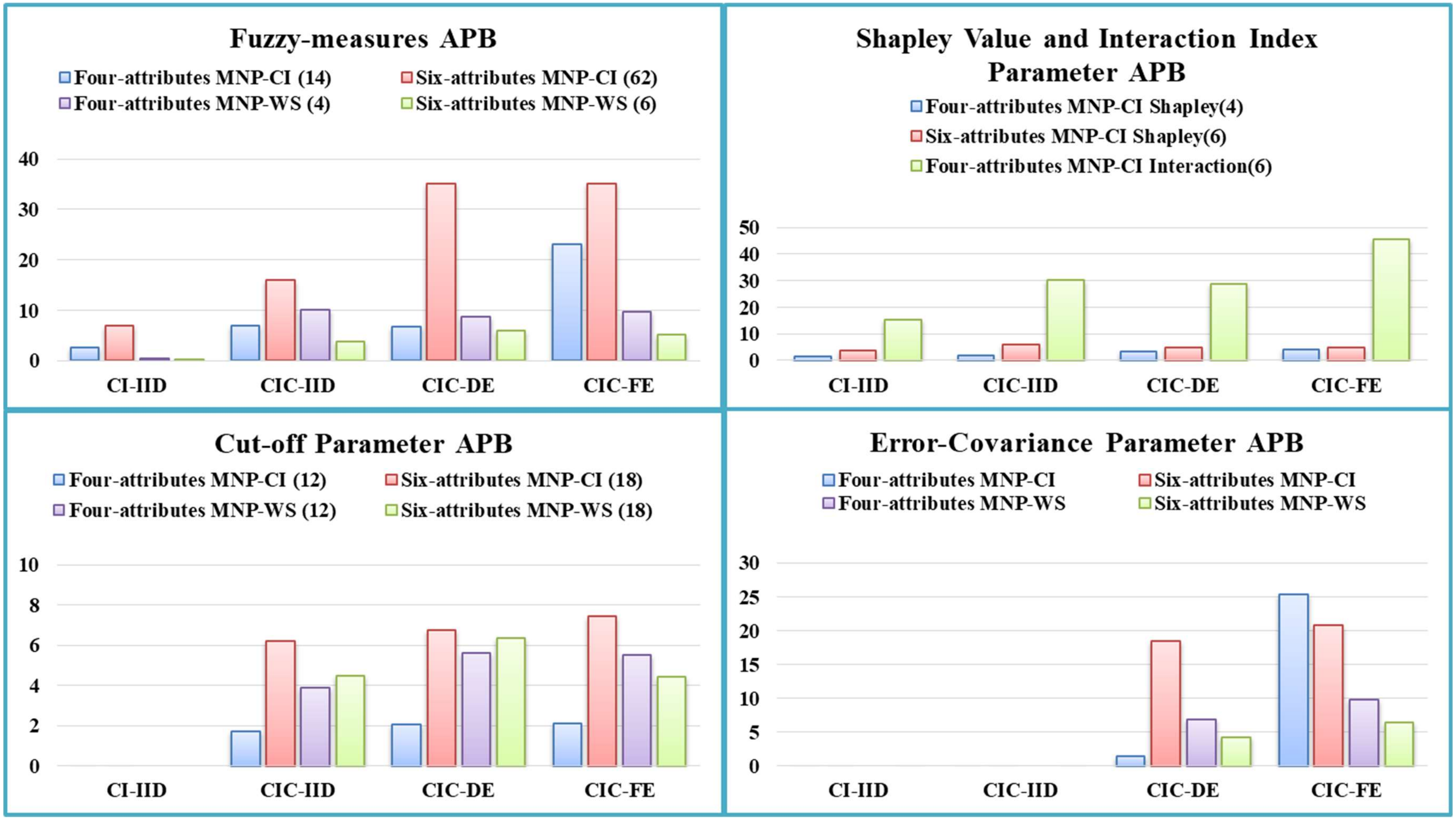

Figure S.2.1: Absolute percentage bias (APB) for various parameter groups (the number of parameters in parenthesis).
(Note: APB for interaction indices is not presented in case of MNP-CI with six attributes because true interaction indices are zero)

S.2.2 Marginal effects

We present additional results of the Monte Carlo study where we evaluate the generality of the MNP-CI model. In data generating process and estimation, full error covariance and attribute cut-offs are considered. MNP-CI and MNP-WS only differs in terms of aggregation function.

Table S.2.2.1: Change in probability when data generating process follows MNP-CI

Variable	Quantile	MNP-CI Model					MNP-WS Model				
		Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5
1	0.10	-0.153	-0.124	-0.114	-0.114	-0.123	-0.025	-0.014	-0.019	-0.018	-0.020
1	0.20	-0.147	-0.112	-0.108	-0.109	-0.117	-0.024	-0.014	-0.018	-0.017	-0.019
1	0.30	-0.143	-0.105	-0.104	-0.104	-0.111	-0.023	-0.013	-0.017	-0.017	-0.019
1	0.40	-0.139	-0.100	-0.101	-0.100	-0.108	-0.023	-0.013	-0.017	-0.017	-0.018
1	0.50	-0.136	-0.096	-0.097	-0.097	-0.105	-0.022	-0.013	-0.017	-0.016	-0.018
1	0.60	-0.134	-0.093	-0.095	-0.094	-0.102	-0.022	-0.013	-0.016	-0.016	-0.018
1	0.70	-0.132	-0.090	-0.092	-0.092	-0.099	-0.022	-0.012	-0.016	-0.016	-0.017
1	0.80	-0.130	-0.087	-0.089	-0.090	-0.097	-0.021	-0.012	-0.016	-0.016	-0.017
1	0.90	-0.128	-0.086	-0.087	-0.088	-0.095	-0.021	-0.012	-0.016	-0.016	-0.017
1	0.99	-0.126	-0.084	-0.085	-0.086	-0.093	-0.021	-0.012	-0.016	-0.015	-0.017
2	0.10	-0.107	-0.080	-0.072	-0.083	-0.081	-0.008	-0.005	-0.006	-0.006	-0.006
2	0.20	-0.100	-0.072	-0.067	-0.074	-0.076	-0.008	-0.004	-0.006	-0.006	-0.006
2	0.30	-0.096	-0.067	-0.063	-0.068	-0.073	-0.008	-0.004	-0.005	-0.006	-0.006
2	0.40	-0.092	-0.064	-0.061	-0.064	-0.071	-0.008	-0.004	-0.005	-0.005	-0.006
2	0.50	-0.090	-0.062	-0.058	-0.061	-0.069	-0.008	-0.004	-0.005	-0.005	-0.006
2	0.60	-0.088	-0.060	-0.057	-0.059	-0.067	-0.007	-0.004	-0.005	-0.005	-0.006
2	0.70	-0.086	-0.058	-0.055	-0.057	-0.065	-0.007	-0.004	-0.005	-0.005	-0.006
2	0.80	-0.084	-0.057	-0.054	-0.055	-0.064	-0.007	-0.004	-0.005	-0.005	-0.006
2	0.90	-0.083	-0.055	-0.053	-0.054	-0.063	-0.007	-0.004	-0.005	-0.005	-0.005
2	0.99	-0.082	-0.054	-0.051	-0.053	-0.062	-0.007	-0.004	-0.005	-0.005	-0.005
3	0.10	-0.344	-0.231	-0.226	-0.243	-0.260	-0.037	-0.022	-0.028	-0.028	-0.029
3	0.20	-0.331	-0.214	-0.211	-0.230	-0.246	-0.036	-0.021	-0.027	-0.026	-0.028
3	0.30	-0.322	-0.202	-0.198	-0.221	-0.234	-0.035	-0.020	-0.026	-0.026	-0.027
3	0.40	-0.314	-0.193	-0.188	-0.213	-0.224	-0.035	-0.019	-0.026	-0.025	-0.027
3	0.50	-0.306	-0.185	-0.179	-0.206	-0.217	-0.034	-0.019	-0.025	-0.025	-0.026
3	0.60	-0.299	-0.179	-0.172	-0.200	-0.210	-0.034	-0.019	-0.025	-0.024	-0.026
3	0.70	-0.292	-0.173	-0.165	-0.195	-0.203	-0.033	-0.018	-0.024	-0.024	-0.025
3	0.80	-0.286	-0.167	-0.159	-0.188	-0.197	-0.033	-0.018	-0.024	-0.024	-0.025
3	0.90	-0.280	-0.162	-0.154	-0.183	-0.190	-0.032	-0.018	-0.024	-0.023	-0.025
3	0.99	-0.274	-0.158	-0.149	-0.178	-0.185	-0.032	-0.018	-0.023	-0.023	-0.025
4	0.10	-0.201	-0.139	-0.132	-0.148	-0.150	-0.015	-0.009	-0.011	-0.011	-0.012
4	0.20	-0.190	-0.124	-0.121	-0.131	-0.140	-0.015	-0.008	-0.011	-0.011	-0.012
4	0.30	-0.180	-0.117	-0.115	-0.124	-0.132	-0.014	-0.008	-0.010	-0.010	-0.011
4	0.40	-0.173	-0.111	-0.110	-0.119	-0.127	-0.014	-0.008	-0.010	-0.010	-0.011
4	0.50	-0.167	-0.107	-0.106	-0.115	-0.123	-0.014	-0.008	-0.010	-0.010	-0.011
4	0.60	-0.162	-0.104	-0.103	-0.112	-0.120	-0.013	-0.007	-0.010	-0.010	-0.011
4	0.70	-0.158	-0.101	-0.100	-0.109	-0.117	-0.013	-0.007	-0.009	-0.010	-0.010
4	0.80	-0.154	-0.098	-0.098	-0.106	-0.114	-0.013	-0.007	-0.009	-0.010	-0.010
4	0.90	-0.151	-0.096	-0.096	-0.104	-0.112	-0.013	-0.007	-0.009	-0.009	-0.010
4	0.99	-0.148	-0.094	-0.094	-0.102	-0.110	-0.013	-0.007	-0.009	-0.009	-0.010

Table S.2.2.2: Change in probability when data generating process follows MNP-WS

Variable	Quantile	MNP-CI Model					MNP-WS Model				
		Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5
1	0.10	-0.076	-0.050	-0.050	-0.048	-0.053	-0.053	-0.034	-0.038	-0.042	-0.043
1	0.20	-0.065	-0.044	-0.043	-0.043	-0.046	-0.051	-0.032	-0.036	-0.041	-0.041
1	0.30	-0.058	-0.041	-0.038	-0.039	-0.042	-0.050	-0.031	-0.035	-0.039	-0.039
1	0.40	-0.054	-0.039	-0.036	-0.037	-0.039	-0.049	-0.030	-0.034	-0.038	-0.039
1	0.50	-0.051	-0.038	-0.034	-0.036	-0.038	-0.049	-0.029	-0.033	-0.038	-0.038
1	0.60	-0.048	-0.037	-0.033	-0.035	-0.037	-0.048	-0.028	-0.033	-0.037	-0.037
1	0.70	-0.047	-0.036	-0.032	-0.034	-0.036	-0.048	-0.028	-0.032	-0.036	-0.037
1	0.80	-0.046	-0.035	-0.030	-0.033	-0.035	-0.047	-0.027	-0.032	-0.036	-0.036
1	0.90	-0.045	-0.035	-0.030	-0.033	-0.034	-0.046	-0.027	-0.031	-0.035	-0.036
1	0.99	-0.044	-0.034	-0.029	-0.032	-0.034	-0.046	-0.026	-0.031	-0.035	-0.035
2	0.10	-0.052	-0.039	-0.035	-0.037	-0.040	-0.048	-0.030	-0.035	-0.036	-0.038
2	0.20	-0.049	-0.035	-0.031	-0.034	-0.038	-0.047	-0.029	-0.033	-0.035	-0.037
2	0.30	-0.046	-0.033	-0.030	-0.032	-0.036	-0.047	-0.027	-0.032	-0.034	-0.036
2	0.40	-0.043	-0.031	-0.028	-0.030	-0.034	-0.046	-0.027	-0.031	-0.033	-0.035
2	0.50	-0.042	-0.030	-0.027	-0.029	-0.032	-0.045	-0.026	-0.030	-0.032	-0.035
2	0.60	-0.041	-0.029	-0.026	-0.028	-0.031	-0.045	-0.026	-0.030	-0.032	-0.034
2	0.70	-0.039	-0.027	-0.025	-0.027	-0.030	-0.044	-0.025	-0.029	-0.031	-0.034
2	0.80	-0.039	-0.026	-0.024	-0.026	-0.030	-0.044	-0.024	-0.029	-0.031	-0.033
2	0.90	-0.038	-0.026	-0.024	-0.025	-0.029	-0.044	-0.024	-0.029	-0.031	-0.033
2	0.99	-0.037	-0.025	-0.023	-0.025	-0.028	-0.043	-0.024	-0.028	-0.030	-0.033
3	0.10	-0.119	-0.078	-0.074	-0.079	-0.083	-0.122	-0.067	-0.082	-0.090	-0.092
3	0.20	-0.110	-0.073	-0.067	-0.072	-0.077	-0.118	-0.063	-0.078	-0.085	-0.088
3	0.30	-0.103	-0.070	-0.063	-0.068	-0.072	-0.115	-0.060	-0.075	-0.082	-0.085
3	0.40	-0.100	-0.067	-0.061	-0.066	-0.070	-0.113	-0.058	-0.072	-0.080	-0.083
3	0.50	-0.096	-0.065	-0.059	-0.064	-0.068	-0.111	-0.056	-0.071	-0.078	-0.081
3	0.60	-0.094	-0.063	-0.057	-0.062	-0.066	-0.109	-0.055	-0.069	-0.076	-0.080
3	0.70	-0.092	-0.062	-0.056	-0.061	-0.065	-0.108	-0.054	-0.068	-0.075	-0.079
3	0.80	-0.090	-0.06	-0.055	-0.059	-0.063	-0.106	-0.053	-0.066	-0.073	-0.078
3	0.90	-0.088	-0.059	-0.053	-0.058	-0.062	-0.105	-0.052	-0.065	-0.072	-0.077
3	0.99	-0.087	-0.058	-0.053	-0.057	-0.062	-0.104	-0.051	-0.064	-0.071	-0.076
4	0.10	-0.066	-0.047	-0.040	-0.047	-0.051	-0.046	-0.028	-0.032	-0.035	-0.036
4	0.20	-0.057	-0.041	-0.036	-0.041	-0.044	-0.045	-0.026	-0.030	-0.033	-0.034
4	0.30	-0.052	-0.037	-0.033	-0.037	-0.040	-0.043	-0.025	-0.029	-0.032	-0.033
4	0.40	-0.048	-0.035	-0.031	-0.035	-0.037	-0.042	-0.024	-0.028	-0.031	-0.032
4	0.50	-0.046	-0.033	-0.029	-0.033	-0.035	-0.042	-0.023	-0.027	-0.030	-0.032
4	0.60	-0.045	-0.031	-0.028	-0.031	-0.033	-0.041	-0.023	-0.027	-0.030	-0.031
4	0.70	-0.043	-0.030	-0.027	-0.030	-0.032	-0.040	-0.022	-0.026	-0.029	-0.031
4	0.80	-0.042	-0.029	-0.026	-0.029	-0.031	-0.040	-0.022	-0.026	-0.029	-0.030
4	0.90	-0.041	-0.028	-0.025	-0.028	-0.030	-0.039	-0.021	-0.025	-0.028	-0.030
4	0.99	-0.040	-0.027	-0.025	-0.028	-0.029	-0.039	-0.021	-0.025	-0.028	-0.029

S.2.3 Additional Results of the Empirical Study

Table S.2.3.1: Choquet integral fuzzy-measure estimates (T-statistics in parenthesis)

Variables	CI-NAC	CI-CAC	CI-GAC	CI-AGAC	ACI-AGAC	
	All modes	All modes	All modes	All modes	Current mode	Uber and Uberpool
IVTT/Km	0.068 (1.6)	0.000 (0.0)	0.000 (0.0)	0.000 (0.0)	0.000 (0.0)	0.060 (0.6)
OVTT/Km	0.173 (3.5)	0.143 (3.9)	0.076 (1.9)	0.000 (0.0)	0.003 (0.1)	0.000 (0.0)
Cost/Km	0.427 (8.9)	0.318 (6.8)	0.361 (7.7)	0.297 (7.0)	0.302 (6.9)	0.270 (2.3)
IVTT/Km, OVTT/Km	0.381 (7.5)	0.353 (4.5)	0.366 (3.4)	0.468 (7.5)	0.515 (7.2)	0.427 (4.1)
IVTT/Km, Cost/Km	0.577 (10.4)	0.668 (6.8)	0.725 (6.4)	0.578 (9.2)	0.569 (8.5)	0.683 (8.4)
OVTT/Km, Cost/Km	0.626 (10.3)	0.928 (10.0)	0.984 (13.3)	1.000 (13.7)	1.000 (13.4)	0.862 (8.0)
IVTT/Km, OVTT/Km, Cost/Km	1.000 (16.5)	1.000 (9.1)	1.000 (9.7)	1.000 (12.9)	1.000 (12.6)	1.000 (11.5)

Note: IVTT and OVTT imply in-vehicle and out-of-vehicle travel time.

Table S.2.3.2: Attribute cut-off heterogeneity in CI-AGAC model for current travel mode (T-statistic in parenthesis)

Explanatory variables		IVTT/Km		OVTT/Km		Cost/Km	
		Lower Cut-off	Upper Cut-off	Lower Cut-off	Upper Cut-off	Lower Cut-off	Upper Cut-off
	Constant	1.11 (18.5)	-0.7 (-0.9)	-0.6 (-3.6)	2.11 (31.9)	-1.27 (-7.3)	0.76 (13.3)
Household income * travel distance (in USD * km) [Base: >125K]	(<=50K) * distance						-0.58 (-6.5)
	(> 50K & <=125K) * distance						-0.36 (-5.1)
Distance to Bus stop (in km) [Base: ≤ 0.5]	(> 0.5 & ≤ 1)				-0.53 (-3.9)		
	(> 1 & ≤ 2)				-2.75 (-5.6)		
	(> 2)				-2.75 (-5.6)		
Distance to subway (in km) [Base: ≤ 0.5]	(> 0.5 & ≤ 1)				-0.20 (-1.8)		
	(> 1 & ≤ 2)				-0.63 (-3.7)		
	(> 2)				-0.95 (-6.3)		
Male							
Years since owing a driver's license							
Age (in years) [Base: 23 – 38]	Age (7 - 22)				0.23 (1.8)		
	Age (39 - 54)						
	Age (55 - 73)				-0.83 (-5.9)		

Table S.2.3.3: Attribute cut-off heterogeneity in CI-AGAC model for Uber (T-statistic in parenthesis)

Explanatory variables		IVTT/Km		OVTT/Km		Cost/Km	
		Lower Cut-off	**Upper Cut-off**	**Lower Cut-off**	**Upper Cut-off**	**Lower Cut-off**	**Upper Cut-off**
	Constant	-0.13 (-0.2)	1.46 (5.2)	0.66 (25.7)	0.95 (5.7)	-3.13 (-1.2)	1.01 (11.2)
Household income * travel distance (in USD * km) [Base: >125K]	(<=50K) * distance						
	(> 50K & <=125K) * distance						
Distance to Bus stop (in km) [Base: ≤ 0.5]	(> 0.5 & ≤ 1)				-0.53 (-3.9)		
	(> 1 & ≤ 2)				-2.75 (-5.6)		
	(> 2)				-2.75 (-5.6)		
Distance to subway (in km) [Base: ≤ 0.5]	(> 0.5 & ≤ 1)				-0.20 (-1.8)		
	(> 1 & ≤ 2)				-0.63 (-3.7)		
	(> 2)				-0.95 (-6.3)		
Male							
Years since owing a driver's license							
Age (in years) [Base: 23 – 38]	Age (7 - 22)				0.23 (1.8)		
	Age (39 - 54)						-0.5 (-4.6)
	Age (55 - 73)				-0.83 (-5.9)		-3.24 (-1.4)

Table S.2.3.4: Attribute cut-off heterogeneity in CI-AGAC model for Uberpool (T-statistic in parenthesis)

Explanatory variables		**IVTT/Km**		**OVTT/Km**		**Cost/Km**	
		Lower Cut-off	**Upper Cut-off**	**Lower Cut-off**	**Upper Cut-off**	**Lower Cut-off**	**Upper Cut-off**
	Constant	-0.64 (-0.3)	2.07 (13.8)	-1.11 (-6.4)	1.37 (12.7)	-2.31 (-5.8)	1.23 (13.2)
Household income * travel distance (in USD * km) [Base: >125K]	(<=50K) * distance						-0.61 (-6.9)
	(> 50K & <=125K) * distance						-0.47 (-5.6)
Distance to Bus stop (in km) [Base: ≤ 0.5]	(> 0.5 & ≤ 1)				-0.53 (-3.9)		
	(> 1 & ≤ 2)				-2.75 (-5.6)		
	(> 2)				-2.75 (-5.6)		
Distance to subway (in km) [Base: ≤ 0.5]	(> 0.5 & ≤ 1)				-0.20 (-1.8)		
	(> 1 & ≤ 2)				-0.63 (-3.7)		
	(> 2)				-0.95 (-6.3)		
Male							
Years since owing a driver's license							
Age (in years) [Base: 23 – 38]	Age (7 - 22)				0.23 (1.8)		0.34 (2.7)
	Age (39 - 54)						-0.59 (-5.2)
	Age (55 - 73)				-0.83 (-5.9)		-1.24 (-6.7)

Table S.2.3.5: Attribute cut-off heterogeneity in ACI-AGAC model for current travel mode (T-statistic in parenthesis)

Explanatory variables		IVTT/Km		OVTT/Km		Cost/Km	
		Lower Cut-off	Upper Cut-off	Lower Cut-off	Upper Cut-off	Lower Cut-off	Upper Cut-off
	Constant	1.11 (20.5)	-0.71 (-0.9)	-0.59 (-3.0)	2.1 (31.1)	-1.29 (-6.7)	0.74 (12.2)
Household income * travel distance (in USD * km) [Base: >125K]	(<=50K) * distance						-0.55 (-6.7)
	(> 50K & <=125K) * distance						-0.35 (-4.8)
Distance to Bus stop (in km) [Base: ≤ 0.5]	(> 0.5 & ≤ 1)				-0.53 (-3.9)		
	(> 1 & ≤ 2)				-2.79 (-4.2)		
	(> 2)				-2.79 (-4.2)		
Distance to subway (in km) [Base: ≤ 0.5]	(> 0.5 & ≤ 1)				-0.19 (-1.6)		
	(> 1 & ≤ 2)				-0.61 (-3.4)		
	(> 2)				-0.91 (-6.0)		
Male							
Years since owing a driver's license							
Age (in years) [Base: 23 – 38]	Age (7 - 22)				0.23 (1.7)		
	Age (39 - 54)						
	Age (55 - 73)				-0.82 (-5.5)		

Table S.2.3.6: Attribute cut-off heterogeneity in ACI-AGAC model for Uber (T-statistic in parenthesis)

Explanatory variables		**IVTT/Km**		**OVTT/Km**		**Cost/Km**	
		Lower Cut-off	**Upper Cut-off**	**Lower Cut-off**	**Upper Cut-off**	**Lower Cut-off**	**Upper Cut-off**
	Constant	-0.16 (-0.2)	1.47 (5.3)	0.66 (8.6)	0.95 (4.4)	-3.15 (-1.2)	1.06 (10.0)
Household income * travel distance (in USD * km) [Base: >125K]	(<=50K) * distance						
	(> 50K & <=125K) * distance						
Distance to Bus stop (in km) [Base: ≤ 0.5]	(> 0.5 & ≤ 1)				-0.53 (-3.9)		
	(> 1 & ≤ 2)				-2.79 (-4.2)		
	(> 2)				-2.79 (-4.2)		
Distance to subway (in km) [Base: ≤ 0.5]	(> 0.5 & ≤ 1)				-0.19 (-1.6)		
	(> 1 & ≤ 2)				-0.61 (-3.4)		
	(> 2)				-0.91 (-6.0)		
Male							
Years since owing a driver's license							
Age (in years) [Base: 23 – 38]	Age (7 - 22)				0.23 (1.7)		
	Age (39 - 54)						-0.55 (-4.2)
	Age (55 - 73)				-0.82 (-5.5)		-3.26 (-2.4)

Table S.2.3.7: Attribute cut-off heterogeneity in ACI-AGAC model for Uberpool (T-statistic in parenthesis)

Explanatory variables		**IVTT/Km**		**OVTT/Km**		**Cost/Km**	
		Lower Cut-off	**Upper Cut-off**	**Lower Cut-off**	**Upper Cut-off**	**Lower Cut-off**	**Upper Cut-off**
	Constant	-0.65 (-0.2)	2.06 (12.6)	-1.12 (-5.1)	1.34 (10.3)	-2.28 (-4.0)	1.26 (11.3)
Household income * travel distance (in USD * km) [Base: >125K]	(<=50K) * distance						-0.49 (-4.8)
	(> 50K & <=125K) * distance						-0.47 (-4.8)
Distance to Bus stop (in km) [Base: ≤ 0.5]	(> 0.5 & ≤ 1)				-0.53 (-3.9)		
	(> 1 & ≤ 2)				-2.79 (-4.2)		
	(> 2)				-2.79 (-4.2)		
Distance to subway (in km) [Base: ≤ 0.5]	(> 0.5 & ≤ 1)				-0.19 (-1.6)		
	(> 1 & ≤ 2)				-0.61 (-3.4)		
	(> 2)				-0.91 (-6.0)		
Male							-0.37 (-3.8)
Years since owing a driver's license							
Age (in years) [Base: 23 – 38]	Age (7 - 22)				0.23 (1.7)		0.36 (2.4)
	Age (39 - 54)						-0.61 (-5)
	Age (55 - 73)				-0.82 (-5.5)		-1.27 (-6.2)

Table S.2.3.8: Distribution of attribute cut-off for current travel mode in CI-AGAC model

Percentile	IVTT/Km		OVTT/Km		Cost/Km	
	Lower Cut-off	Upper Cut-off	Lower Cut-off	Upper Cut-off	Lower Cut-off	Upper Cut-off
10	3.02	3.52	0.55	1.36	0.28	1.18
20	3.02	3.52	0.55	3.74	0.28	1.48
30	3.02	3.52	0.55	4.12	0.28	1.73
40	3.02	3.52	0.55	5.49	0.28	1.89
50	3.02	3.52	0.55	7.28	0.28	2.01
60	3.02	3.52	0.55	8.76	0.28	2.08
70	3.02	3.52	0.55	8.76	0.28	2.21
80	3.02	3.52	0.55	8.76	0.28	2.43
90	3.02	3.52	0.55	8.76	0.28	2.43
100	3.02	3.52	0.55	10.83	0.28	2.43

Table S.2.3.9: Distribution of attribute cut-off for Uber in CI-AGAC model

Percentile	IVTT/Km		OVTT/Km		Cost/Km	
	Lower Cut-off	Upper Cut-off	Lower Cut-off	Upper Cut-off	Lower Cut-off	Upper Cut-off
10	0.88	5.19	1.93	2.19	0.04	0.2
20	0.88	5.19	1.93	2.94	0.04	1.71
30	0.88	5.19	1.93	3.06	0.04	2.41
40	0.88	5.19	1.93	3.49	0.04	2.79
50	0.88	5.19	1.93	4.06	0.04	2.79
60	0.88	5.19	1.93	4.52	0.04	2.79
70	0.88	5.19	1.93	4.52	0.04	2.79
80	0.88	5.19	1.93	4.52	0.04	2.79
90	0.88	5.19	1.93	4.52	0.04	3.95
100	0.88	5.19	1.93	5.18	0.04	3.95

Table S.2.3.10: Distribution of attribute cut-off for Uberpool in CI-AGAC model

Percentile	IVTT/Km		OVTT/Km		Cost/Km	
	Lower Cut-off	Upper Cut-off	Lower Cut-off	Upper Cut-off	Lower Cut-off	Upper Cut-off
10	0.53	8.45	0.33	0.72	0.1	0.76
20	0.53	8.45	0.33	1.86	0.1	1.09
30	0.53	8.45	0.33	2.04	0.1	1.37
40	0.53	8.45	0.33	2.7	0.1	1.61
50	0.53	8.45	0.33	3.56	0.1	1.97
60	0.53	8.45	0.33	4.27	0.1	2.24
70	0.53	8.45	0.33	4.27	0.1	2.56
80	0.53	8.45	0.33	4.27	0.1	2.95
90	0.53	8.45	0.33	4.27	0.1	3.52
100	0.53	8.45	0.33	5.27	0.1	3.52

Table S.2.3.11: Distribution of attribute cut-off for current travel mode in ACI-AGAC model

Percentile	IVTT/Km		OVTT/Km		Cost/Km	
	Lower Cut-off	Upper Cut-off	Lower Cut-off	Upper Cut-off	Lower Cut-off	Upper Cut-off
10	3.03	3.52	0.55	1.40	0.28	1.20
20	3.03	3.52	0.55	3.83	0.28	1.49
30	3.03	3.52	0.55	4.12	0.28	1.71
40	3.03	3.52	0.55	5.50	0.28	1.86
50	3.03	3.52	0.55	7.29	0.28	1.98
60	3.03	3.52	0.55	8.69	0.28	2.06
70	3.03	3.52	0.55	8.69	0.28	2.16
80	3.03	3.52	0.55	8.69	0.28	2.37
90	3.03	3.52	0.55	8.69	0.28	2.37
100	3.03	3.52	0.55	10.74	0.28	2.37

Table S.2.3.12: Distribution of attribute cut-off for Uber in ACI-AGAC model

Percentile	IVTT/Km		OVTT/Km		Cost/Km	
	Lower Cut-off	Upper Cut-off	Lower Cut-off	Upper Cut-off	Lower Cut-off	Upper Cut-off
10	0.85	5.19	1.93	2.20	0.04	0.20
20	0.85	5.19	1.93	2.98	0.04	1.71
30	0.85	5.19	1.93	3.07	0.04	2.47
40	0.85	5.19	1.93	3.51	0.04	2.93
50	0.85	5.19	1.93	4.08	0.04	2.93
60	0.85	5.19	1.93	4.52	0.04	2.93
70	0.85	5.19	1.93	4.52	0.04	2.93
80	0.85	5.19	1.93	4.52	0.04	2.93
90	0.85	5.19	1.93	4.52	0.04	4.24
100	0.85	5.19	1.93	5.18	0.04	4.24

Table S.2.3.13: Distribution of attribute cut-off for Uberpool in ACI-AGAC model

Percentile	IVTT/Km		OVTT/Km		Cost/Km	
	Lower Cut-off	Upper Cut-off	Lower Cut-off	Upper Cut-off	Lower Cut-off	Upper Cut-off
10	0.52	8.37	0.33	0.73	0.10	0.79
20	0.52	8.37	0.33	1.87	0.10	1.10
30	0.52	8.37	0.33	2.01	0.10	1.43
40	0.52	8.37	0.33	2.66	0.10	1.78
50	0.52	8.37	0.33	3.50	0.10	2.03
60	0.52	8.37	0.33	4.15	0.10	2.42
70	0.52	8.37	0.33	4.15	0.10	2.77
80	0.52	8.37	0.33	4.15	0.10	3.16
90	0.52	8.37	0.33	4.15	0.10	3.64
100	0.52	8.37	0.33	5.12	0.10	3.64

Table S.2.3.14: MNP-WS estimates with and without interaction (T-statistic in parenthesis)

Variables	MNP-WS with no-interactions and no attribute cut-offs			MNP-WS with interactions and no attribute cut-offs		
	Current mode	Uber	Uberpool	Current mode	Uber	Uberpool
Constant		-0.28 (-6.0)	-0.59 (-8.2)		-0.37 (-7.5)	-0.68 (-9.7)
Electric		-0.08 (-2.3)	-0.09 (-2.5)		-0.06 (-1.6)	-0.07 (-2.0)
Automated		-0.14 (-4.1)	-0.10 (-2.9)		-0.13 (-3.6)	-0.10 (-2.7)
IVTT/Km	-0.05 (-7.9)			-0.08 (-10.2)		
OVTT/Km	-0.05 (-13.4)			-0.11 (-15.2)		
Cost/Km	-0.16 (-26.9)			-0.33 (-21.8)		
IVTT/Km, OVTT/Km				0.003 (7.5)		
IVTT/Km, Cost/Km				0.008 (14.2)		
OVTT/Km, Cost/Km				0.012 (16.0)		
IVTT/Km, OVTT/Km, Cost/Km				-0.0001 (-10.6)		
Error-covariance	$\begin{bmatrix} 1.00\ (\text{fixed}) & \\ 0.422\ (3.8) & 1.108\ (7.8) \end{bmatrix}$			$\begin{bmatrix} 1.00\ (\text{fixed}) & \\ 0.179\ (1.6) & 1.020\ (6.9) \end{bmatrix}$		

Chapter 3 – Understanding Preference for Mobility-on-Demand Services through a Context Aware Survey and Non-Compensatory Strategy

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.

This chapter is based on the following article:

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3.1 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.

Several studies have attempted to understand the factors affecting the propensity of individuals towards MOD service. In particular, 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 work, 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; Martinez et al., 2009) and utility-regulating functions (Elord et al., 2004) either require pre-knowledge of cut-offs or are computationally cumbersome.

The current study makes several non-trivial substantial and empirical contributions. 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. Finally, through the analysis of service fee derivation, we also highlight how false assumptions about the underlying behavioural mechanism can lead to erroneous policy decisions.

The remainder of the chapter is organized as follows: Section 3.2 provides an overview of the literature on the determinants of MOD choice dimensions followed by a description of survey design in Section 3.3. Section 3.4 describes the Choquet-Integral followed by model formulation and estimation strategy. Section 3.5 describes survey data, model results and performance measures. Conclusions, limitations, and avenues of future research are discussed in Section 3.6.

3.2 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.

3.2.1 Service Reliability and Learning

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.

3.2.2 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 Jr, 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 minutes) 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.

3.2.3 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).

3.3 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.

3.3.1 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). Figure 3.1 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 2km 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. Figure 3.2 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 minutes) 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.

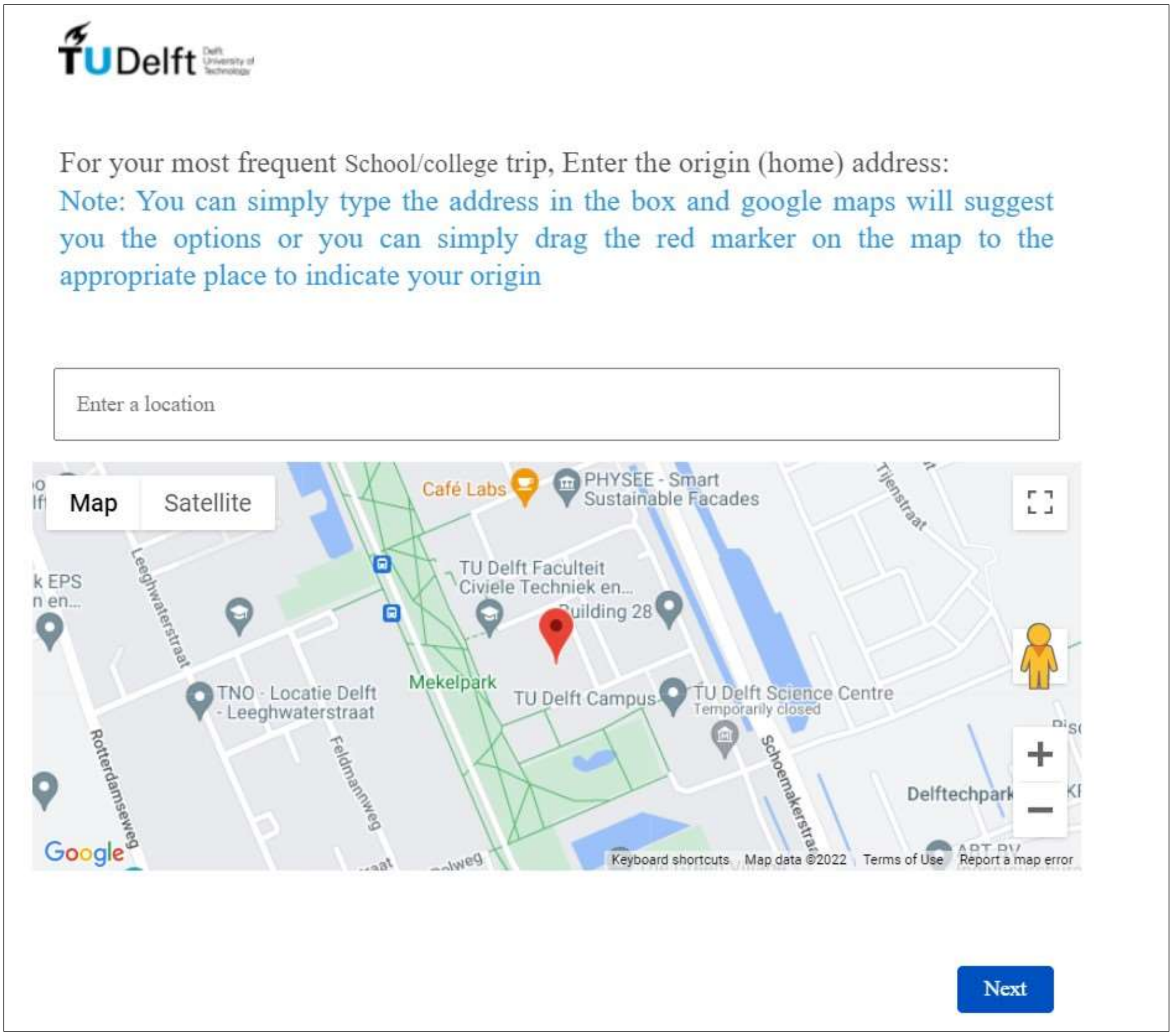


Figure 3.1: Origin-Destination module in the survey

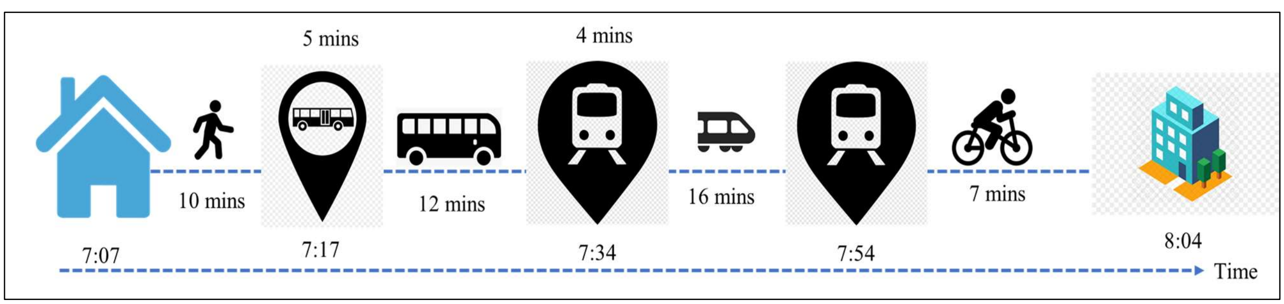


Figure 3.2: Illustration of a public transport trip

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 * 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)[6].

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 minutes earlier
3. MOD option 15 minutes earlier
4. MOD option at reported departure window
5. MOD option 15 minutes later

3.3.2 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 3.1.1.

Table 3.1.1: Attribute levels

Attributes	Levels		
	1	2	3
Travel time	[tt-3, tt+2]	[tt-1, tt+2.5]	[tt+1, tt+3]
Waiting time of MOD	[2, 5)	[5, 10)	[10, 15]
Travel cost/km for 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]

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

[6] 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.

3.3.3 SP Survey Example

Figure 3.3a 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 Figure 3.3b (screenshots of the choice experiment and symbol explanation for car users are provided in Supplement-3 section S.3.1). 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 Figure 3.4. 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 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 3.1.1. 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 drawn from a range as shown in Table 3.1.2. 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.

Table 3.1.2: 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

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

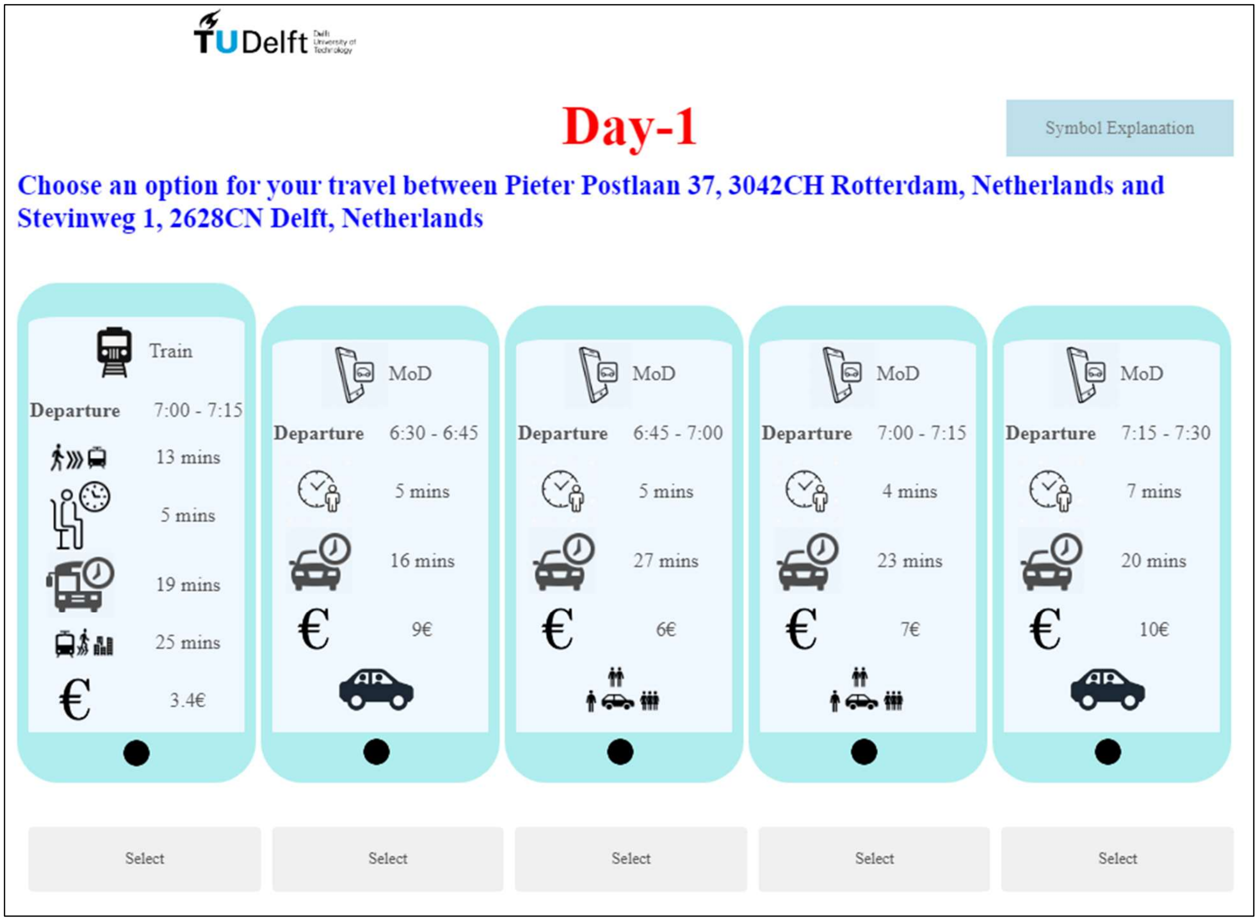


Figure 3.3a: Choice experiment for train users

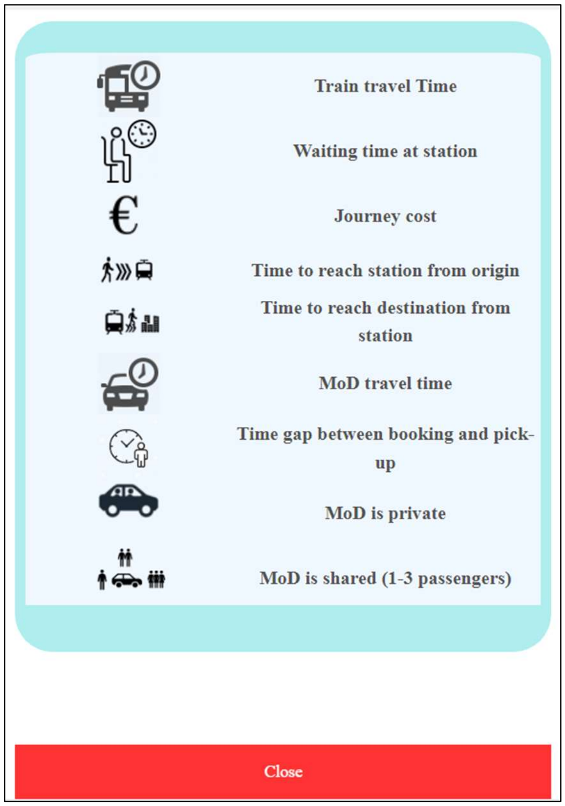


Figure 3.3b: Pop-up window of "Symbol Explanation" for train users

Figure 3.4: Feedback information

3.4 Choquet Integral (Generic Aggregation Function)

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 $\mathrm{Z}\left(\{\phi\},\{1\},\{2\},...,\{K\},\{1,2\},...,\{1,2,...,K\}\right)$ denote the collection of all subsets (size: 2^K) of K including the null set $\left(\{\phi\}\right)$. Each element in the 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, the larger the coalition, the higher the amount of information $\left(\mu(1,2) \geq \mu(1)+\mu(2)\right)$ known as monotonicity in the number of attributes. The value of all coalitions is captured by a characteristic function $\left(\mu : 2^K \rightarrow \mathbb{R}\right)$. 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 (μ), 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:

$$CI = \sum_{k=1}^{K} h\left(x_{\pi_k}\right)\left(\mu\left(A_k\right) - \mu\left(A_{k-1}\right)\right) \tag{3.1}$$

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

$$\begin{aligned} &h\left(x_{\pi_k}\right) \rightarrow h\left(x_{\pi_1}\right) \geq h\left(x_{\pi_2}\right) \geq ... \geq h\left(x_{\pi_K}\right) \geq 0; \qquad 0 \leq h\left(x_{\pi_k}\right) \leq 1 \\ &\boldsymbol{A}_K = \left\{x_1, x_2, ..., x_K\right\} \\ &\mu(\phi) = 0 \quad \mu\left(\boldsymbol{A}_K\right) = 1 \quad \mu(\boldsymbol{C}) \leq \mu(\boldsymbol{D}); \boldsymbol{C} \subseteq \boldsymbol{D} \subseteq \boldsymbol{A}_K \quad 0 \leq \mu(.) \leq 1 \end{aligned} \tag{3.2}$$

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

$$h\left(x_k^i\right) = \frac{x_k^i - \min\left(\psi\left(x_k\right)\right)}{\max\left(\psi\left(x_k\right)\right) - \min\left(\psi\left(x_k\right)\right)} \tag{3.3}$$

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

$$h\left(x_k^i\right)=\frac{\max\left(\psi\left(x_k\right)\right)-x_k^i}{\max\left(\psi\left(x_k\right)\right)-\min\left(\psi\left(x_k\right)\right)} \tag{3.4}$$

Next, monotonicity constraints in Eq. 3.2 are represented using fuzzy measures $\left[\mu(.)\right]$. 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:

$$\sum_{H\subseteq A_K} m\left(H\right)=1;\quad \text{where } A_K=\left\{x_1,x_2,...,x_K\right\}$$

$$\sum_{H\subseteq A_K\backslash k} m\left(H\cup k\right)\geq 0\ \forall k;$$

where $A_K\backslash k$ represents the collection of all attributes except the k^{th} attribute

$\cup$ represents the union of two sets

$m(.)$ is the Möbius representation of $\mu(.)$ and one-to-one mapping between them is as follows:

$$m\left(H\right)=\sum_{F\subseteq H}\left(-1\right)^{\left|H\backslash F\right|}\mu\left(F\right)$$

$$\mu\left(F\right)=\sum_{H\subseteq F} m\left(H\right)$$

Next, one can also obtain explicit attribute importance value based on CI estimates using Eq. 3.5 known as the Shapley value

$$S\left(k\right)=\sum_{A\subset Z\backslash k}\frac{Fact\left(\left|\boldsymbol{K}\right|-\left|A\right|-1\right)Fact\left(\left|A\right|\right)}{Fact\left(\left|\boldsymbol{K}\right|\right)}\left[\mu\left(A\cup\left\{k\right\}\right)-\mu\left(A\right)\right]\quad 0\leq S\left(k\right)\leq 1, \tag{3.5}$$

where $Fact(.)$ represents the factorial, $|.|$ indicates the cardinality of the set and $\boldsymbol{K}=\left\{1,2,...,K\right\}$ 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)[7].

3.4.1 Choquet Integral as a Non-Compensatory Approximation Function

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

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

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

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

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

Hence $h\left(x_k^i\right) \rightarrow h\left(x_2^i\right) > h\left(x_1^i\right) > h\left(x_3^i\right)$.

With this, the CI can be written as follows:

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

Three observations can be made based on the calculation of CI. First, $\left(x_3^i\right)$ does not impact the choice probability as long as it is below a normalized value of 0.2. Second, the impact of $\left(x_1^i\right)$ 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.

3.4.2 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 Supplement-3 section S.3.1). 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 (19×19)[8] 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 $(t = 1,2,...,T)$ (15 repeated choice scenarios in the SP stage), i be the index for alternative $(i = 1,2,...,I)$ and k be the index for the number of attributes

[8] A (3×3) block for the RP stage and a (4×4) block for each of the four primary mode users.

($k=1,2,...,K$) (travel time, waiting time, and travel cost). Then, we can write the utility of alternative i in the time period t as follows:

$$U_{i,t}=CI_{i,t}+\varepsilon_{i,t} \tag{3.6}$$

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:

$$CI_{i,t}=\sum_{k=1}^{K}h\left(x_{N_k}^{i,t}\right)\left(\mu_i\left(A_k^{i,t}\right)-\mu_i\left(A_{k-1}^{i,t}\right)\right) \tag{3.7}$$

Therefore, $CI_{i,t}$ can be termed the observed part of utility calculated using a Choquet aggregation function. Eq. 3.7 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. 3.3 and Eq. 3.4.

Normalization requires that attribute values take a real number with a definite direction (effect on choice outcome). Hence, only 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)[9] approach to account for the effect of non-continuous/un-ordered attributes[10]. Therefore, Eq. 3.6 can be extended as follows:

$$U_{i,t}=CI_{i,t}+\boldsymbol{\beta}_i'\boldsymbol{x}_{i,t}+\varepsilon_{i,t} \tag{3.8}$$

where $\boldsymbol{x}_{i,t}$ is a $(k\times1)$ vector of exogenous variables, $\boldsymbol{\beta}_i$ is the corresponding $(k\times1)$ vector of coefficients, and $\boldsymbol{\beta}_i'\boldsymbol{x}_{i,t}$ 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:

$$U_{i,t}=CI_{i,t}+\boldsymbol{\beta}_i'\boldsymbol{x}_{i,t}+R_{i,t}+\varepsilon_{i,t} \tag{3.9}$$

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

In Eq. 3.9, $\rho(0,\infty)$ 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

[9] The weighted sum (WS) approach is also known as the additive utility function in the discrete choice literature. However, we use the term weighted sum throughout the chapter to distinguish the functional form of CI from the additive utility.
[10] 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 a minimum and still achieve the necessary outcome.

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. 3.9 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.3.1. With the help of notations, Eq. 3.9 can be written in matrix notations as follows:

$$\boldsymbol{U} = \left[sumc[(\boldsymbol{\beta}\ .*\ \boldsymbol{X})'] + \boldsymbol{CI} + \boldsymbol{R} + \boldsymbol{\psi}\right] \tag{3.10}$$

where $\boldsymbol{R} = \boldsymbol{1}_T \text{ - } \exp\left\{\vartheta * sumc\left[\left(\left(\hat{\boldsymbol{X}}_{TE} - \hat{\boldsymbol{X}}_{TD}\right).*\hat{\boldsymbol{X}}_{Chosen}\right)'\right] + \tau * sumc\left[\left(\left(\hat{\boldsymbol{X}}_{WE} - \hat{\boldsymbol{X}}_{WD}\right).*\hat{\boldsymbol{X}}_{Chosen}\right)'\right]\right\}$,

$\boldsymbol{1}_T$ 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., $\varepsilon_{i,t} = \eta_i$,

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

Eq. 3.10 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.

$$\begin{aligned}
\boldsymbol{U}_{RP} &= \left[sumc[(\boldsymbol{\beta}\ .*\ \boldsymbol{X})']_{RP} + \boldsymbol{\psi}_{RP}\right] \\
\boldsymbol{U}_{car-SP} &= \left[sumc[(\boldsymbol{\beta}\ .*\ \boldsymbol{X})']_{car-SP} + \boldsymbol{CI}_{car-SP} + \boldsymbol{R}_{car-SP} + \boldsymbol{\psi}_{car-SP}\right] \\
\boldsymbol{U}_{train/metro-SP} &= \left[sumc[(\boldsymbol{\beta}\ .*\ \boldsymbol{X})']_{train/metro-SP} + \boldsymbol{CI}_{train/metro-SP} + \boldsymbol{R}_{train/metro-SP} + \boldsymbol{\psi}_{train/metro-SP}\right] \\
\boldsymbol{U}_{bus/tram/light-rail-SP} &= \left[sumc[(\boldsymbol{\beta}\ .*\ \boldsymbol{X})']_{bus/tram/light-rail-SP} + \boldsymbol{CI}_{bus/tram/light-rail-SP} + \boldsymbol{R}_{bus/tram/light-rail-SP} + \boldsymbol{\psi}_{bus/tram/light-rail-SP}\right] \\
\boldsymbol{U}_{bike-SP} &= \left[sumc[(\boldsymbol{\beta}\ .*\ \boldsymbol{X})']_{bike-SP} + \boldsymbol{CI}_{bike-SP} + \boldsymbol{R}_{bike-SP} + \boldsymbol{\psi}_{bike-SP}\right]
\end{aligned} \tag{3.11}$$

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

$$\boldsymbol{U} = \mathbf{B} + \boldsymbol{\xi} \tag{3.12}$$

where

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

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

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

Therefore, $\boldsymbol{U} \sim MVN\left[\mathbf{B}, \tilde{\boldsymbol{\Theta}}\right]$ (3.13)

where

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

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 $\tilde{\boldsymbol{\Theta}}$) as respondents only complete one SP task depending on the RP stage mode.

Eq. 3.13 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 $\left[I * (I-1) * 0.5\right] - 1$ 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:

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

where

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

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 $\mathbf{\Theta}$ to perform utility difference. Also, for ease of notation, we re-write the differenced error-covariance matrix $\tilde{\mathbf{\Theta}}$ as follows:

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

Next, define a set of matrices as follows:

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

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

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

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

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

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

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

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

$$\hat{\mathbf{B}} = \mathbf{H}_{mean}\mathbf{B}, and\ \hat{\mathbf{\Theta}} = \mathbf{H}_{error}\tilde{\mathbf{\Theta}}\mathbf{H}'_{error}.$$

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

$$\mathbf{D} = zeros\left(I_{RP}+I_{SP}, I_{RP}+I_{SP}-2\right),$$

$$\mathbf{D}\left[2:I_{RP}, 1:I_{RP}-1\right] = \mathbf{I}_{RP-1},$$

$$\mathbf{D}\left[I_{RP}+2:I_{RP}+I_{SP}, I_{RP}:I_{RP}+I_{SP}-2\right] = \mathbf{I}_{SP-1},$$

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

$$\hat{\mathbf{\Theta}} = \mathbf{D}\hat{\mathbf{\Theta}}\mathbf{D}'$$

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:

$$U_{i,t} = \pi U_{i,t-1} + U_{i,t} \tag{3.14}$$

where $U_{i,t} = V_{i,t} + \sigma_{i,t}$, and $0 \le \pi \le 1$ 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. 3.14 can be re-written as follows:

$$U_{i,t} = \pi_1 U_{i,t-1} + \pi_2 U_{i,t-2} + \ldots + \pi_r U_{i,t-r} + U_{i,t}; \quad 0 \le \pi_j \le 1 \forall j = 1:r \text{ and } t > r \tag{3.15}$$

Further, assume a time-invariant error-covariance matrix, i.e., $\sigma_{i,t} = \eta_i$. Therefore, we can re-write Eq. 3.15 as follows:

$$U_{i,t} = \left(U_{i,t} + \eta_i\right) + \pi_1 \left(U_{i,t-1} + \eta_i\right) + \pi_2 \left(U_{i,t-2} + \eta_i\right) + \ldots + \pi_r \left(U_{i,t-r} + \eta_i\right) \tag{3.16}$$

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 $\boldsymbol{\pi}_{SP1} = (\pi_1, \pi_2, ..., \pi_r)'\left[(r \times 1) \text{ vector}\right], and\ \boldsymbol{\pi}_{SP} = (\boldsymbol{\pi}'_{SP1}, \boldsymbol{\pi}'_{SP2}, ..., \boldsymbol{\pi}'_{SP4})'\left[(4 \times r) \text{ matrix}\right]$.
Define a matrix $\boldsymbol{F}_{TI}$ of size $\left[TI_{SP} \times TI_{SP}\right]$ 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 $\widehat{\boldsymbol{\Theta}}$ as follows:

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

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:

$$\widehat{\mathbf{B}}_{SP} = \boldsymbol{S}\widehat{\mathbf{B}}_{SP}, and\ \widehat{\mathbf{\Theta}}_{SP} = \boldsymbol{S}\left[(\mathbf{I}_T\ .*.\ \widehat{\mathbf{\Theta}}_{SP})\right]\boldsymbol{S}',$$

$$where\ \boldsymbol{S} = \left[\mathbf{I}_{TI_{SP}} - \boldsymbol{F}_{TI_{SP}}\right]^{-1}$$

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

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

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.3.2. 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:

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

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

$$L_n(\boldsymbol{\theta}) = \int_{-\infty}^{\bar{\mathbf{B}}} f_{(I_{RP}-1)+T(I_{SP}-1)}\left(\boldsymbol{r}\middle|\bar{\mathbf{B}}\ ,\bar{\mathbf{\Theta}}\right)d\mathbf{r}\,. \tag{3.17}$$

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

$$\max_{\boldsymbol{\theta}} \sum_{n=1}^{N} Log\left(L_n(\boldsymbol{\theta})\right) \tag{3.18}$$

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

$$\sum_{H\subseteq A_K} m\left(H\right) = 1; \quad \text{where } A_K = \left\{x_1, x_2, ..., x_K\right\}$$

$$\sum_{H\subseteq A_K\setminus k} m\left(H\cup k\right) \geq 0 \forall k; \forall i$$

where $A_K \setminus k$ represents collection of all attributes except the k^{th} attribute (3.19)

$\cup$ represents the union of two sets

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 $\boldsymbol{\theta} = \left[\text{Vech}\left(\boldsymbol{m}\right), \text{Vech}\left(\boldsymbol{\beta}\right), \vartheta, \rho, \tau, \pi, \text{Vech}(\tilde{\mathbf{\Omega}})\right]$, where the $\text{Vech}(.)$ operator vectorises the unique element of a matrix and the vector $\boldsymbol{m}$ 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 $63\ \left[(4-1)+15(5-1)\right]$. 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. 3.17) can be written as follows using the CML approach:

$$L_{CML}(\boldsymbol{\theta})=\left(\prod_{r=1}^{T-1}\prod_{r'=r+1}^{T}\Pr(i_r=i_{m,SP,r},i_{r'}=i_{m,SP,r'},i_{RP}=i_{m,RP})\right) \tag{3.20}$$

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

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

$$\mathbf{L}=zeros\left((I_{RP}-1)+2(I_{SP}-1),(I_{RP}-1)+T(I_{SP}-1)\right),$$

$$\mathbf{L}\left[1:(I_{RP}-1),1:(I_{RP}-1)\right]=\mathbf{I}_{I_{RP}-1},$$

$$\mathbf{L}\left[I_{RP}:(I_{RP}-1)+(I_{SP}-1),(I_{RP}-1)+(r-1)(I_{SP}-1)+1:(I_{RP}-1)+r(I_{SP}-1)\right]=\mathbf{I}_{I_{SP}-1},$$

$$\mathbf{L}\left[(I_{RP}-1)+(I_{SP}-1)+1:(I_{RP}-1)+2(I_{SP}-1),(I_{RP}-1)(r'-1)(I_{SP}-1)+1:(I_{RP}-1)+r'(I_{SP}-1)\right]=\mathbf{I}_{I_{SP}-1},$$

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

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. 3.17 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, pages 529-562) 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 $0\le\mu(.)\le 1$ 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):

$$m(TT)\geq 0 \qquad \Rightarrow \mu(TT)\geq 0$$

$$m(WT)\geq 0 \qquad \Rightarrow \mu(WT)\geq 0$$

$$m(TC)\geq 0 \qquad \Rightarrow \mu(TC)\geq 0$$

$$m(TT)+m(TT,WT)\geq 0 \qquad \Rightarrow \mu(TT,WT)-\mu(WT)\geq 0$$

$$m(TT)+m(TT,TC)\geq 0 \qquad \Rightarrow \mu(TT,TC)-\mu(TC)\geq 0$$

$$m(WT)+m(TT,WT)\geq 0 \qquad \Rightarrow \mu(TT,WT)-\mu(TT)\geq 0$$

$$m(WT)+m(WT,TC)\geq 0 \qquad \Rightarrow \mu(WT,TC)-\mu(TC)\geq 0$$

$$m(TC)+m(TT,TC)\geq 0 \qquad \Rightarrow \mu(TT,TC)-\mu(TT)\geq 0$$

$$m(TC)+m(WT,TC)\geq 0 \qquad \Rightarrow \mu(WT,TC)-\mu(WT)\geq 0$$

$$m(TT)+m(TT,WT)+m(TT,TC)+m(TT,WT,TC)\geq 0 \qquad \Rightarrow \mu(TT,WT,TC)-\mu(WT,TC)\geq 0$$

$$m(WT)+m(TT,WT)+m(WT,TC)+m(TT,WT,TC)\geq 0 \qquad \Rightarrow \mu(TT,WT,TC)-\mu(TT,TC)\geq 0$$

$$m(TC)+m(TT,TC)+m(WT,TC)+m(TT,WT,TC)\geq 0 \qquad \Rightarrow \mu(TT,WT,TC)-\mu(TT,WT)\geq 0$$

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 $\tilde{\boldsymbol{\Theta}}$. 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:

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

3.4.3 Choice set construction and additional RP stage explanatory variables

As discussed in section 3.3.1, 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[11]) 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 3.2 provides the distribution of overall access to various primary modes obtained in the survey.

[11] Travel cost for car is calculated assuming a 0.5 euros/km cost based on sample average operating cost (see Figure 3.6). Public transport travel cost is calculated using the equation discussed in section 3.3.1.

Table 3.2: Revealed choice mode availability

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

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 (CBS, 2019)[12]. Finally, the sample is split into 80/20 for estimation and validation purposes.

3.5 Sample Description and Estimation Results

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

3.5.1 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[13]. Figure 3.5a provides the distribution of survey completion time. Based on an initial pilot, respondents with survey completion time shorter than 7 minutes or longer than 30 minutes were excluded, resulting in the exclusion of 43 respondents. The average survey completion time is 12.5 minutes. Figures 3.5b to 3.5e 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%).

Figure 3.6 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 3.6)

[12] In the survey, information on household income was not mandatory and about 15% of respondents did not report their personal or household-level income. The distribution of socio-economic variables at the zip code level is available in Supplement-3 section S.3.2.

[13] The data cleaning involved checking the validity of the OD pair, unusual travel times and survey duration.

indicating a downward bias in self-reported values (Elgar et al., 2005). The average car trip time (based on reported OD) is around 25 minutes and very few trips are over 75 minutes or longer. Figure 3.7 provides the time distribution for various legs of a train/metro trip[14]. The majority of train/metro trips have an access time of 20 minutes. 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 minutes. The average in-vehicle travel time is about 45 minutes 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.

Figure 3.8 provides the time distribution for various legs of a bus/tram/light-rail trip[15]. 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 minutes. Finally, bike users have an average biking time of 20 minutes (Figure 3.9).

Next, Figures 3.10a and 3.10b 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/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.

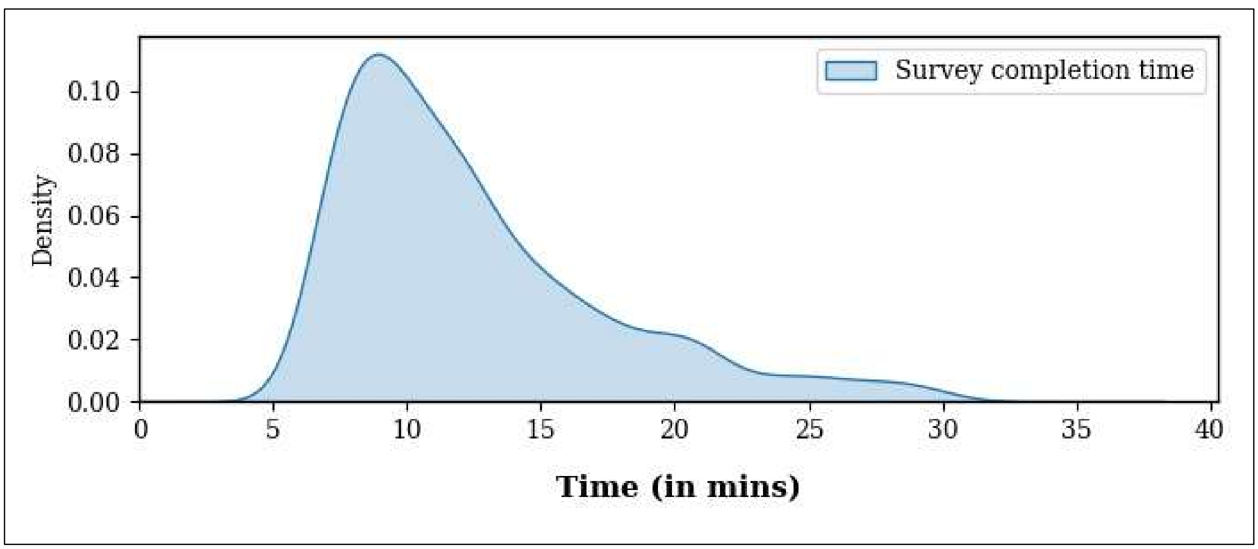


Figure 3.5a: Survey completion time distribution

[14] The PT label included both train/metro and bus/tram/light-rail.
[15] The PT label included both train/metro and bus/tram/light-rail.

Figure 3.5b: Age and gender distribution in the sample

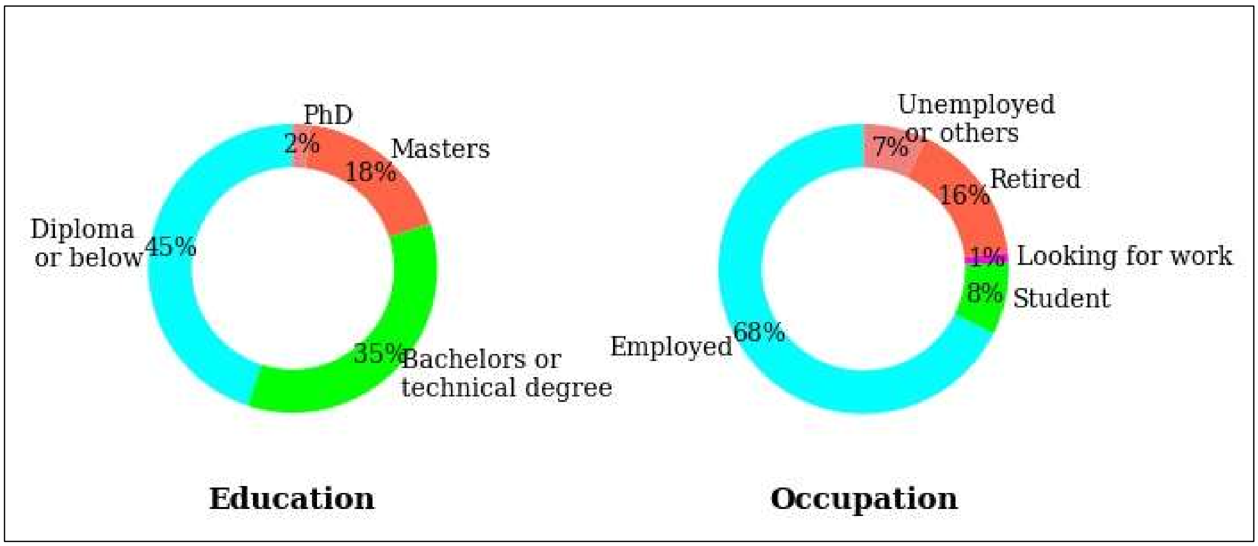


Figure 3.5c: Education and occupation distribution in the sample

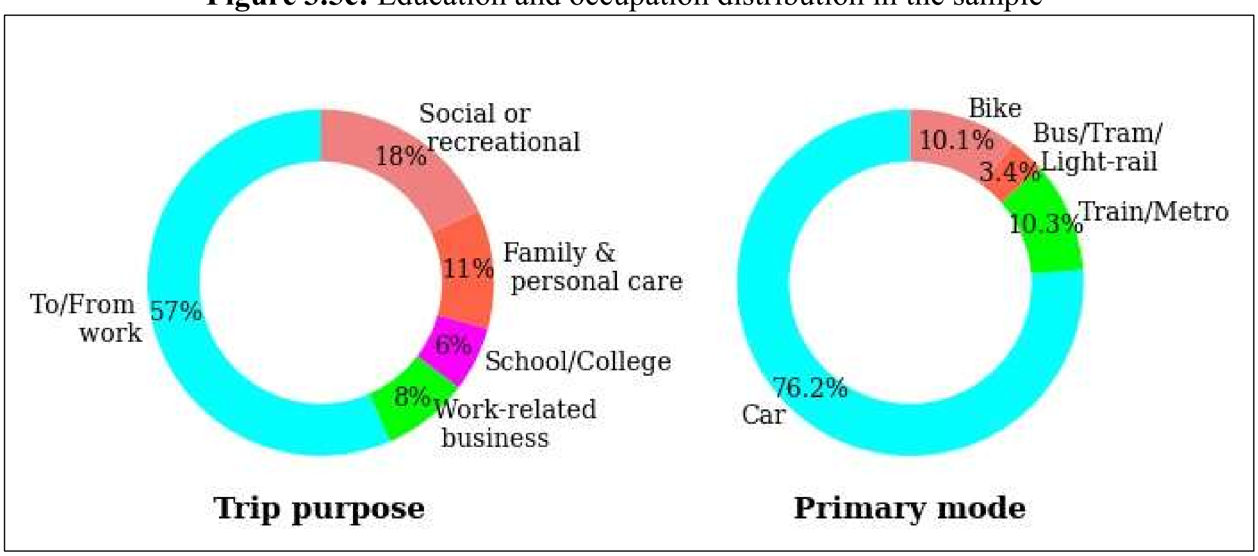


Figure 3.5d: Trip purpose and primary mode distribution in the sample

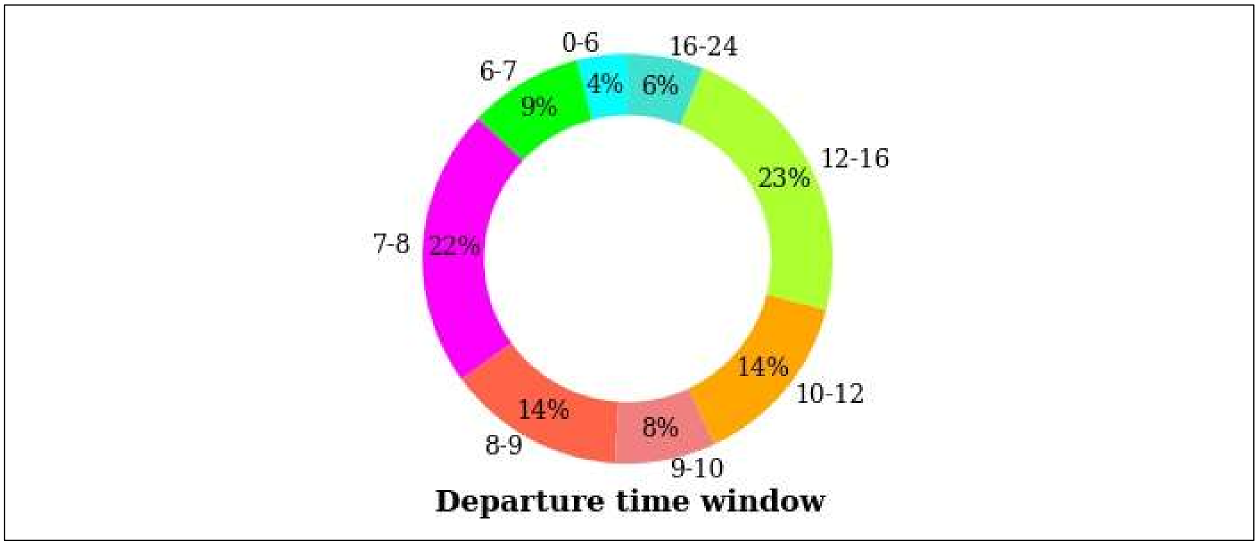


Figure 3.5e: Temporal distribution of trips in the sample

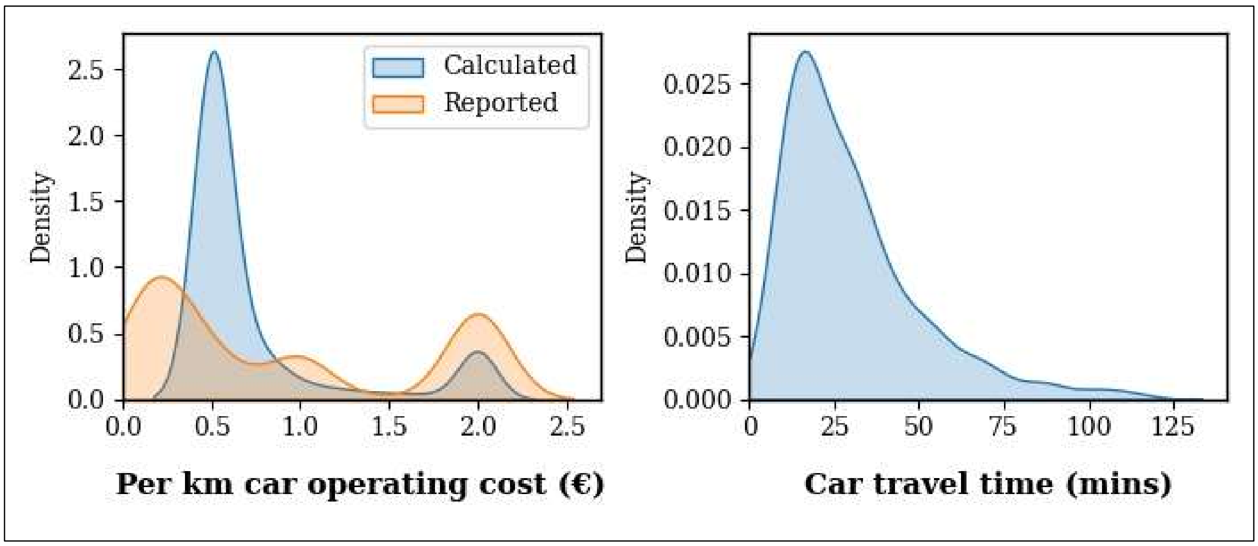


Figure 3.6: Time and cost distribution for car users

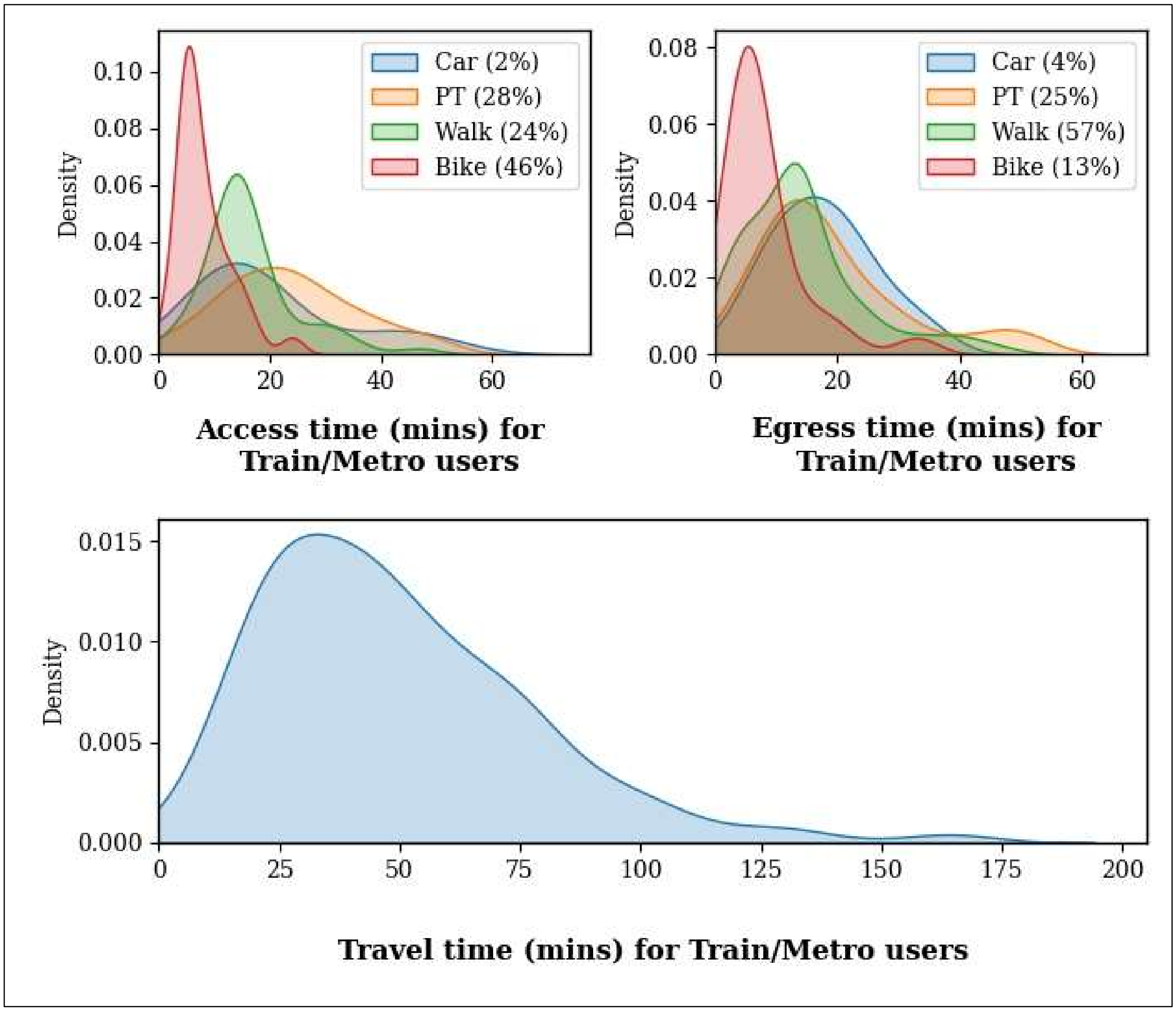


Figure 3.7: Access, egress and in-vehicle time distribution for Train/Metro users

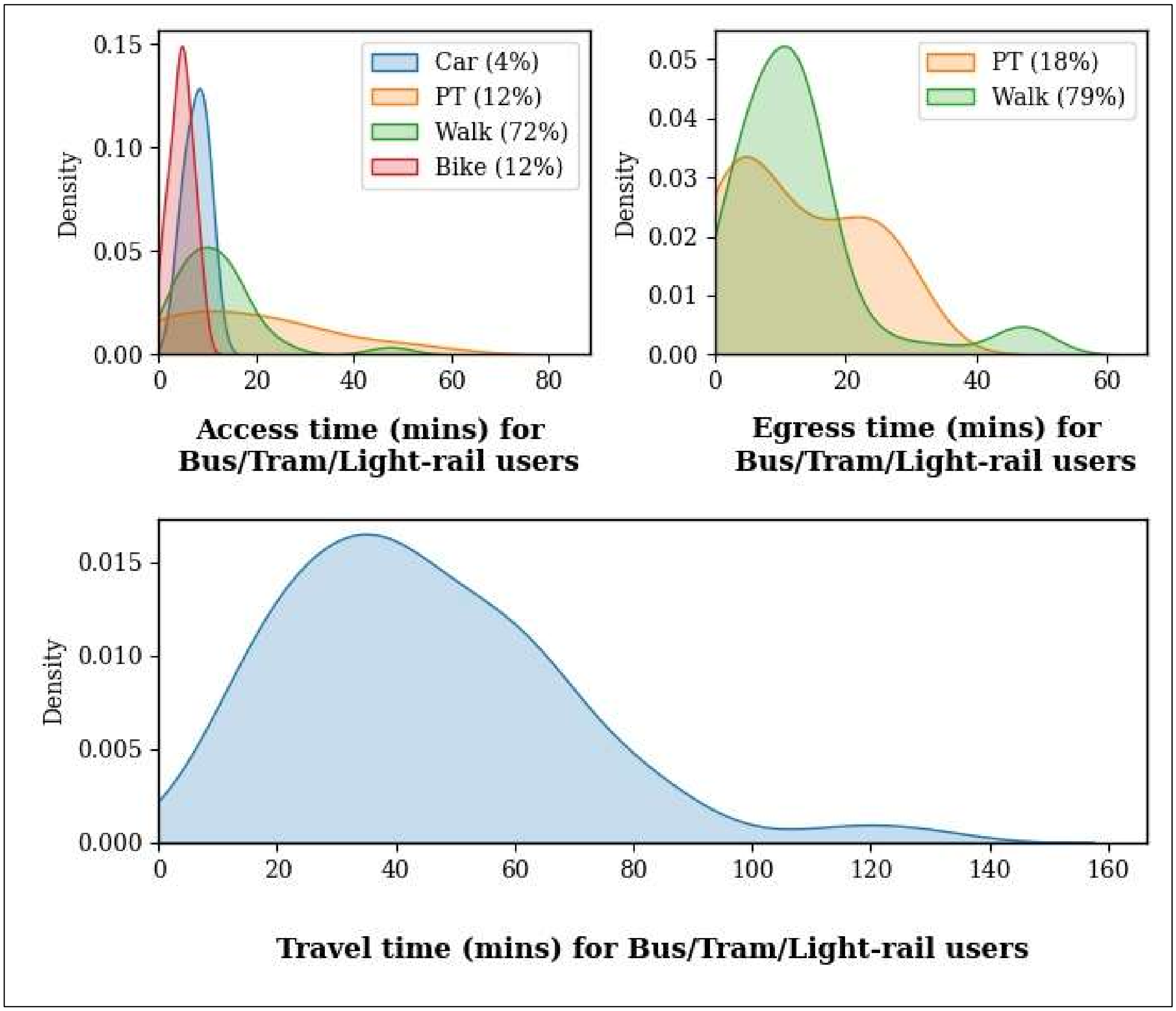


Figure 3.8: Access, egress and in-vehicle time distribution for Bus/Tram/Light-rail users

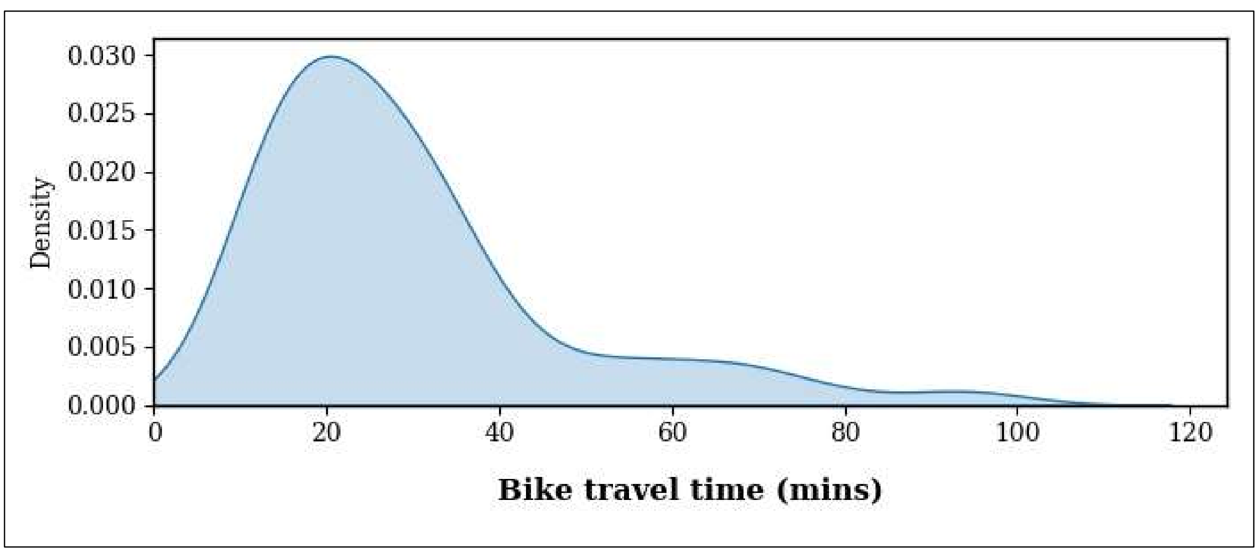


Figure 3.9: Travel time distribution for bike users

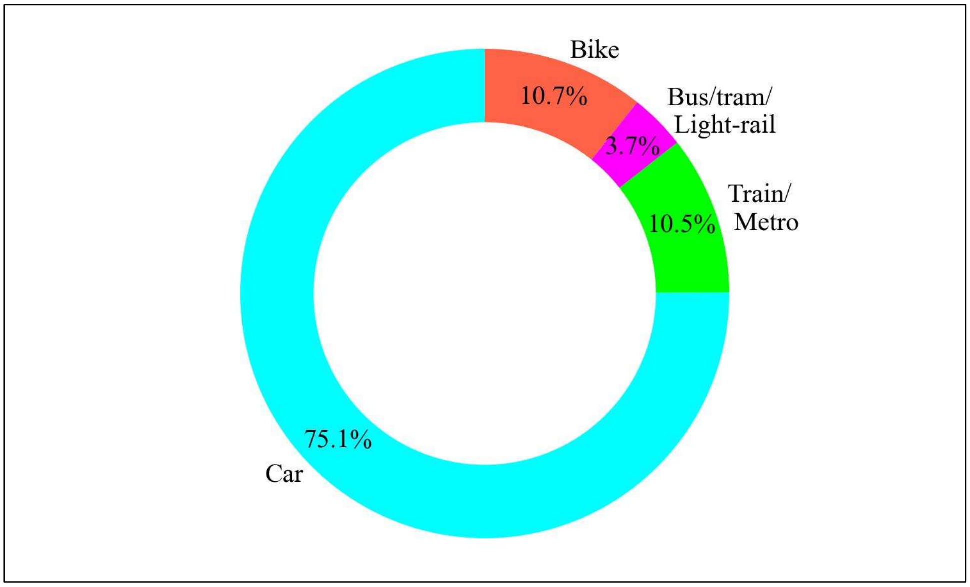
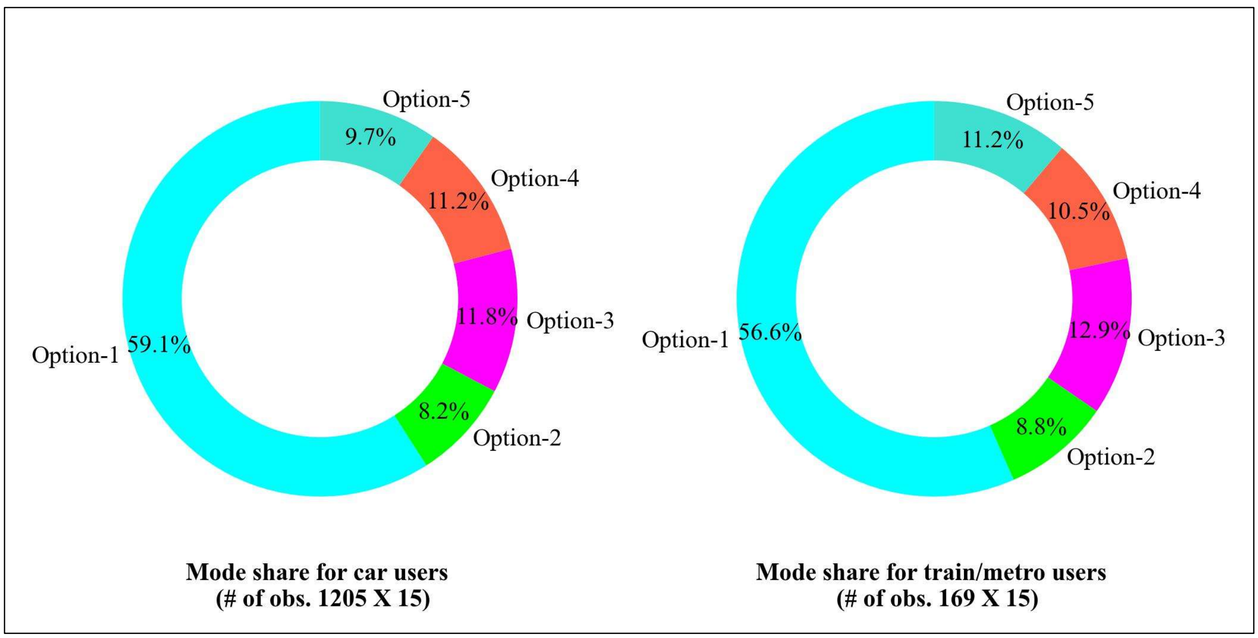


Figure 3.10a: Revealed preference (Primary) mode share



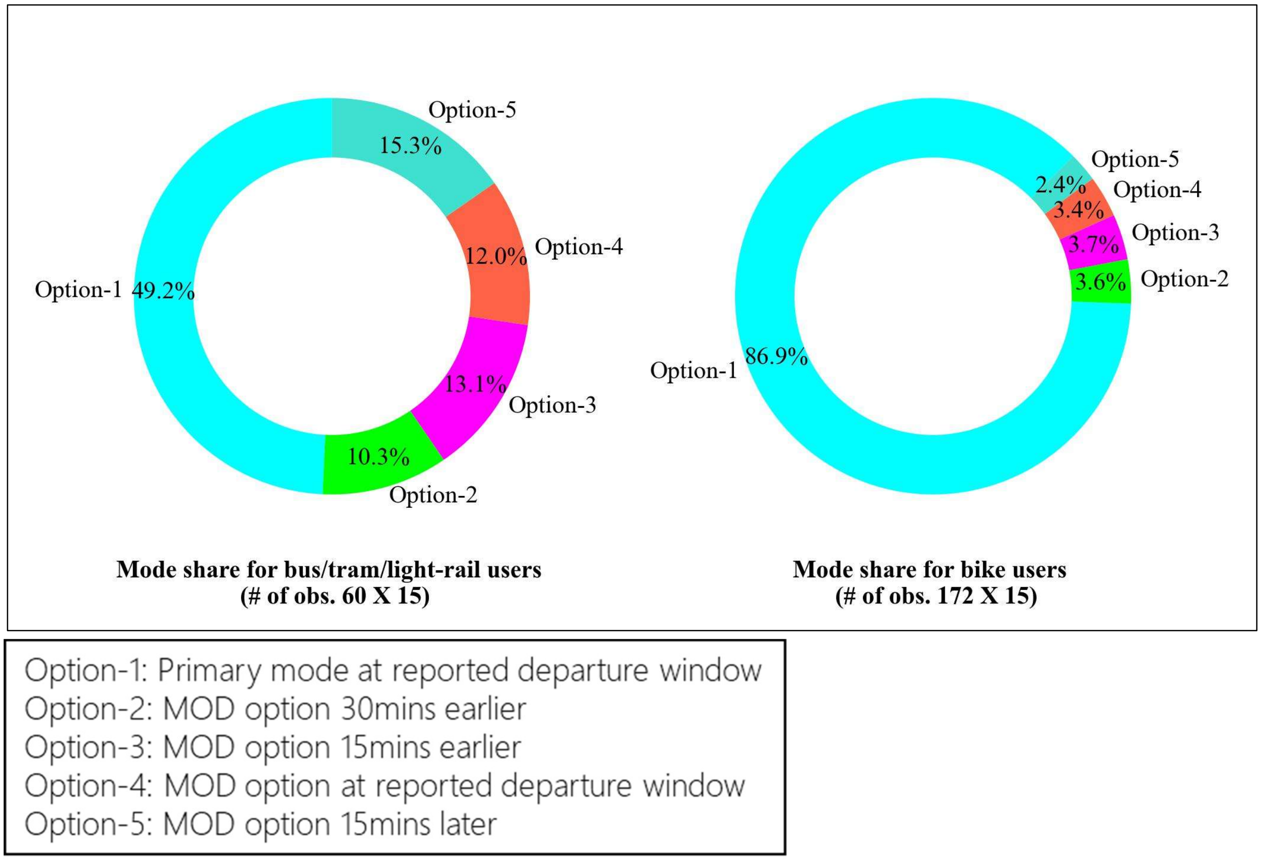


Figure 3.10b: Mode share distribution in the stated-preference choice experiment

3.5.2 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 departure time change in the presence of MOD service
5. Endogeneity effect
6. Price estimate required to achieve critical mass

3.5.2.1 Primary Mode Results (RP-stage)

Tables 3.3.1 and 3.3.2 provide the estimates of explanatory variables for the primary mode. In particular, Table 3.3.1 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 3.3.2.

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)[16]. 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 (50km 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 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

[16] In the Netherlands, majority of bus routes have bus-only lanes.

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 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.

Table 3.3.1: 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)	---	---	---	---	---	---

----: highly insignificant, p>0.35

Table 3.3.1 (Cont.): Choquet-Integral based MNP model estimation results (t-statistics in brackets)

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-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	---	---	---	---	---	---	---	---	---	---

----: highly insignificant, p>0.35

Table 3.3.1 (Cont.): Choquet-Integral based MNP model estimation results (t-statistics in brackets)

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)
	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

Table 3.3.2: 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 km²))				
Strongly urban (1500-2000 addresses per km²)		---	---	-0.168 (-16.03)
Moderately urban (1000-1500 addresses per km²)		---	---	---
Few urban (500-1000 addresses per km²)		---	---	---
Non-urban (< 500 addresses per km²)		-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 km²))				
Urban (1000-2000 addresses per km²)		-0.249 (-17.07)	-0.31 (-13.58)	-0.209 (-17.41)
Non-urban (up to 1000 addresses per km²)		-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 100s)				
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

Table 3.3.3: 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	$ln\left(\frac{Expected\ TT}{Actual\ TT}\right)$	$ln\left(\frac{Expected\ WT}{Actual\ WT}\right)$
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)		

----: highly insignificant, p>0.35

Table 3.3.3 (Cont.): Choquet-Integral based MNP model estimation results (t-statistics in brackets)

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								
	MOD at the reported 15-minute departure window								
	MOD 15 mins later								

----: highly insignificant, p>0.35

Table 3.3.4: 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

Table 3.3.5: 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 (18.35)	0.999 (24.37)																	
	0.748 (49.30)	0.696 (1.67)	0.962 (28.42)																
Car users	-0.045 (-0.30)	-0.015 (-0.04)	0.197 (1.38)	1.000 (fixed)															
	0.005 (0.06)	0.040 (0.22)	0.038 (0.27)	-0.254 (-3.00)	0.345 (5.60)														
	-0.001 (-0.02)	-0.002 (-0.01)	0.146 (2.29)	-0.050 (-1.46)	-0.059 (-2.49)	0.295 (3.57)													
	-0.025 (-0.37)	0.123 (1.35)	0.189 (3.15)	-0.118 (-2.27)	-0.052 (-3.19)	0.088 (2.16)	0.329 (0.54)												
Train or Metro users	0.109 (0.95)	0.142 (0.22)	-0.148 (-0.67)	-0.189*	-0.016*	-0.123*	-0.108*	1.000 (fixed)											
	0.150 (1.50)	0.236 (0.65)	-0.065 (-1.27)	-0.173*	-0.014*	-0.115*	-0.077*	0.840 (2.22)	0.882 (1.38)										
	0.227 (1.43)	0.289 (0.66)	-0.123 (-1.47)	-0.260*	-0.021*	-0.170*	-0.136*	0.900 (3.22)	0.834 (0.23)	1.002 (0.71)									
	0.138 (1.43)	0.257 (1.00)	-0.129 (-1.42)	-0.218*	-0.016*	-0.145*	-0.103*	0.888 (4.11)	0.848 (0.46)	0.917 (0.31)	0.952 (2.04)								
Tram or Bus or Light-Rail users	-0.104 (-0.140)	0.124 (0.36)	0.308 (0.64)	0.233*	0.032*	0.146*	0.201*	-0.243*	-0.199*	-0.322*	-0.254*	1.000 (fixed)							
	0.189 (0.74)	0.020 (0.50)	0.200 (0.42)	0.056*	0.001*	0.044*	0.019*	-0.067*	-0.063*	-0.084*	-0.090*	-0.180 (-0.31)	0.191 (0.18)						
	-0.004 (-0.01)	0.020 (0.12)	0.187 (0.68)	0.129*	0.013*	0.084*	0.095*	-0.144*	-0.126*	-0.193*	-0.162*	0.051 (0.32)	0.093 (0.06)	0.196 (0.50)					
	0.228 (0.71)	-0.011 (-0.61)	0.228 (0.54)	0.068*	-0.001*	0.054*	0.015*	-0.087*	-0.086*	-0.112*	-0.119*	-0.055 (-0.17)	0.096 (0.48)	0.061 (0.29)	0.219 (1.23)				
Bike users	0.011 (0.02)	-0.183 (-0.14)	0.038 (0.17)	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 (fixed)			
	-0.080 (-0.24)	-0.126 (-0.14)	-0.035 (-0.28)	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 (-0.34)	0.29 (1.23)		
	-0.096 (-0.29)	-0.056 (0.01)	-0.046 (-0.16)	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 (-0.46)	-0.068 (-0.70)	0.235 (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 (-1.3)	-0.144 (-1.27)	-0.022 (-1.28)	0.602 (1.31)

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

3.5.2.2 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.

3.5.2.2.1 Non-Compensatory Behaviour:

Table 3.3.4 reports the CI fuzzy measure estimates[17]. 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[18].

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 3.4.1) 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. 3.5 in section 3.4). 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

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

[18] 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 to estimate separate parameters for those variables. However, the estimates could not be empirically identified.

importance of these two attributes may be close to zero (non-significant role in the decision process of bus users when comparing the currently used mode with MOD options).

3.5.2.2.2 Feature Importance (Shapley value)

Figure 3.11 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. 3.5. In contrast, Eq. 3.5 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 Supplement-3 (section S.3.4). It is plausible that feature importance derived based on this marginal-effect approach may be different from true feature importance[19]. 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.

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[19] The Shapley equivalent feature importance in weighted-sum-based models can be derived using the approach suggested by Mishra (2016). The approach essentially requires the estimation of $2^{\#\text{ of attributes}}$ models with all possible interactions. The data-fit estimate (R^2 value) of the models is then used as fuzzy measure values in Eq. 3.5 to obtain Shapley values.

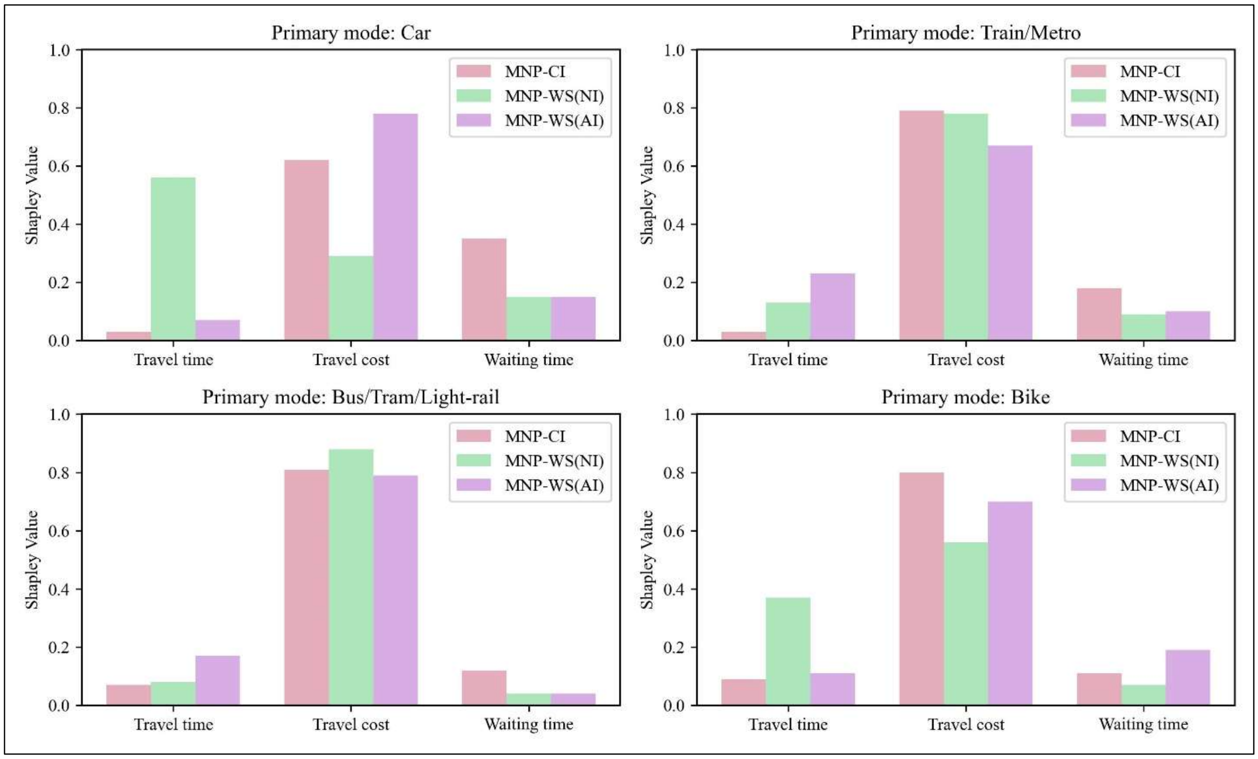

Figure 3.11: Feature importance (Shapley value)

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 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 3.5.2.2.1) 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.

3.5.2.2.3 Aggregate Model Validation

Table 3.4 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 3.4: Data-fit statistics for CI and WS models

Model	CML value (# of parameters)	AIC
MNP-CI	-24807.36 (257)	50129
MNP-WS(NI)	-26380.98 (237)	53236
MNP-WS(AI)	-25355.02 (253)	51216

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

3.5.2.2.4 Disaggregate Model Validation

The three criteria (fuzzy measure values, feature importance and AIC criterion) used to compare CI and WS-based model 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.

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

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

where $i_{accuracy}$ is the accuracy of option i and i_{share} is the observed share of option i in the sample and $0 \le \text{WA} \le 1$.

Figure 3.12 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 Supplement-3 (see section S.3.5). The CI-based model consistently has a higher weighted accuracy value across all primary modes in both estimation and validation samples[20]. This demonstrates that the CI model can reduce the divergence between modelled and true behaviour and hence able to provide improved individual-level predictions.

[20] We also report the un-weighted accuracy and average implied shares for all the models in Supplement-3 (see section S.3.5 & S.3.6).

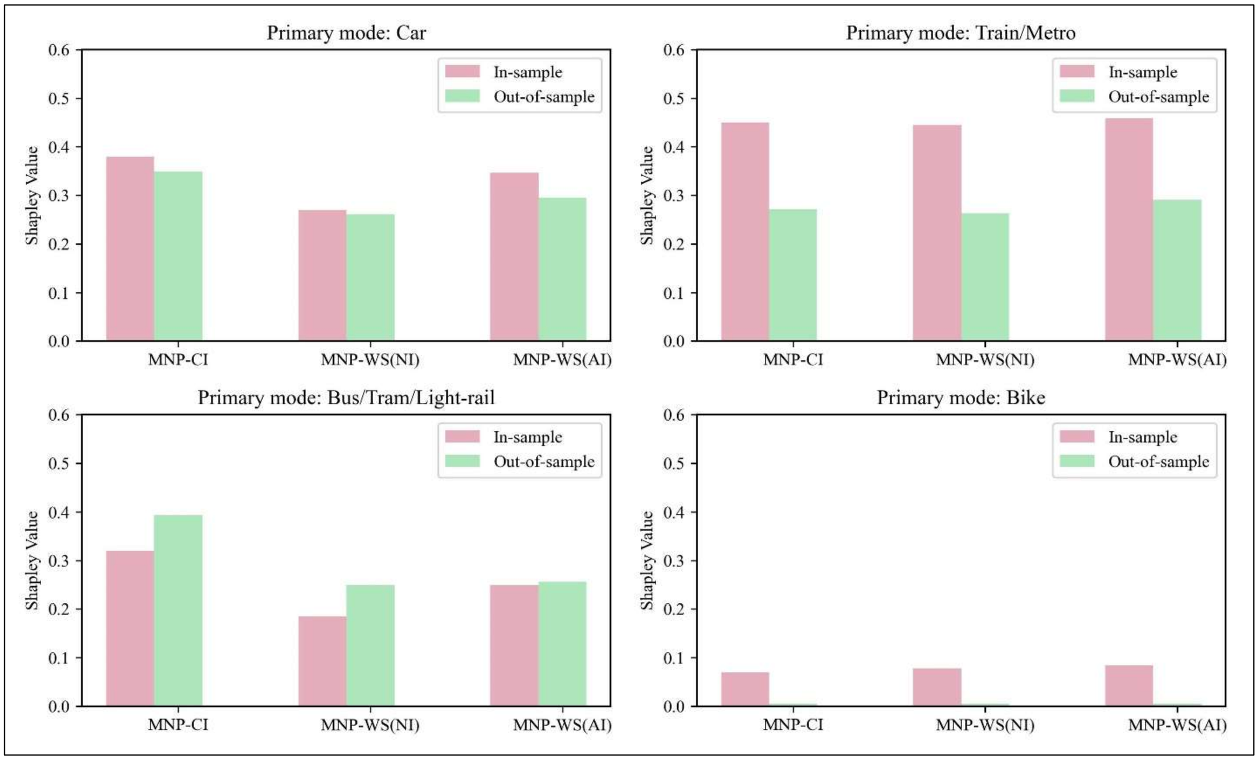

Figure 3.12: Weighted accuracy value

3.5.2.2.5 Regret Due to Difference in Stated vs. Actual Information or Reliability Effect

Table 3.3.3 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 (ρ) parameter (see section 3.4.2) and hence tried both linear difference and ratio. The ratio approach was found to provide the best results. In particular, we used $log\left({Expected\ Value}\middle/{Actual\ value} \right)$. 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.

3.5.2.2.6 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 3.4.2. 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: $\beta_{CC}\left(\#of\ \ times\ chosen\, until\, t\text{ - }1\right)^{\frac{1}{\alpha}}$, where $\alpha > 0$. A positive β_{CC}

implies a higher likelihood of choosing an alternative, ceteris paribus. The curvature parameter (α) 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 $\alpha \geq 5$ indicates the absence of any inertia at all. For all the primary mode and MOD combinations, the value of β_{CC} is positive. Table 3.3.3 provides the estimates related to past choices based on the MNP-CI model.

In the case of car users, the value of α 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 α is 1.85 for the train/metro mode and 1.0 for the remaining four MOD options[21]. 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 α coefficient and only estimated an intercept. One can parametrize the α 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.

Further, the AR coefficient $(\pi,\ \text{see Eq. 3.16})$ 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.

3.5.2.2.7 Temporal Mode Shift

To capture the temporal mode shift effect, we added the time of day as a dummy variable (see Figure 3.5e). The estimates are provided in Table 3.3.1. 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.

[21] All the curvature parameters with a 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.

3.5.2.2.8 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 3.3.3). 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.

3.5.2.2.9 Effect of Trip Purpose and Sharing/Private Option

The trip purpose (see Figure 3.5d) 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 a propensity towards shared rides as compared to private MOD rides. Train/metro users also exhibit a 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.

3.5.2.2.10 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).

3.5.2.2.11 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.3.1 in Supplement-3). 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.

3.5.2.2.12 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 3.3.5). 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.

Based on estimates provided in Table 3.3.5, 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[22]. 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.

3.5.2.2.13 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[23]. Figure 3.13 shows the aggregate MOD market share for each of the primary travel modes and MOD combinations[24]. 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 (Figure 3.13 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.

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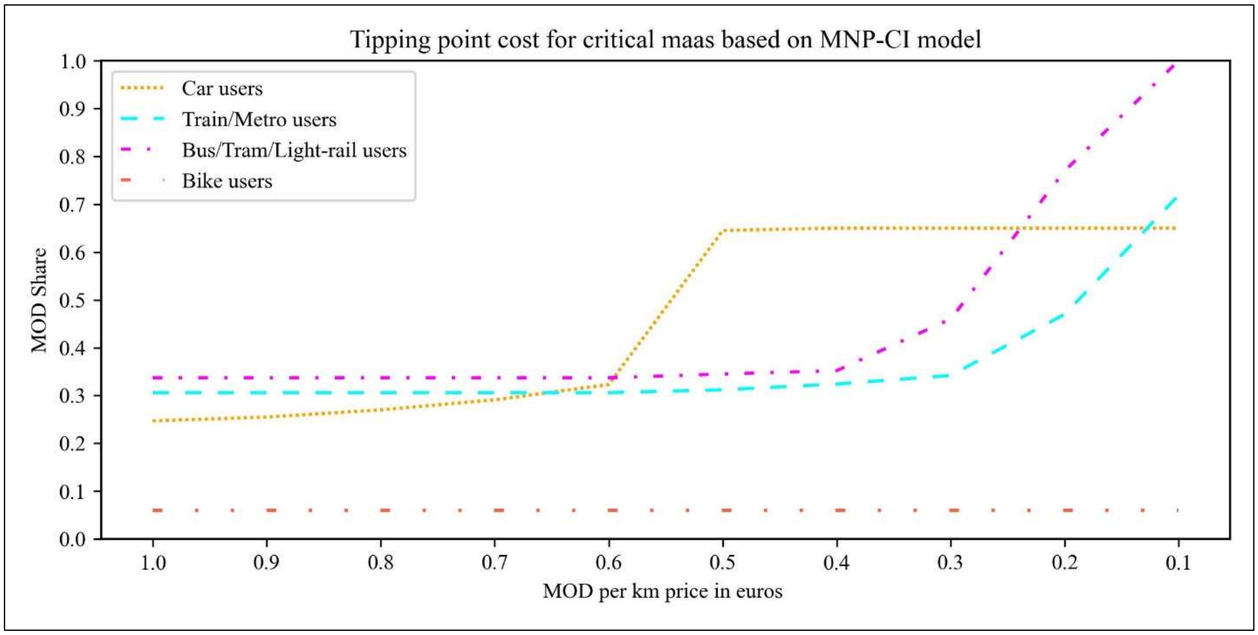
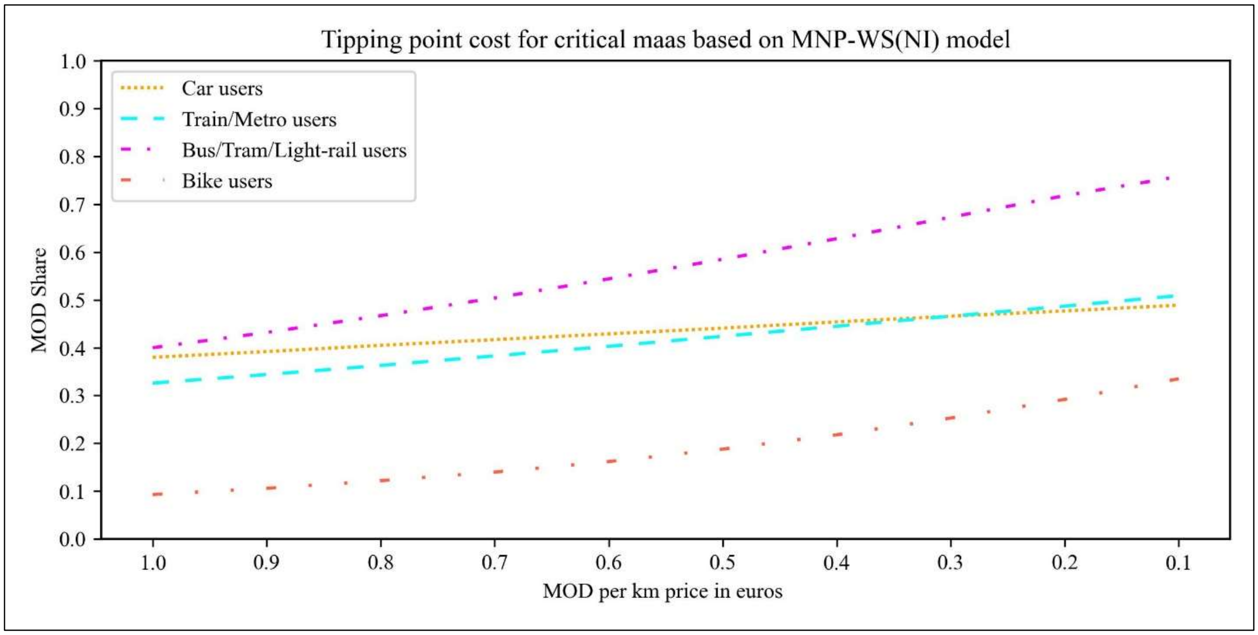
[22] Note that the off-diagonal blocks between various SP choices may have non-zero but relatively small numerical values due to the estimation of the Cholesky matrix during model estimation.

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

[24] 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 Supplement-3 (see section S.3.7)


Tipping point cost for critical maas based on MNP-CI model
Car users
Train/Metro users
Bus/Tram/Light-rail users
Bike users
MOD Share
MOD per km price in euros
1.0
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0.0


Tipping point cost for critical maas based on MNP-WS(NI) model
Car users
Train/Metro users
Bus/Tram/Light-rail users
Bike users
MOD Share
MOD per km price in euros
1.0
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
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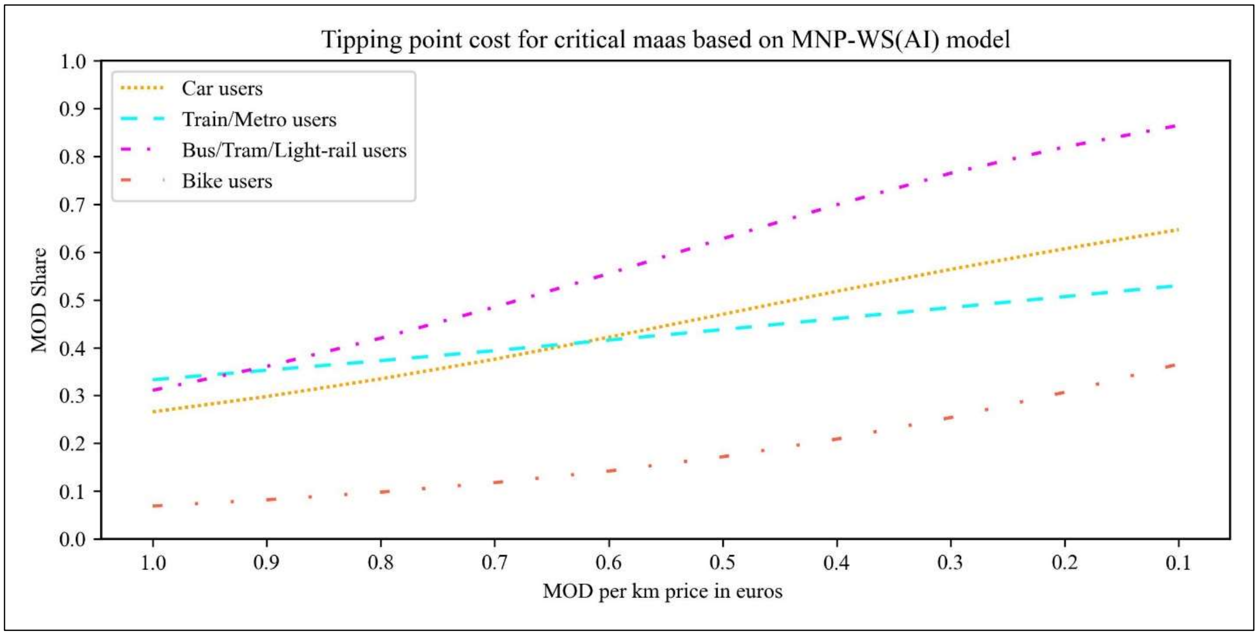


Figure 3.13: MOD share as a function of price

3.6. 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.

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 waiting time difference (actual vs. reported) as compared to travel time difference. The trend is the opposite for train/metro users. Bus/tram/light-rail and bike users seem insensitive to such differences.

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 MOD. 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.

Fifth, 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. Second, 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.

Finally, the CI model without endogeneity correction provides 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. Upon correction, these values changed to 0.62, 0.79, 0.81, and 0.80 for car, train/metro, bus/tram/light-rail and bike users, respectively. However, the Shapley value of travel time remains very low although bigger in magnitude compared to the model with no endogeneity correction. The Shapley value for travel time is 0.03, 0.03, 0.07, and 0.09 for car, train/metro, bus/tram/light-rail and bike users, respectively. Since the in-vehicle travel time does not differ substantially between MOD option, car and train/metro in most instances. It has very low alternative discernability power in distinguishing between alternatives and hence low Shapley values are not completely unreasonable. For the bus/tram/light-rail and bike users, the travel time does have a slightly bigger Shapley value as the travel time for these modes is significantly different as compared to the MOD option. Nonetheless, the use of the Choquet-Integral (CI) function can lead to a high Shapley value for the cost variable in the current survey due to the design. In the current design, cost varies substantially between existing primary modes and MOD options followed by waiting time and travel time, especially for car and train users. Therefore, during CI calculation, the ordered set is more likely to have cost and waiting time as the first and second variables (see section 3.4.1). Therefore, the marginal contribution of cost is going to be highest followed by waiting and travel time leading to a higher Shapley value for the cost variable. Alternatively, we can calculate the Shapley value for the attributes with weighted-sum-based models using the approach suggested by Mishra (2016). Essentially, the approach entails estimating 2^K models using all combinations of K attributes. Then the R^2 value of the models can be treated as fuzzy measures and equation 3.3.5 can be used to obtain Shapley values. Future works should explore alternative approaches.

Appendix-3

A.3.1 Model Formulation Matrix Notations

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

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

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

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

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

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

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

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

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

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

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.3.2 Utility Difference Matrix Pseudocode

$\mathbf{M} = zeros\left(\left(I_{RP}-1\right)+T(I_{SP}-1)\times\left(I_{RP}\right)+T(I_{SP})\right)$

Iden_mat = $\boldsymbol{I}_{I_{RP}-1}$

O_neg = -1*ones($I_{RP}-1,1$)

if($i_{m,RP} == 1$)

temp_mat = O_neg~Iden_mat

elseif($i_{m,RP} == I_{RP}$)

temp_mat = Iden_mat ~ O_neg

else

temp_mat = Iden_mat[.,1:$i_{m,RP}$-1] ~ O_neg~Iden_mat[.,$i_{m,RP}$:$I_{RP}-1$]

$\mathbf{M}[1{:}I_{RP}-1, 1{:}I_{RP}]$ = temp_mat

for m = 1 to T

Iden_mat = $\boldsymbol{I}_{I_{SP}-1}$

O_neg = -1*ones($I_{SP}-1,1$)

if($i_{m,SP,t} == 1$)

temp_mat = O_neg~Iden_mat

elseif($i_{m,SP,t} == I$)

temp_mat = Iden_mat ~ O_neg

else

temp_mat = Iden_mat[.,1:$i_{m,SP,t}$-1] ~ O_neg~Iden_mat[.,$i_{m,SP,t}$:$I_{SP}-1$]

end

$row\_start = \left(I_{RP}-1\right)+\left(m-1\right)\left(I_{SP}-1\right)+1$

$row\_end = \left(I_{RP}-1\right)+\left(m\right)\left(I_{SP}-1\right)$

$col\_start = \left(I_{RP}\right)+\left(m-1\right)\left(I_{SP}\right)+1$

$col\_end = \left(I_{RP}\right)+\left(m\right)\left(I_{SP}\right)$

$\mathbf{M}[row\_start{:}row\_end, col\_start{:}col\_end]$ = temp_mat

where " ~ " refers to horizontal concatenation and $i_{m,SP,t}$ is the chosen SP alternative at time t

Supplement-3

S.3.1 Survey Modules

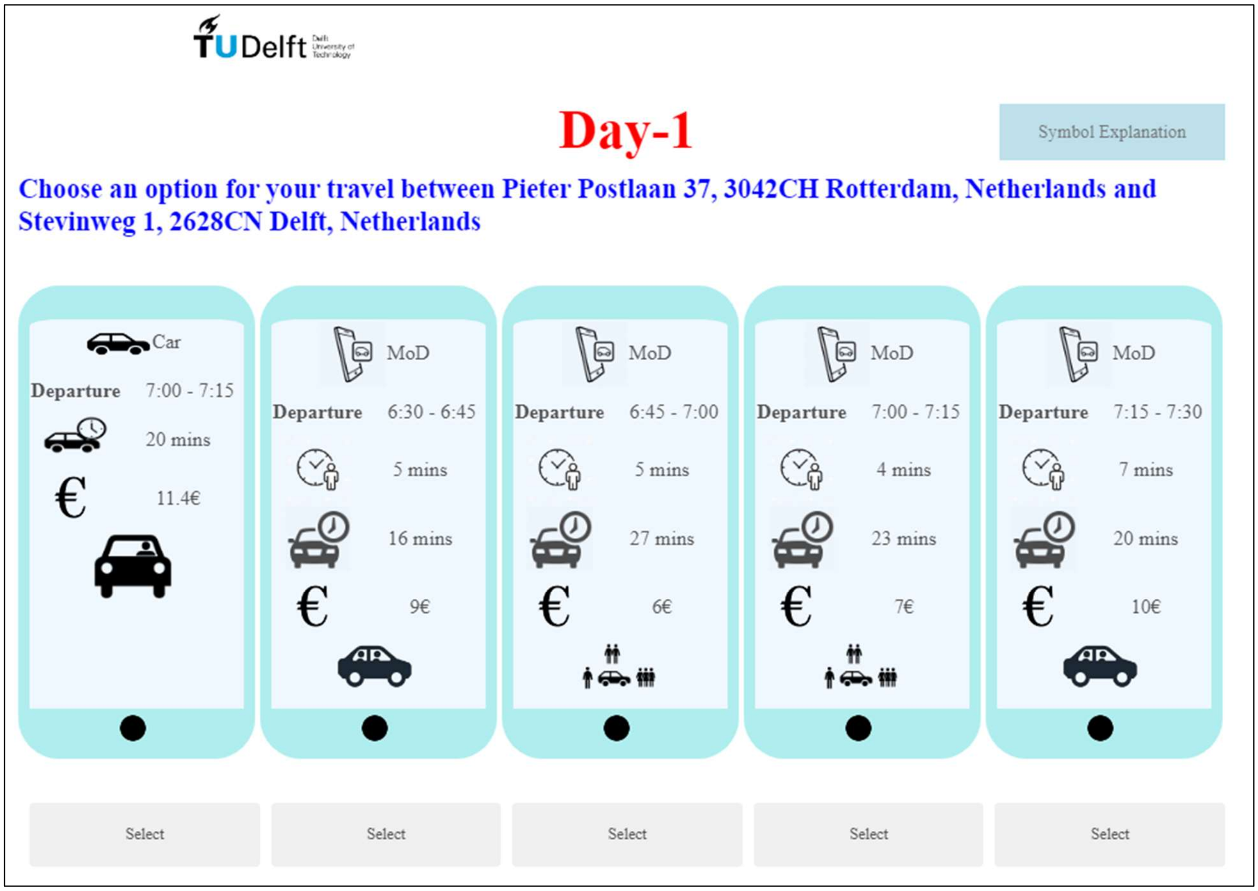


Figure S.3.1: Choice experiment for car users

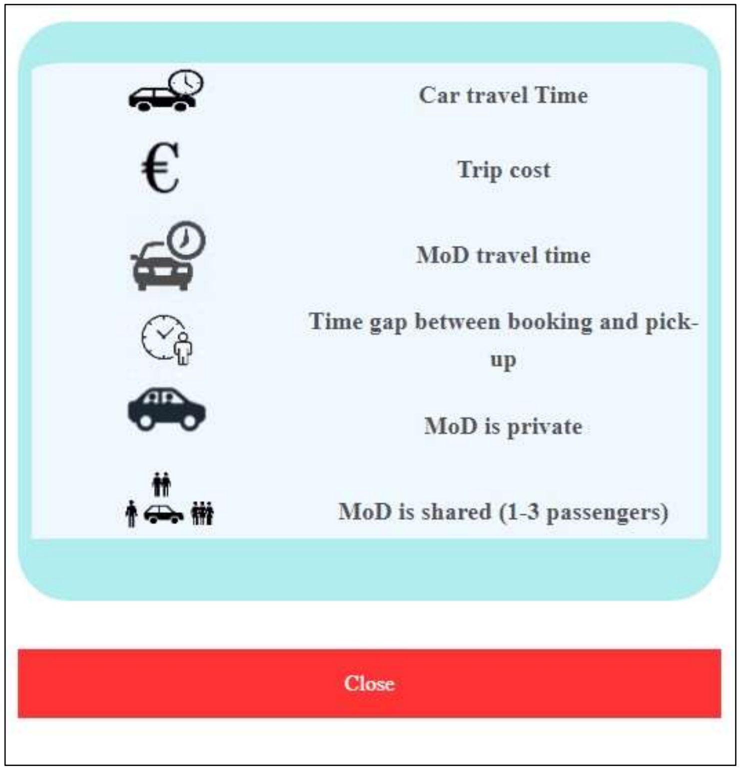
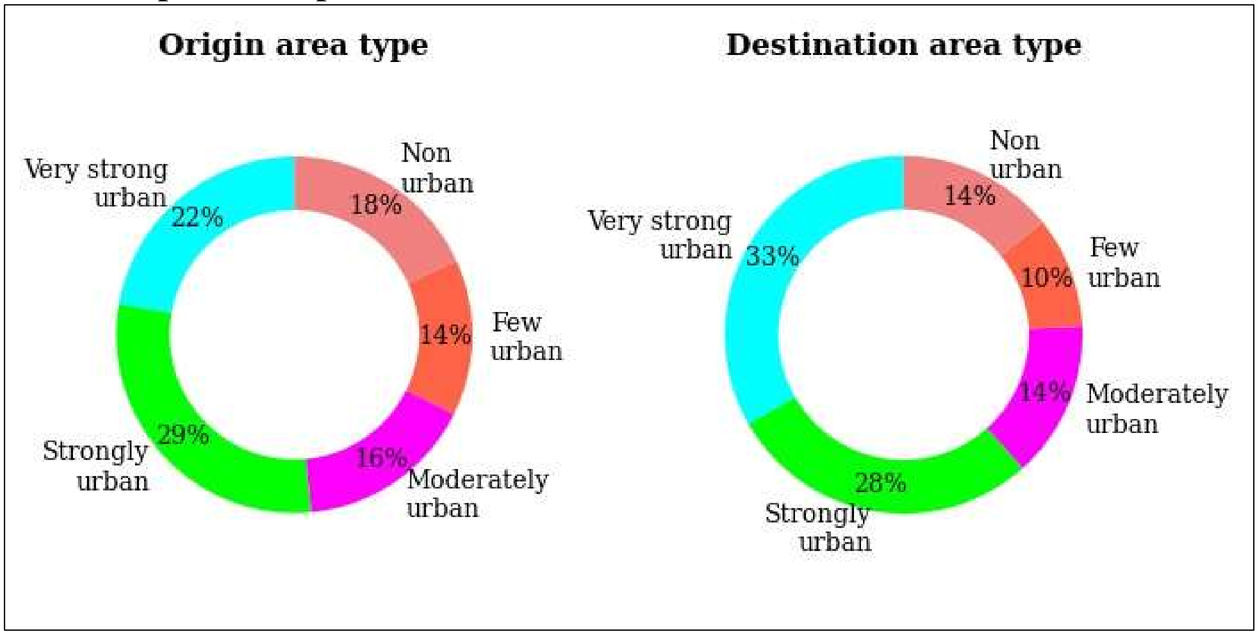
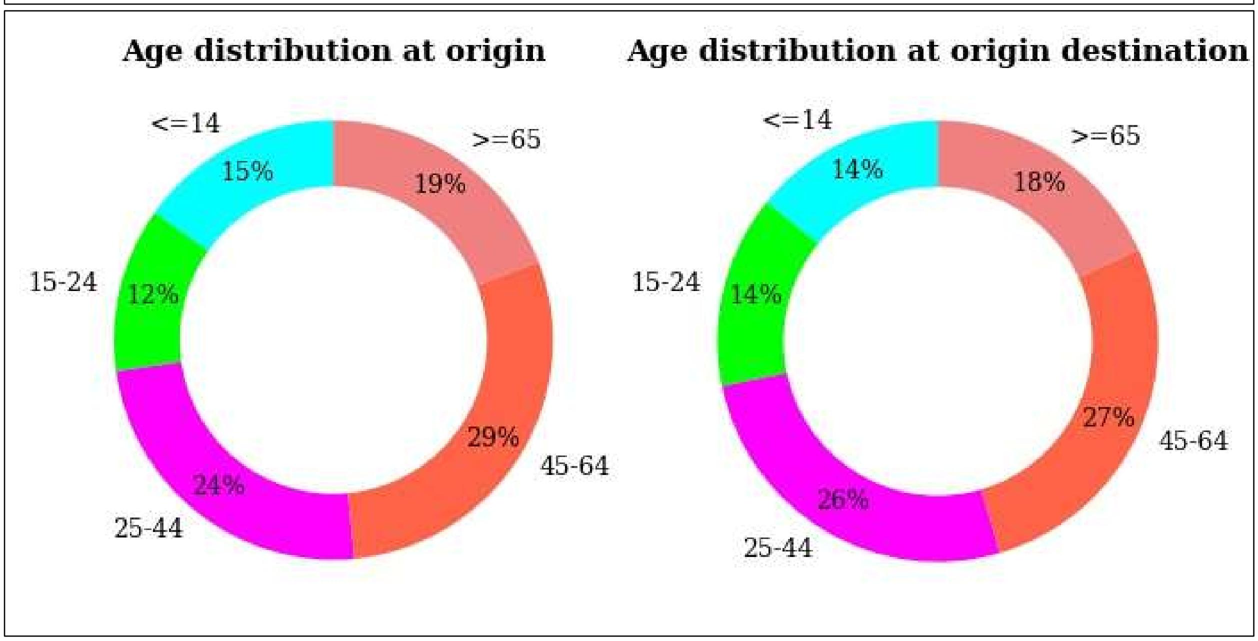
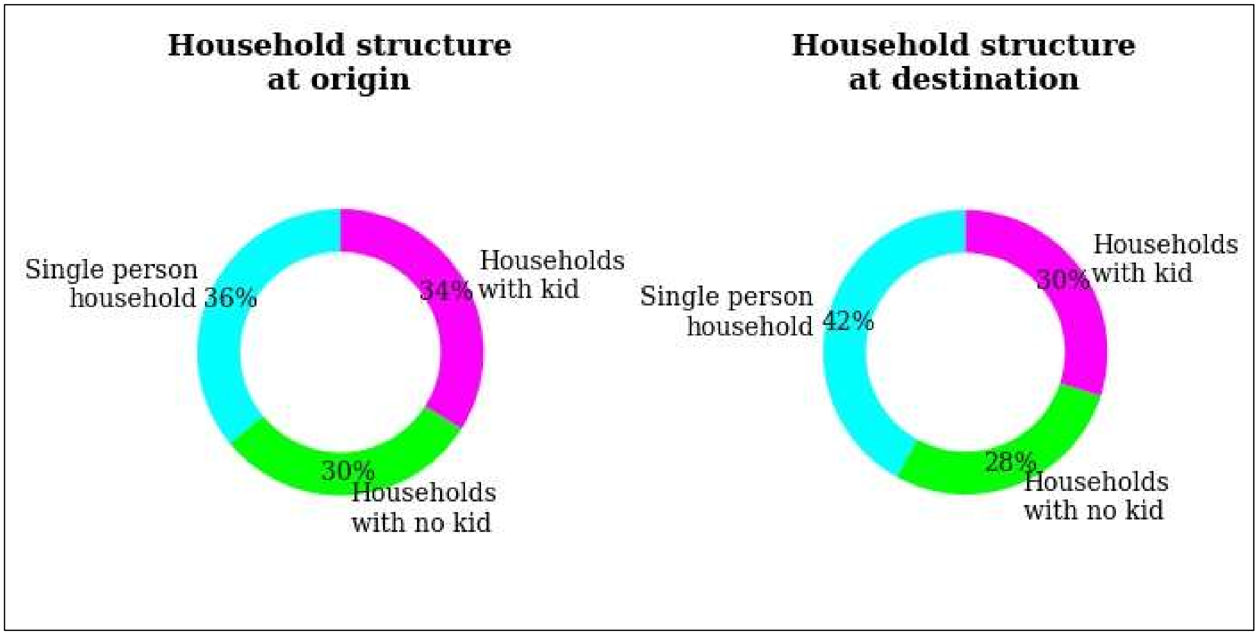


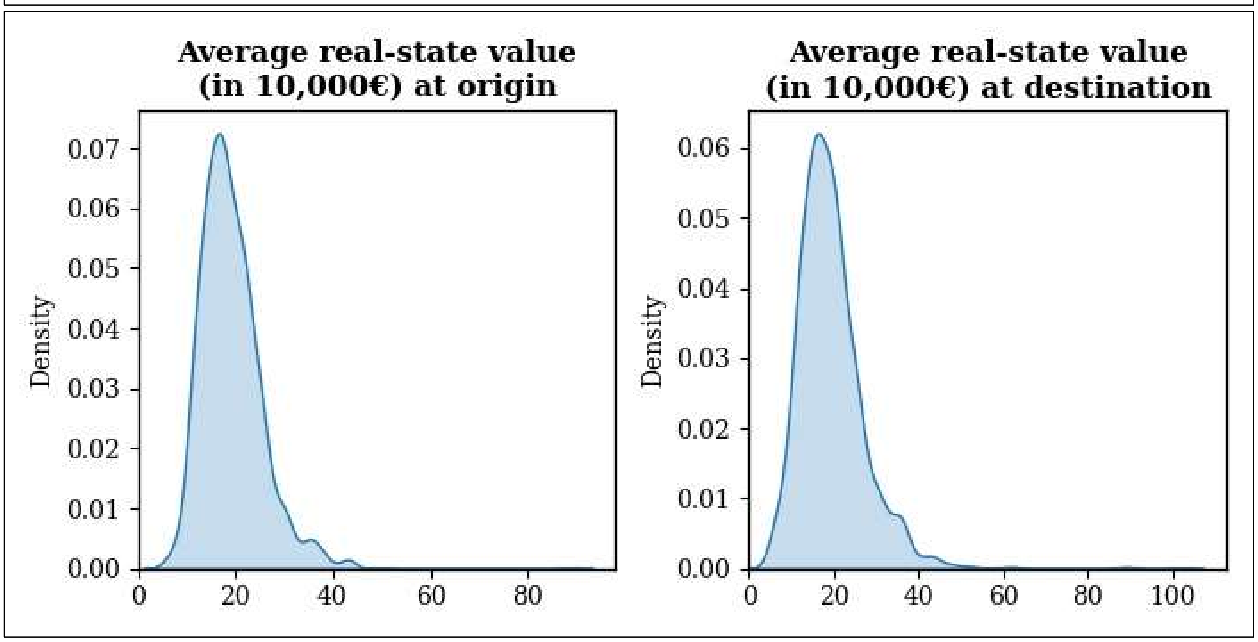
Figure S.3.2: Pop-up window of "Symbol Explanation" for car users

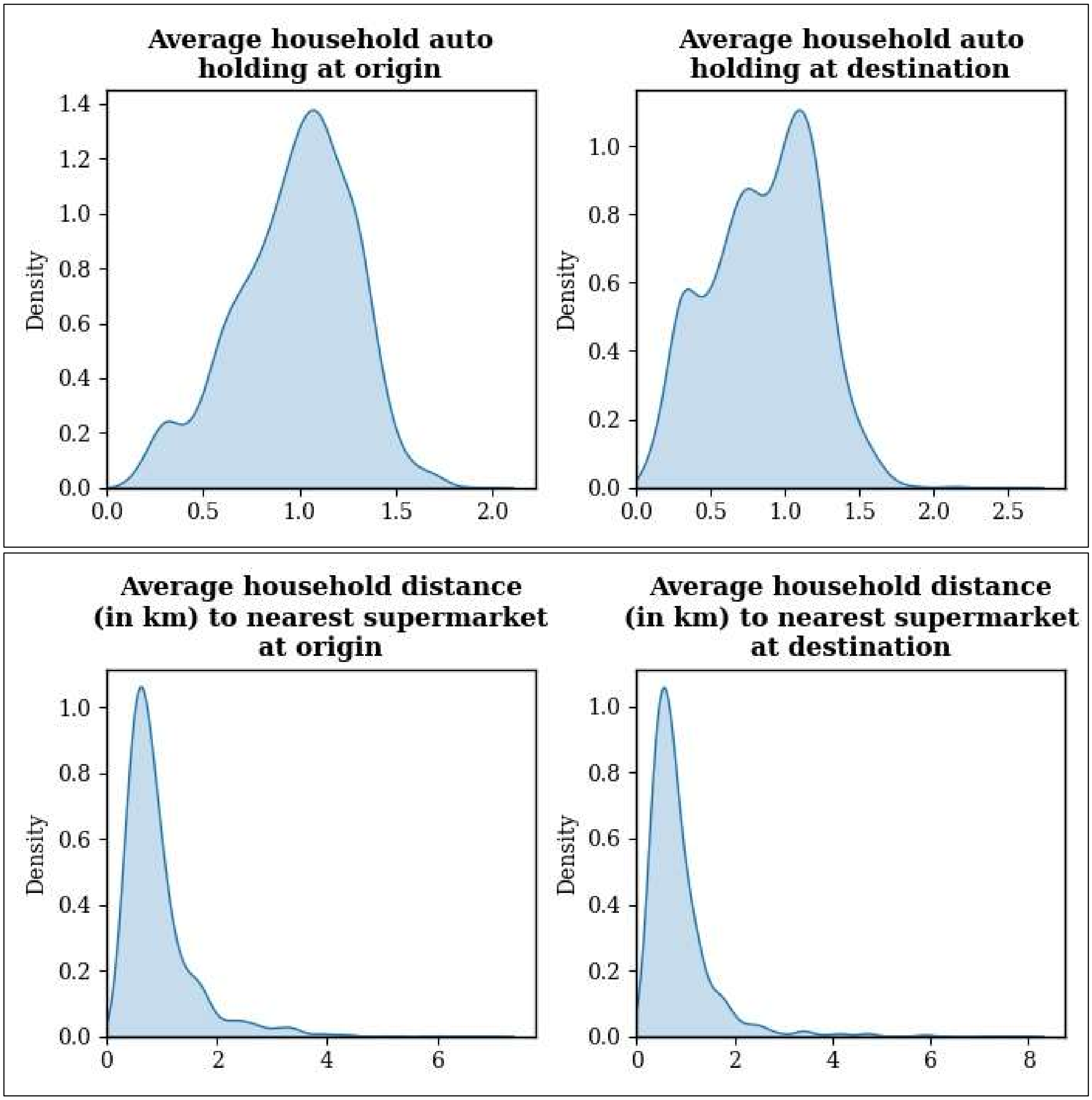
S.3.2 Sample Description of Postcode Level Variables

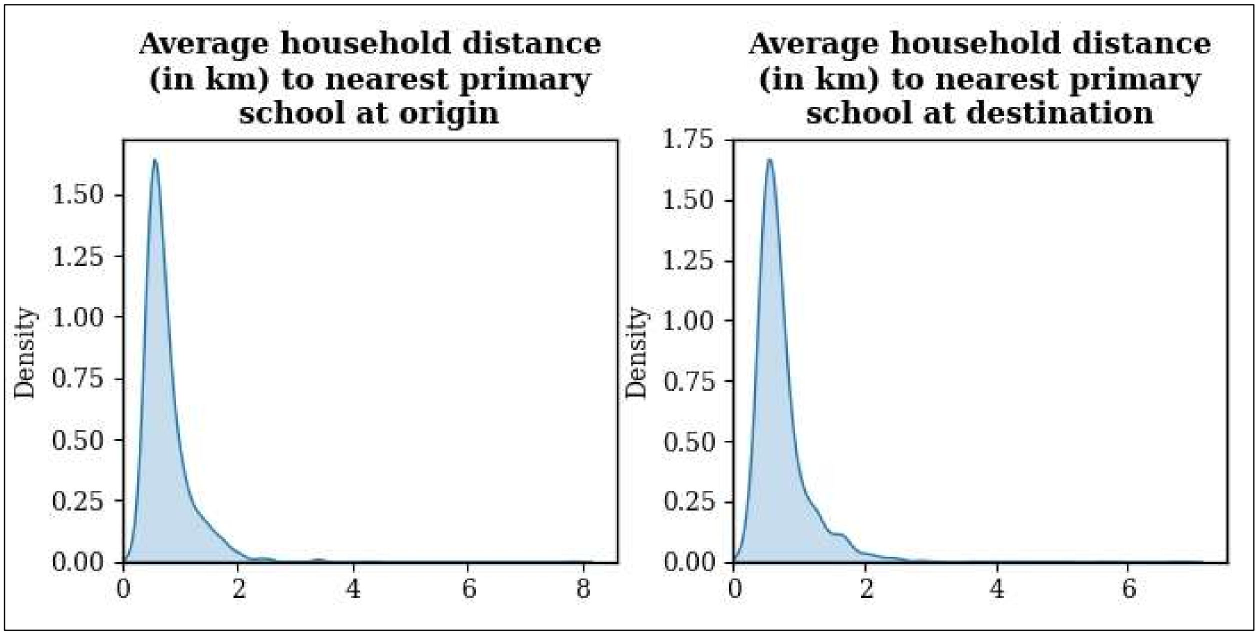


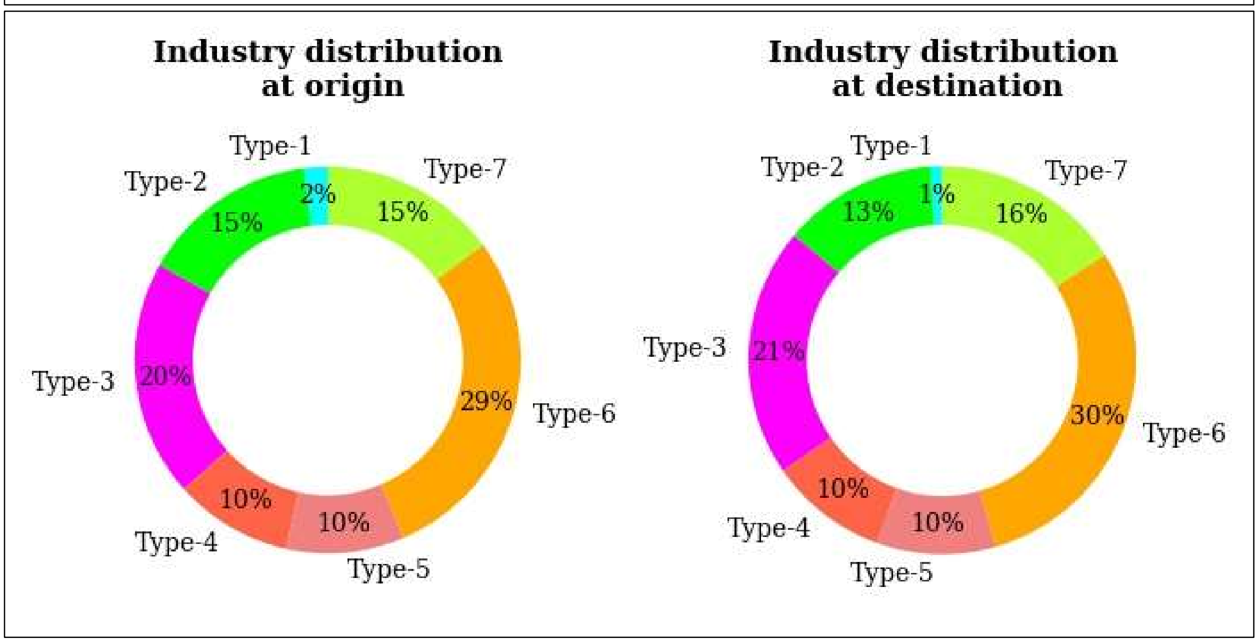



Household structure at origin
Single person household 36%
34% Households with kid
30% Households with no kid
Household structure at destination
Single person household 42%
30% Households with kid
28% Households with no kid


Average real-state value (in 10,000€) at origin
Density
0.00
0.01
0.02
0.03
0.04
0.05
0.06
0.07
0
20
40
60
80
Average real-state value (in 10,000€) at destination
Density
0.00
0.01
0.02
0.03
0.04
0.05
0.06
0
20
40
60
80
100


Average household auto holding at origin
Density
1.4
1.2
1.0
0.8
0.6
0.4
0.2
0.0
0.0 0.5 1.0 1.5 2.0
Average household auto holding at destination
Density
1.0
0.8
0.6
0.4
0.2
0.0
0.0 0.5 1.0 1.5 2.0 2.5
Average household distance (in km) to nearest supermarket at origin
Density
1.0
0.8
0.6
0.4
0.2
0.0
0 2 4 6
Average household distance (in km) to nearest supermarket at destination
Density
1.0
0.8
0.6
0.4
0.2
0.0
0 2 4 6 8





Type-1: Agriculture, forestry and fisheries
Type-2: Industry and energy
Type-3: Trade and catering
Type-4: Transport, information and communication
Type-5: Financial services and real estate
Type-6: Business services
Type-7: Culture, recreation, other services

S.3.3 Model Estimation Results

Table S.3.3.1.1: MNP-WS(NI) 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	-0.750 (-19.84)	---	0.791 (27.48)	---	---	0.179 (14.69)	0.211 (14.65)
	Bus/Tram/Light-rail	-0.541 (-13.12)	---	1.286 (24.62)	-0.675 (-9.86)	---	---	---
	Bike	-0.313 (-17.50)	---	---	-0.188 (-13.7)	---	---	---
Car users	Car at the reported 15-minute departure window							
	MOD 30 mins earlier	-0.925 (-7.11)	---	---	---	---	---	0.056 (0.99)
	MOD 15 mins earlier	-1.182 (-5.01)	---	---	-0.086 (-1.11)	---	---	---
	MOD at the reported 15-minute departure window	-0.967 (-4.86)	-0.096 (-1.37)	---	-0.188 (-2.10)	-0.120 (-1.37)	---	0.049 (0.85)
	MOD 15 mins later	-0.811 (-5.04)	-0.113 (-1.43)	---	-0.152 (-1.74)	-0.102 (-1.33)	---	0.058 (1.15)
Train/ metro users	Train/metro at the reported 15-minute departure window							
	MOD 30 mins earlier	0.605 (4.97)	---	---	---	---	---	---
	MOD 15 mins earlier	0.658 (4.40)	---	---	---	---	---	---
	MOD at the reported 15-minute departure window	0.484 (4.24)	---	---	---	---	---	---
	MOD 15 mins later	0.671 (4.60)	---	---	---	---	---	---
Bus/tram/ light-rail users	Bus/tram/light-rail at the reported 15-minute departure window							
	MOD 30 mins earlier	-0.657 (-1.83)	---	---	---	---	---	---
	MOD 15 mins earlier	0.056 (0.21)	---	---	---	---	---	---
	MOD at the reported 15-minute departure window	-0.670 (-0.79)	---	---	---	---	---	---
	MOD 15 mins later	0.222 (0.92)	---	---	---	---	---	---
Bike users	Bike at the reported 15-minute departure window							
	MOD 30 mins earlier	-1.957 (-11.55)	---	---	0.324 (2.04)	---	---	---
	MOD 15 mins earlier	-0.958 (-0.84)	---	---	---	---	---	---
	MOD at the reported 15-minute departure window	-0.949 (-1.29)	---	---	---	---	---	---
	MOD 15 mins later	-1.424 (-0.82)	---	---	---	---	---	---

----: highly insignificant, p>0.35

Table S.3.3.1.1 (Cont.): MNP-WS(NI) model estimation results (t-statistics in brackets)

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	---	0.283 (16.38)	-0.253 (-14.25)	---	-0.328 (-19.42)	-0.365 (-17.83)	-0.782 (-10.91)	-0.782 (-10.91)	-0.782 (-10.91)	-0.782 (-10.91)
	Bus/Tram/Light-rail	---	---	---	---	---	---	---	---	---	---
	Bike	---	---	---	---	---	---	-0.598 (-19.09)	-0.598 (-19.09)	-0.598 (-19.09)	-0.598 (-19.09)
Car users	Car at the reported 15-minute departure window										
	MOD 30 mins earlier	---	---	---	0.131 (1.91)	---	0.045 (0.87)	---	---	---	---
	MOD 15 mins earlier	---	---	---	---	---	---	---	---	---	---
	MOD at the reported 15-minute departure window	-0.115 (-1.09)	---	0.070 (1.29)	---	---	---	---	---	---	---
	MOD 15 mins later	---	---	---	---	0.095 (1.68)	0.079 (1.73)	---	---	---	---
Train/ metro users	Train/metro at the reported 15-minute departure window										
	MOD 30 mins earlier	---	---	0.101 (1.21)	---	---	---	---	---	---	---
	MOD 15 mins earlier	---	---	---	---	---	---	---	---	---	---
	MOD at the reported 15-minute departure window	---	---	---	0.111 (2.17)	---	---	---	---	---	---
	MOD 15 mins later	---	---	---	0.067 (1.04)	---	---	---	---	---	---
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

Table S.3.3.1.1 (Cont.): MNP-WS(NI) model estimation results (t-statistics in brackets)

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	0.384 (19.21)	---	---	---	---	0.904 (30.98)	---	0.349 (14.03)
	Bus/Tram/Light-rail	---	---	---	-0.426 (-6.06)	---	0.735 (17.31)	0.173 (5.84)	0.51 (15.26)
	Bike	---	-0.348 (-25.45)	---	---	---	1.213 (56.25)	---	---
Car users	Car at the reported 15-minute departure window								
	MOD 30 mins earlier	0.186 (2.35)	0.047 (0.71)	0.057 (0.9)	---	---	---	---	---
	MOD 15 mins earlier	0.152 (1.69)	0.064 (0.97)	0.072 (1.04)	0.097 (1.64)	---	---	---	---
	MOD at the reported 15-minute departure window	0.153 (1.68)	0.074 (0.99)	0.093 (1.17)	0.070 (1.00)	---	---	---	---
	MOD 15 mins later	0.089 (0.95)	0.029 (0.49)	0.098 (1.51)	---	---	---	---	---
Train/ metro users	Train/metro at the reported 15-minute departure window								
	MOD 30 mins earlier	0.153 (1.69)	0.153 (1.69)	---	---	-0.183 (-2.01)	---	---	---
	MOD 15 mins earlier	0.261 (1.87)	0.261 (1.87)	0.125 (0.96)	0.125 (0.96)	-0.230 (-2.29)	---	---	---
	MOD at the reported 15-minute departure window	0.280 (3.17)	0.280 (3.17)	0.143 (2.16)	0.143 (2.16)	-0.258 (-3.29)	---	---	---
	MOD 15 mins later	0.228 (1.90)	0.228 (1.90)	0.129 (1.10)	0.129 (1.10)	-0.311 (-3.81)	---	---	---
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

Table S.3.3.1.2: MNP-WS(NI) 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)	-0.232 (-25.69)	-0.318 (-26.80)	-0.514 (-9.00)	-1.906 (-76.26)
Out-of-vehicle distance (km)		-0.086 (-12.41)	-0.239 (-16.74)	---
Travel cost (€)	-0.015 (-2.40)	-0.036 (-7.16)	-0.082 (-25.79)	
Trip origin area characteristics				
Area type (base: very strong urban (≥ 2000 addresses per km²))				
Strongly urban (1500-2000 addresses per km²)		---	---	-0.184 (-18.92)
Moderately urban (1000-1500 addresses per km²)		---	---	---
Few urban (500-1000 addresses per km²)		---	---	---
Non-urban (< 500 addresses per km²)		-0.500 (-11.50)	0.397 (11.04)	---
Average value of real-state (in 1000 euros)		-0.723 (-7.54)	---	---
Number of cars per household		---	---	---
Average distance to the closest supermarket (in km)		0.236 (11.32)	---	---
Average distance to closest primary school (in km)		-0.554 (-19.11)	-0.645 (-16.51)	---
Trip destination area characteristics				
Area type (base: very strong urban (≥ 2000 addresses per km²))				
Urban (1000-2000 addresses per km²)		-0.25 (-18.12)	-0.296 (-14.00)	-0.209 (-17.09)
Non-urban (up to 1000 addresses per km²)		-0.504 (-19.57)	-0.473 (-11.02)	-0.294 (-17.51)
Average value of real-state (in 1000 euros)		1.028 (14.25)	---	---
Number of cars per household		-0.537 (-23.88)	---	---
Average distance to the closest supermarket (in km)		---	---	0.134 (18.97)
Average distance to the closest primary school (in km)		---	---	---
Number of establishments per industry (in 100s)				
Agriculture, forestry and fisheries		---	---	---
Industry and energy		---	---	---
Trade and catering		0.341 (24.26)	---	---
Transport, information and communication		---	---	---
Financial services, real estate		---	---	-0.713 (-15.19)
Business services		---	---	0.517 (22.2)
Culture, recreation, other services		-0.572 (-19.66)	---	-0.434 (-13.16)

----: highly insignificant, p>0.35

Table S.3.3.1.3: MNP-WS(NI) 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	$ln\left(\frac{Expected\ TT}{Actual\ TT}\right)$	$ln\left(\frac{Expected\ WT}{Actual\ WT}\right)$
Car users	Car at the reported 15-minute departure window		0.347 (6.34)	1.543 (30.64)		
	MOD 30 mins earlier	---	0.590 (6.08)	5.071 (3.1)	0.476 (1.24)	-0.336 (-0.89)
	MOD 15 mins earlier	0.566 (5.76)	0.630 (5.44)	7.736 (2.05)		
	MOD at the reported 15-minute departure window	0.209 (4.20)	0.586 (5.43)	3.315 (5.01)		
	MOD 15 mins later	0.128 (2.67)	0.432 (5.36)	2.114 (6.45)		
Train/ metro users	Train/metro at the reported 15-minute departure window		0.703 (7.96)	1.859 (10.08)		
	MOD 30 mins earlier	0.073 (1.61)	0.025 (1.29)	1 (fixed)	-0.288 (-0.70)	0.300 (0.73)
	MOD 15 mins earlier	---	---	1 (fixed)		
	MOD at the reported 15-minute departure window	0.063 (1.44)	---	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	---	0.996 (6.04)	3.007 (1.25)	---	---
	MOD 15 mins earlier	---	0.270 (1.25)	1 (fixed)		
	MOD at the reported 15-minute departure window	---	0.297 (1.09)	1 (fixed)		
	MOD 15 mins later	---	---	1 (fixed)		

----: highly insignificant, p>0.35

Table S.3.3.1.3 (Cont.): MNP-WS(NI) model estimation results (t-statistics in brackets)

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	0.301 (3.73)	---	---	---	---	---	---	---
	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	---	---	---	0.526 (1.88)	---	---	---	---
	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

Table S.3.3.1.4: MNP-WS(NI) model estimation results (t-statistics in brackets)

Explanatory variables	**Dependent variable**			
	Car users	***Train/ metro users***	***Bus/tram/ light-rail users***	***Bike users***
TT (hours)	-0.978 (-3.06)	-0.619 (-3.90)	-0.425 (-1.59)	-0.945 (-1.32)
TC (€)	-0.093 (-6.80)	-0.080 (-5.53)	-0.079 (-1.82)	-0.585 (-1.35)
WT (mins)	-0.017 (-5.05)	-0.004 (-2.94)	-0.002 (-1.14)	-0.007 (-0.96)
(TT, TC)				
(TT, WT)				
(TC, WT)				
(TT, TC, WT)				

*TT: Travel time, TC: Travel cost, WT: Pick-up time, ---: Not significant

Table S.3.3.1.5: MNP-WS(NI) 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)																		
	0.696 (26.73)	0.970 (26.71)																	
	0.722 (39.05)	0.703 (0.00)	0.966 (32.20)																
Car users	-0.072 (-0.44)	-0.050 (-0.00)	0.192 (1.28)	1.000 (fixed)															
	0.000	-0.052 (-0.16)	0.059 (0.57)	-0.143 (-1.23)	0.944 (4.98)														
	0.035 (0.27)	-0.097 (-0.36)	0.276 (1.75)	-0.093 (-0.96)	-0.254 (-1.93)	1.119 (2.08)													
	-0.028 (-0.20)	0.140 (0.72)	0.333 (2.20)	0.075 (0.63)	-0.093 (-1.04)	0.104 (0.88)	0.913 (3.11)												
Train or Metro users	0.099 (1.23)	0.102 (0.42)	-0.022 (-1.34)	-0.080*	-0.027*	-0.094*	-0.077*	1.000 (fixed)											
	0.100 (1.59)	0.156 (1.15)	0.006 (1.17)	-0.076*	-0.032*	-0.103*	-0.056*	0.898 (8.44)	0.947 (4.97)										
	0.172 (3.11)	0.178 (0.91)	-0.105 (-3.85)	-0.183*	-0.062*	-0.219*	-0.187*	0.992 (35.72)	0.931 (3.45)	1.061 (1.59)									
	0.108 (1.84)	0.158 (1.12)	-0.094 (-2.86)	-0.147*	-0.055*	-0.189*	-0.140*	0.975 (15.23)	0.936 (2.11)	1.026 (2.08)	1.020 (2.41)								
Tram or Bus or Light-Rail users	-0.032 (-0.09)	0.146 (0.63)	0.417 (1.16)	0.252*	0.064*	0.265*	0.350*	-0.102*	-0.078*	-0.244*	-0.186*	1.000 (fixed)							
	0.163 (1.12)	0.091 (0.14)	0.315 (1.07)	0.128*	0.048*	0.184*	0.152*	-0.047*	-0.046*	-0.119*	-0.104*	0.217 (1.04)	0.264 (1.13)						
	0.009 (0.02)	0.131 (0.30)	0.497 (0.98)	0.295*	0.084*	0.335*	0.389*	-0.121*	-0.101*	-0.290*	-0.228*	0.499 (2.01)	0.362 (2.15)	1.346 (1.59)					
	0.190 (1.14)	0.065 (0.48)	0.348 (1.91)	0.147*	0.060*	0.222*	0.162*	-0.057*	-0.061*	-0.142*	-0.127*	0.375 (2.36)	0.206 (1.18)	0.421 (2.19)	0.311 (1.51)				
Bike users	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*	1.000 (fixed)			
	-0.124 (-0.26)	-0.123 (-0.06)	-0.108 (-0.02)	0.007*	0.003*	0.002*	-0.011*	-0.014*	-0.018*	-0.024*	-0.018*	-0.012*	-0.020*	-0.014*	-0.021*	-0.236 (-0.27)	0.373 (1.15)		
	-0.109 (-0.24)	-0.083 (-0.01)	-0.081 (-0.56)	0.008*	0.001*	-0.002*	0.001*	-0.011*	-0.012*	-0.020*	-0.013*	0.001*	-0.017*	-0.002*	-0.019*	-0.219 (-0.29)	-0.090 (-0.35)	0.342 (1.81)	
	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*	-0.280 (-0.21)	-0.174 (-0.35)	-0.085 (-0.40)	0.648 (1.05)

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

Table S.3.3.2.1: MNP-WS(AI) 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	-0.759 (-18.19)	---	0.801 (29.58)	---	---	0.182 (14.11)	0.209 (12.98)
	Bus/Tram/Light-rail	-0.546 (-9.94)	---	1.332 (21.55)	-0.7 (-10.2)	---	---	---
	Bike	-0.289 (-15.03)	---	---	-0.197 (-13.52)	---	---	---
Car users	Car at the reported 15-minute departure window							
	MOD 30 mins earlier	-1.074 (-9.49)	---	---	---	---	---	0.117 (2.1)
	MOD 15 mins earlier	-1.053 (-6.82)	---	---	-0.112 (-1.59)	---	---	---
	MOD at the reported 15-minute departure window	-0.703 (-6.02)	-0.076 (-1.47)	---	-0.177 (-2.61)	-0.115 (-1.69)	---	0.09 (1.97)
	MOD 15 mins later	-0.645 (-6.01)	-0.111 (-1.75)	---	-0.164 (-2.21)	-0.095 (-1.54)	---	0.103 (2.43)
Train/ metro users	Train/metro at the reported 15-minute departure window							
	MOD 30 mins earlier	0.570 (3.1)	---	---	---	---	---	---
	MOD 15 mins earlier	0.700 (3.41)	---	---	---	---	---	---
	MOD at the reported 15-minute departure window	0.459 (2.43)	---	---	---	---	---	---
	MOD 15 mins later	0.668 (3.56)	---	---	---	---	---	---
Bus/tram/ light-rail users	Bus/tram/light-rail at the reported 15-minute departure window							
	MOD 30 mins earlier	-0.689 (-0.92)	---	---	---	---	---	---
	MOD 15 mins earlier	-0.025 (-0.04)	---	---	---	---	---	---
	MOD at the reported 15-minute departure window	-0.505 (-0.6)	---	---	---	---	---	---
	MOD 15 mins later	0.273 (0.63)	---	---	---	---	---	---
Bike users	Bike at the reported 15-minute departure window							
	MOD 30 mins earlier	-1.900 (-7.69)	---	---	0.3 (1.54)	---	---	---
	MOD 15 mins earlier	-0.939 (-0.95)	---	---	---	---	---	---
	MOD at the reported 15-minute departure window	-0.87 (-1.11)	---	---	---	---	---	---
	MOD 15 mins later	-1.447 (-0.75)	---	---	---	---	---	---

----: highly insignificant, p>0.35

Table S.3.3.2.1 (Cont.): MNP-WS(AI) model estimation results (t-statistics in brackets)

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	---	0.286 (15.37)	-0.263 (-14.32)	0 (0)	-0.338 (-19.84)	-0.374 (-19.07)	-0.797 (-13.51)	-0.797 (-13.51)	-0.797 (-13.51)	-0.797 (-13.51)
	Bus/Tram/Light-rail	---	---	---	---	---	---	---	---	---	---
	Bike	---	---	---	---	---	---	-0.599 (-14.48)	-0.599 (-14.48)	-0.599 (-14.48)	-0.599 (-14.48)
Car users	Car at the reported 15-minute departure window										
	MOD 30 mins earlier	---	---	---	0.113 (1.78)	---	0.047 (0.89)	---	---	---	---
	MOD 15 mins earlier	---	---	---	---	---	---	---	---	---	---
	MOD at the reported 15-minute departure window	-0.131 (-1.64)	---	0.070 (1.64)	---	---	---	---	---	---	---
	MOD 15 mins later	---	---	---	---	0.099 (2.07)	0.066 (1.69)	---	---	---	---
Train/ metro users	Train/metro at the reported 15-minute departure window										
	MOD 30 mins earlier	---	---	0.121 (0.86)	---	---	---	---	---	---	---
	MOD 15 mins earlier	---	---	---	---	---	---	---	---	---	---
	MOD at the reported 15-minute departure window	---	---	---	0.109 (1.15)	---	---	---	---	---	---
	MOD 15 mins later	---	---	---	0.065 (0.76)	---	---	---	---	---	---
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

Table S.3.3.2.1 (Cont.): MNP-WS(AI) model estimation results (t-statistics in brackets)

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	0.381 (17.15)	---	---	---	---	0.891 (28.63)	---	0.352 (13.22)
	Bus/Tram/Light-rail	---	---	---	-0.451 (-7.42)	---	0.700 (13.52)	0.183 (4.33)	0.529 (14.46)
	Bike	---	-0.340 (-23.57)	---	---	---	1.182 (50.97)	---	---
Car users	Car at the reported 15-minute departure window								
	MOD 30 mins earlier	0.203 (2.64)	0.080 (1.19)	0.073 (1.15)	---	---	---	---	---
	MOD 15 mins earlier	0.157 (2.01)	0.095 (1.52)	0.079 (1.25)	0.078 (1.49)	---	---	---	---
	MOD at the reported 15-minute departure window	0.105 (1.55)	0.081 (1.42)	0.068 (1.14)	0.042 (0.78)	---	---	---	---
	MOD 15 mins later	0.076 (0.94)	0.074 (1.44)	0.098 (1.86)	---	---	---	---	---
Train/ metro users	Train/metro at the reported 15-minute departure window								
	MOD 30 mins earlier	0.202 (1.68)	0.202 (1.68)	---	---	-0.176 (-1.83)	---	---	---
	MOD 15 mins earlier	0.275 (1.88)	0.275 (1.88)	0.108 (0.7)	0.108 (0.7)	-0.248 (-2.64)	---	---	---
	MOD at the reported 15-minute departure window	0.341 (2.71)	0.341 (2.71)	0.136 (1.15)	0.136 (1.15)	-0.211 (-2.19)	---	---	---
	MOD 15 mins later	0.257 (1.89)	0.257 (1.89)	0.154 (1.03)	0.154 (1.03)	-0.328 (-3.12)	---	---	---
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

Table S.3.3.2.2: MNP-WS(AI) 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)	-0.216 (-25.04)	-0.323 (-27.02)	-0.542 (-8.59)	-1.949 (-71.58)
Out-of-vehicle distance (km)		-0.089 (-12.34)	-0.244 (-14.28)	---
Travel cost (€)	-0.015 (-2.15)	-0.036 (-7.01)	-0.081 (-20.63)	
Trip origin area characteristics				
Area type (base: very strong urban (≥ 2000 addresses per km²))				
Strongly urban (1500-2000 addresses per km^2)		---	---	-0.189 (-18.16)
Moderately urban (1000-1500 addresses per km^2)		---	---	---
Few urban (500-1000 addresses per km^2)		---	---	---
Non-urban (< 500 addresses per km^2)		-0.526 (-12.08)	0.403 (11.39)	---
Average value of real-state (in 1000 euros)		-0.705 (-6.92)	---	---
Number of cars per household		---	---	---
Average distance to the closest supermarket (in km)		0.248 (12.08)	---	---
Average distance to closest primary school (in km)		-0.558 (-19.25)	-0.664 (-15.53)	---
Trip destination area characteristics				
Area type (base: very strong urban (≥ 2000 addresses per km²))				
Urban (1000-2000 addresses per km^2)		-0.253 (-17.20)	-0.301 (-12.99)	-0.208 (-16.62)
Non-urban (up to 1000 addresses per km^2)		-0.52 (-19.31)	-0.479 (-9.75)	-0.297 (-17.02)
Average value of real-state (in 1000 euros)		1.015 (13.37)	---	---
Number of cars per household		-0.533 (-22.52)	---	---
Average distance to the closest supermarket (in km)		---	---	0.136 (19.11)
Average distance to the closest primary school (in km)		---	---	---
Number of establishments per industry (in 100s)		---	---	---
Agriculture, forestry and fisheries		---	---	---
Industry and energy		---	---	---
Trade and catering		0.347 (25.36)	---	---
Transport, information and communication		---	---	---
Financial services, real estate		---	---	-0.770 (-15.70)
Business services		---	---	0.538 (22.24)
Culture, recreation, other services		-0.583 (-20.18)	---	-0.445 (-12.65)

----: highly insignificant, p>0.35

Table S.3.3.2.3: MNP-WS(AI) 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	$ln\left(\frac{Expected\ TT}{Actual\ TT}\right)$	$ln\left(\frac{Expected\ WT}{Actual\ WT}\right)$
Car users	Car at the reported 15-minute departure window		0.269 (7.88)	1.452 (29.56)		
	MOD 30 mins earlier	0.150 (3.48)	0.566 (7.26)	3.906 (4.49)	0.509 (1.51)	-0.371 (-1.11)
	MOD 15 mins earlier	0.377 (6.29)	0.587 (6.76)	7.412 (2.33)		
	MOD at the reported 15-minute departure window	0.297 (6.67)	0.415 (6.03)	3.076 (5.2)		
	MOD 15 mins later	0.018 (0.5)	0.398 (6.46)	2.302 (6.47)		
Train/ metro users	Train/metro at the reported 15-minute departure window		0.656 (6.89)	1.803 (9.67)		
	MOD 30 mins earlier	0.119 (1.7)	0.032 (0.83)	1 (fixed)	-0.275 (-0.44)	0.289 (0.46)
	MOD 15 mins earlier	---	---	1 (fixed)		
	MOD at the reported 15-minute departure window	0.088 (1.03)	---	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	---	1.004 (5.29)	3.028 (1.14)	---	---
	MOD 15 mins earlier	---	0.274 (1.45)	1 (fixed)		
	MOD at the reported 15-minute departure window	---	0.273 (1.07)	1 (fixed)		
	MOD 15 mins later	---	---	1 (fixed)		

----: highly insignificant, p>0.35

Table S.3.3.2.3 (Cont.): MNP-WS(AI) model estimation results (t-statistics in brackets)

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	0.200 (2.38)	---	---	---	---	---	---	---
	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	---	---	---	0.676 (1.76)	---	---	---	---
	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

Table S.3.3.2.4: MNP-WS(AI) model estimation results (t-statistics in brackets)

Explanatory variables	**Dependent variable**			
	Car users	***Train/ metro users***	***Bus/tram/ light-rail users***	***Bike users***
TT (hours)	-1.557 (-5.60)	-0.693 (-5.03)	-0.546 (-1.11)	-0.739 (-1.34)
TC (€)	-0.188 (-8.69)	-0.115 (-3.67)	-0.152 (-2.28)	-0.719 (-1.06)
WT (mins)	-0.021 (-6.28)	-0.007 (-2.98)	-0.006 (0.59)	-0.005 (-0.26)
(TT, TC)	0.138 (8.68)	0.182 (3.85)	0.629 (1.61)	0.574 (0.42)
(TT, WT)	0.148 (8.84)	0.012 (3.72)	0.004 (0.36)	0.050 (0.66)
(TC, WT)	-0.528 (-8.87)	-0.049 (-1.86)	-0.126 (-0.71)	-0.409 (-0.39)
(TT, TC, WT)	0.151 (8.32)	-0.003 (-3.01)	-0.011 (-1.43)	0.407 (0.19)

*TT: Travel time, TC: Travel cost, WT: Pick-up time, ---: Not significant

Table S.3.3.2.5: MNP-WS(AI) 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)																		
	0.689 (21.56)	0.989 (20.28)																	
	0.708 (36.05)	0.695 (2.13)	0.967 (31.56)																
Car users	-0.011 (-0.07)	0.064 (0.22)	0.284 (1.57)	1.000 (fixed)															
	0.019 (0.17)	0.111 (0.43)	0.055 (0.02)	-0.310 (-2.47)	0.793 (6.25)														
	0.051 (0.53)	0.030 (0.02)	0.274 (2.06)	-0.068 (-1.45)	-0.283 (-3.11)	0.636 (2.46)													
	0.075 (0.70)	0.227 (0.95)	0.207 (0.75)	-0.151 (-1.62)	-0.129 (-2.86)	0.084 (2.07)	0.586 (1.71)												
Train or Metro users	0.074 (0.70)	0.121 (1.38)	-0.043 (-1.06)	-0.076*	0.014*	-0.074*	0.003*	1.000 (fixed)											
	0.079 (0.99)	0.162 (1.40)	-0.008 (-1.07)	-0.060*	0.021*	-0.064*	0.019*	0.908 (8.14)	0.937 (3.14)										
	0.155 (2.19)	0.239 (1.48)	-0.138 (-3.38)	-0.190*	0.026*	-0.182*	-0.009*	0.934 (5.41)	0.882 (2.45)	0.992 (2.39)									
	0.086 (1.04)	0.181 (1.55)	-0.115 (-2.47)	-0.138*	0.024*	-0.138*	-0.001*	0.934 (9.79)	0.914 (1.81)	0.954 (2.98)	0.976 (3.01)								
Tram or Bus or Light-Rail users	-0.078 (-0.12)	0.106 (0.30)	0.322 (0.58)	0.238*	0.031*	0.191*	0.117*	-0.085*	-0.060*	-0.217*	-0.153*	1.000 (fixed)							
	0.343 (0.92)	0.089 (0.44)	0.363 (0.59)	0.099*	-0.021*	0.131*	0.015*	-0.053*	-0.054*	-0.126*	-0.111*	-0.160 (-0.14)	0.667 (0.71)						
	-0.005 (-0.01)	0.090 (0.21)	0.328 (0.67)	0.215*	0.020*	0.183*	0.096*	-0.082*	-0.063*	-0.208*	-0.151*	0.100 (-0.10)	0.290 (0.11)	0.996 (1.89)					
	0.413 (1.03)	0.038 (0.64)	0.415 (0.88)	0.114*	-0.038*	0.163*	-0.004*	-0.075*	-0.081*	-0.174*	-0.153*	0.035 (0.02)	0.347 (2.05)	0.294 (1.19)	0.679 (1.98)				
Bike users	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*	1.000 (fixed)			
	-0.103 (-0.18)	-0.140 (-0.10)	-0.097 (-0.02)	-0.006*	-0.015*	-0.003*	-0.031*	-0.018*	-0.024*	-0.036*	-0.027*	-0.011*	-0.014*	-0.010*	-0.007*	-0.243 (-0.23)	0.375 (1.15)		
	-0.090 (-0.18)	-0.085 (-0.03)	-0.069 (-0.02)	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	-0.204 (-1.18)	-0.058 (-0.31)	0.314 (1.81)	
	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*	-0.324 (-2.20)	-0.177 (-0.34)	-0.118 (-1.39)	0.717 (2.04)

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

S.3.4 Marginal effects for MNP-WS(NI) and MNP-WS(AI) models

Table S.3.4.1: Marginal effect (difference in probability) for car users based on in-sample observations

20% reduction in travel time of all MOD options		
Alternatives	**MNP-WS(NI)**	**MNP-WS(AI)**
Car at reported 15 mins departure window	-0.029	-0.005
MOD 30 mins earlier	0.006	0.001
MOD 15 mins earlier	0.008	0.002
MOD at reported 15 mins departure window	0.007	0.002
MOD 15 mins later	0.007	0.000
20% reduction in travel cost of all MOD options		
Alternatives	**MNP-WS(NI)**	**MNP-WS(AI)**
Car at reported 15 mins departure window	-0.015	-0.052
MOD 30 mins earlier	0.003	0.011
MOD 15 mins earlier	0.004	0.014
MOD at reported 15 mins departure window	0.004	0.015
MOD 15 mins later	0.004	0.011
20% reduction in waiting time of all MOD options		
Alternatives	**MNP-WS(NI)**	**MNP-WS(AI)**
Car at reported 15 mins departure window	-0.008	-0.010
MOD 30 mins earlier	0.002	0.003
MOD 15 mins earlier	0.003	0.003
MOD at reported 15 mins departure window	0.002	0.003
MOD 15 mins later	0.002	0.001

Table S.3.4.2: Marginal effect for train/metro users based on in-sample observations

20% reduction in travel time of all MOD options		
Alternatives	**MNP-WS(NI)**	**MNP-WS(AI)**
Train/metro at reported 15 mins departure window	-0.003	-0.007
MOD 30 mins earlier	0.001	0.000
MOD 15 mins earlier	0.001	0.002
MOD at reported 15 mins departure window	0.000	0.001
MOD 15 mins later	0.001	0.003
20% reduction in travel cost of all MOD options		
Alternatives	**MNP-WS(NI)**	**MNP-WS(AI)**
Train/metro at reported 15 mins departure window	-0.018	-0.020
MOD 30 mins earlier	0.007	0.008
MOD 15 mins earlier	0.010	0.009
MOD at reported 15 mins departure window	0.001	0.003
MOD 15 mins later	0.001	0.000
20% reduction in waiting time of all MOD options		
Alternatives	**MNP-WS(NI)**	**MNP-WS(AI)**
Train/metro at reported 15 mins departure window	-0.002	-0.003
MOD 30 mins earlier	0.000	0.001
MOD 15 mins earlier	0.001	0.001
MOD at reported 15 mins departure window	0.000	0.001
MOD 15 mins later	0.000	0.000

Table S.3.4.3: Marginal effect for bus/tram/light-rail users based on in-sample observations

20% reduction in travel time of all MOD options		
Alternatives	**MNP-WS(NI)**	**MNP-WS(AI)**
Bus/tram/light-rail at reported 15 mins departure window	-0.004	-0.015
MOD 30 mins earlier	0.000	0.003
MOD 15 mins earlier	0.001	0.004
MOD at reported 15 mins departure window	0.000	0.001
MOD 15 mins later	0.002	0.007
20% reduction in travel cost of all MOD options		
Alternatives	**MNP-WS(NI)**	**MNP-WS(AI)**
Bus/tram/light-rail at reported 15 mins departure window	-0.044	-0.071
MOD 30 mins earlier	0.004	0.012
MOD 15 mins earlier	0.012	0.017
MOD at reported 15 mins departure window	0.005	0.009
MOD 15 mins later	0.024	0.033
20% reduction in waiting time of all MOD options		
Alternatives	**MNP-WS(NI)**	**MNP-WS(AI)**
Bus/tram/light-rail at reported 15 mins departure window	-0.002	-0.004
MOD 30 mins earlier	0.000	0.001
MOD 15 mins earlier	0.001	0.001
MOD at reported 15 mins departure window	0.000	0.000
MOD 15 mins later	0.001	0.002

Table S.3.4.4: Marginal effect for bike users based on in-sample observations

20% reduction in travel time of all MOD options		
Alternatives	**MNP-WS(NI)**	**MNP-WS(AI)**
Bike at reported 15 mins departure window	-0.019	-0.003
MOD 30 mins earlier	0.003	0.001
MOD 15 mins earlier	0.007	0.001
MOD at reported 15 mins departure window	0.006	0.001
MOD 15 mins later	0.003	0.000
20% reduction in travel cost of all MOD options		
Alternatives	**MNP-WS(NI)**	**MNP-WS(AI)**
Bike at reported 15 mins departure window	-0.029	-0.0187
MOD 30 mins earlier	0.005	0.0058
MOD 15 mins earlier	0.010	0.0052
MOD at reported 15 mins departure window	0.009	0.0046
MOD 15 mins later	0.005	0.0032
20% reduction in waiting time of all MOD options		
Alternatives	**MNP-WS(NI)**	**MNP-WS(AI)**
Bike at reported 15 mins departure window	-0.004	-0.005
MOD 30 mins earlier	0.001	0.001
MOD 15 mins earlier	0.001	0.001
MOD at reported 15 mins departure window	0.001	0.001
MOD 15 mins later	0.001	0.001

S.3.5 Accuracy

Table S.3.5.1: In-sample and out-of-sample accuracy (Car users)

Alternatives	In-sample (# of RP/SP observations: 964/14460)				Out-of-sample (# of RP/SP observations: 241/3615)			
	Weights (i_{share})	Predicted accuracy ($i_{accuracy}$) from model…			Weights (i_{share})	Predicted accuracy ($i_{accuracy}$) from model…		
		MNP-CI	MNP-WS (NI)	MNP-WS (AI)		MNP-CI	MNP-WS (NI)	MNP-WS (AI)
Auto at reported 15 mins departure window	0.584	0.936	0.939	0.93	0.614	0.936	0.936	0.935
MOD 30 mins earlier	0.084	0.172	0.156	0.218	0.074	0.197	0.182	0.175
MOD 15 mins earlier	0.119	0.392	0.282	0.314	0.114	0.409	0.299	0.277
MOD at reported 15 mins departure window	0.114	0.426	0.293	0.377	0.108	0.360	0.267	0.314
MOD 15 mins later	0.099	0.480	0.257	0.397	0.091	0.390	0.223	0.345
Overall Accuracy		0.704	0.654	0.681		0.710	0.671	0.683
Weighted accuracy		0.380	0.269	0.346		0.349	0.261	0.295

Table S.3.5.2: In-sample and out-of-sample accuracy (Train/metro users)

Alternatives	In-sample (# of RP/SP observations: 137/2055)				Out-of-sample (# of RP/SP observations: 32/480)			
	Weights (i_{share})	Predicted accuracy ($i_{accuracy}$) from model…			Weights (i_{share})	Predicted accuracy ($i_{accuracy}$) from model…		
		MNP-CI	MNP-WS (NI)	MNP-WS (AI)		MNP-CI	MNP-WS (NI)	MNP-WS (AI)
Train/Metro at reported 15 mins departure window	0.550	0.891	0.887	0.881	0.637	0.899	0.895	0.889
MOD 30 mins earlier	0.090	0.341	0.324	0.351	0.081	0.154	0.128	0.179
MOD 15 mins earlier	0.136	0.532	0.564	0.589	0.098	0.362	0.383	0.404
MOD at reported 15 mins departure window	0.110	0.304	0.286	0.313	0.079	0.105	0.053	0.105
MOD 15 mins later	0.113	0.579	0.571	0.549	0.104	0.440	0.480	0.460
Overall Accuracy		0.692	0.690	0.693		0.675	0.673	0.677
Weighted accuracy		0.450	0.445	0.459		0.271	0.263	0.291

Table S.3.5.3: In-sample and out-of-sample accuracy (Bus/tram/light-rail users)

Alternatives	In-sample (# of RP/SP observations: 49/735)				Out-of-sample (# of RP/SP observations: 11/165)			
	Weights (i_{share})	Predicted accuracy ($i_{accuracy}$) from model…			Weights (i_{share})	Predicted accuracy ($i_{accuracy}$) from model…		
		MNP-CI	MNP-WS (NI)	MNP-WS (AI)		MNP-CI	MNP-WS (NI)	MNP-WS (AI)
Bus/Tram/Light-rail at reported 15 mins departure window	0.546	0.559	0.756	0.721	0.255	0.786	0.81	0.786
MOD 30 mins earlier	0.094	0.000	0.000	0.000	0.145	0.000	0.000	0.000
MOD 15 mins earlier	0.116	0.494	0.071	0.306	0.200	0.455	0.030	0.182
MOD at reported 15 mins departure window	0.107	0.127	0.000	0.025	0.176	0.172	0.000	0.000
MOD 15 mins later	0.137	0.762	0.683	0.713	0.224	0.865	0.703	0.595
Overall Accuracy		0.480	0.514	0.529		0.515	0.370	0.370
Weighted accuracy		0.319	0.185	0.249		0.393	0.249	0.256

Table S.3.5.4: In-sample and out-of-sample accuracy (Bike users)

Alternatives	In-sample (# of RP/SP observations: 141/2115)				Out-of-sample (# of RP/SP observations: 31/465)			
	Weights (i_{share})	Predicted accuracy ($i_{accuracy}$) from model…			Weights (i_{share})	Predicted accuracy ($i_{accuracy}$) from model…		
		MNP-CI	MNP-WS (NI)	MNP-WS (AI)		MNP-CI	MNP-WS (NI)	MNP-WS (AI)
Bike at reported 15 mins departure window	0.858	0.995	0.991	0.993	0.918	0.998	0.995	0.998
MOD 30 mins earlier	0.041	0.047	0.035	0.058	0.015	0.000	0.000	0.000
MOD 15 mins earlier	0.042	0.146	0.202	0.191	0.015	0.000	0.000	0.000
MOD at reported 15 mins departure window	0.035	0.082	0.082	0.096	0.030	0.000	0.000	0.000
MOD 15 mins later	0.025	0.000	0.000	0.000	0.022	0.000	0.000	0.000
Overall Accuracy		0.865	0.863	0.866		0.916	0.914	0.916
Weighted accuracy		0.069	0.078	0.084		0.005	0.005	0.005

S.3.6 In-Sample and Out-of-Sample Predictions

Table S.3.6.1: In-sample and out-of-sample predictions (Car users)

Alternatives	In-sample (# of RP/SP observations: 964/14460)				Out-of-sample (# of RP/SP observations: 241/3615)			
	Observed share	Predicted share from model…			Observed share	Predicted share from model…		
		MNP-CI	MNP-WS (NI)	MNP-WS (AI)		MNP-CI	MNP-WS (NI)	MNP-WS (AI)
Auto at reported 15 mins departure window	0.584	0.576	0.575	0.571	0.614	0.582	0.582	0.589
MOD 30 mins earlier	0.084	0.085	0.085	0.089	0.074	0.086	0.086	0.086
MOD 15 mins earlier	0.119	0.12	0.118	0.119	0.114	0.119	0.117	0.114
MOD at reported 15 mins departure window	0.114	0.116	0.118	0.118	0.108	0.115	0.116	0.115
MOD 15 mins later	0.099	0.105	0.105	0.104	0.091	0.102	0.103	0.100
Mean absolute percentage error (MAPE)		2.24	2.63	3.35		8.88	8.93	7.33

Table S.3.6.2: In-sample and out-of-sample predictions (Train/metro users)

Alternatives	In-sample (# of RP/SP observations: 137/2055)				Out-of-sample (# of RP/SP observations: 32/480)			
	Observed share	Predicted share from model…			Observed share	Predicted share from model…		
		MNP-CI	MNP-WS (NI)	MNP-WS (AI)		MNP-CI	MNP-WS (NI)	MNP-WS (AI)
Train/Metro at reported 15 mins departure window	0.550	0.592	0.579	0.569	0.637	0.671	0.667	0.664
MOD 30 mins earlier	0.090	0.084	0.086	0.089	0.081	0.063	0.06	0.064
MOD 15 mins earlier	0.136	0.129	0.147	0.145	0.098	0.103	0.115	0.114
MOD at reported 15 mins departure window	0.110	0.078	0.072	0.079	0.079	0.06	0.056	0.059
MOD 15 mins later	0.113	0.117	0.118	0.117	0.104	0.103	0.103	0.100
Mean absolute percentage error (MAPE)		10.42	11.36	8.58		11.53	15.61	14.14

Table S.3.6.3: In-sample and out-of-sample predictions (Bus/tram/light-rail users)

Alternatives	In-sample (# of RP/SP observations: 49/735)				Out-of-sample (# of RP/SP observations: 11/165)			
	Observed share	Predicted share from model…			Observed share	Predicted share from model…		
		MNP-CI	MNP-WS (NI)	MNP-WS (AI)		MNP-CI	MNP-WS (NI)	MNP-WS (AI)
Bus/Tram/Light-rail at reported 15 mins departure window	0.546	0.382	0.441	0.419	0.255	0.389	0.458	0.469
MOD 30 mins earlier	0.094	0.072	0.072	0.077	0.145	0.073	0.071	0.07
MOD 15 mins earlier	0.116	0.169	0.132	0.153	0.200	0.169	0.126	0.139
MOD at reported 15 mins departure window	0.107	0.106	0.107	0.087	0.176	0.102	0.107	0.079
MOD 15 mins later	0.137	0.271	0.248	0.264	0.224	0.266	0.239	0.243
Mean absolute percentage error (MAPE)		39.58	27.49	36.93		35.70	42.71	45.95

Table S.3.6.4: In-sample and out-of-sample predictions (Bike users)

Alternatives	In-sample (# of RP/SP observations: 141/2115)				Out-of-sample (# of RP/SP observations: 31/465)			
	Observed share	Predicted share from model…			Observed share	Predicted share from model…		
		MNP-CI	MNP-WS (NI)	MNP-WS (AI)		MNP-CI	MNP-WS (NI)	MNP-WS (AI)
Bike at reported 15 mins departure window	0.858	0.861	0.838	0.854	0.918	0.885	0.858	0.880
MOD 30 mins earlier	0.041	0.038	0.043	0.043	0.015	0.025	0.031	0.029
MOD 15 mins earlier	0.042	0.044	0.057	0.047	0.015	0.029	0.041	0.030
MOD at reported 15 mins departure window	0.035	0.038	0.044	0.037	0.030	0.036	0.046	0.037
MOD 15 mins later	0.025	0.025	0.024	0.024	0.022	0.025	0.024	0.023
Mean absolute percentage error (MAPE)		4.20	14.53	5.39		39.45	69.79	45.07

S.3.7 Shares as a function of price

Table S.3.7.1: Shares of alternatives for car users based on MNP-CI model

MOD price per km (€)	Car at reported 15 mins departure window	MOD 30 mins earlier	MOD 15 mins earlier	MOD at reported 15 mins departure window	MOD 15 mins later
0.1	0.350	0.131	0.181	0.188	0.151
0.2	0.350	0.131	0.181	0.188	0.151
0.3	0.350	0.131	0.181	0.188	0.151
0.4	0.350	0.131	0.181	0.188	0.151
0.5	0.355	0.131	0.18	0.187	0.149
0.6	0.677	0.074	0.086	0.089	0.075
0.7	0.709	0.069	0.076	0.080	0.068
0.8	0.730	0.065	0.069	0.074	0.063
0.9	0.745	0.062	0.065	0.070	0.059
1.0	0.753	0.061	0.063	0.068	0.057

Table S.3.7.2: Shares of alternatives for train/metro users based on MNP-CI model

MOD price per km (€)	Train/metro at reported 15 mins departure window	MOD 30 mins earlier	MOD 15 mins earlier	MOD at reported 15 mins departure window	MOD 15 mins later
0.1	0.281	0.182	0.227	0.135	0.175
0.2	0.530	0.119	0.144	0.091	0.116
0.3	0.658	0.089	0.100	0.068	0.086
0.4	0.676	0.084	0.094	0.065	0.081
0.5	0.688	0.081	0.089	0.063	0.079
0.6	0.694	0.080	0.088	0.061	0.078
0.7	0.694	0.080	0.088	0.061	0.078
0.8	0.694	0.080	0.088	0.061	0.078
0.9	0.694	0.080	0.088	0.061	0.078
1.0	0.694	0.080	0.088	0.061	0.078

Table S.3.7.3: Shares of alternatives for bus/tram/light-rail users based on MNP-CI model

MOD price per km (€)	Bus/tram/light-rail at reported 15 mins departure window	MOD 30 mins earlier	MOD 15 mins earlier	MOD at reported 15 mins departure window	MOD 15 mins later
0.1	0.000	0.114	0.260	0.170	0.455
0.2	0.230	0.101	0.221	0.144	0.394
0.3	0.540	0.074	0.142	0.091	0.269
0.4	0.648	0.057	0.091	0.056	0.188
0.5	0.655	0.055	0.084	0.051	0.177
0.6	0.663	0.052	0.076	0.046	0.164
0.7	0.663	0.052	0.076	0.046	0.164
0.8	0.663	0.052	0.076	0.046	0.164
0.9	0.663	0.052	0.076	0.046	0.164
1.0	0.663	0.052	0.076	0.046	0.164

Table S.3.7.4: Shares of alternatives for bike users based on MNP-CI model

MOD price per km (€)	Bike at reported 15 mins departure window	MOD 30 mins earlier	MOD 15 mins earlier	MOD at reported 15 mins departure window	MOD 15 mins later
0.1	0.940	0.025	0.018	0.012	0.011
0.2	0.940	0.025	0.018	0.012	0.011
0.3	0.940	0.025	0.018	0.012	0.011
0.4	0.940	0.025	0.018	0.012	0.011
0.5	0.940	0.025	0.018	0.012	0.011
0.6	0.940	0.025	0.018	0.012	0.011
0.7	0.940	0.025	0.018	0.012	0.011
0.8	0.940	0.025	0.018	0.012	0.011
0.9	0.940	0.025	0.018	0.012	0.011
1.0	0.940	0.025	0.018	0.012	0.011

Table S.3.7.5: Shares of alternatives for car users based on MNP-WS(NI) model

MOD price per km (€)	Car at reported 15 mins departure window	MOD 30 mins earlier	MOD 15 mins earlier	MOD at reported 15 mins departure window	MOD 15 mins later
0.1	0.511	0.101	0.135	0.135	0.120
0.2	0.523	0.098	0.132	0.132	0.117
0.3	0.534	0.095	0.128	0.129	0.114
0.4	0.546	0.093	0.125	0.126	0.111
0.5	0.559	0.090	0.121	0.123	0.108
0.6	0.571	0.088	0.118	0.119	0.105
0.7	0.583	0.085	0.115	0.116	0.102
0.8	0.595	0.082	0.111	0.113	0.099
0.9	0.608	0.080	0.108	0.110	0.096
1.0	0.620	0.077	0.104	0.107	0.093

Table S.3.7.6: Shares of alternatives for train/metro users based on MNP-WS(NI) model

MOD price per km (€)	Train/metro at reported 15 mins departure window	MOD 30 mins earlier	MOD 15 mins earlier	MOD at reported 15 mins departure window	MOD 15 mins later
0.1	0.491	0.132	0.193	0.072	0.113
0.2	0.513	0.126	0.184	0.069	0.108
0.3	0.534	0.12	0.175	0.067	0.104
0.4	0.555	0.114	0.167	0.064	0.100
0.5	0.576	0.108	0.158	0.061	0.096
0.6	0.597	0.103	0.150	0.059	0.092
0.7	0.617	0.097	0.142	0.056	0.088
0.8	0.637	0.092	0.134	0.054	0.084
0.9	0.656	0.087	0.127	0.051	0.080
1.0	0.674	0.082	0.120	0.049	0.076

Table S.3.7.7: Shares of alternatives for bus/tram/light-rail users based on MNP-WS(NI) model

MOD price per km (€)	Bus/tram/light-rail at reported 15 mins departure window	MOD 30 mins earlier	MOD 15 mins earlier	MOD at reported 15 mins departure window	MOD 15 mins later
0.1	0.242	0.089	0.186	0.123	0.359
0.2	0.282	0.087	0.172	0.121	0.338
0.3	0.327	0.084	0.157	0.119	0.314
0.4	0.372	0.081	0.142	0.115	0.290
0.5	0.415	0.078	0.129	0.112	0.268
0.6	0.456	0.074	0.116	0.108	0.246
0.7	0.496	0.071	0.105	0.104	0.225
0.8	0.533	0.067	0.094	0.100	0.206
0.9	0.568	0.064	0.084	0.096	0.188
1.0	0.600	0.060	0.076	0.092	0.171

Table S.3.7.8: Shares of alternatives for bike users based on MNP-WS(NI) model

MOD price per km (€)	Bike at reported 15 mins departure window	MOD 30 mins earlier	MOD 15 mins earlier	MOD at reported 15 mins departure window	MOD 15 mins later
0.1	0.665	0.071	0.116	0.101	0.053
0.2	0.708	0.065	0.101	0.086	0.045
0.3	0.747	0.059	0.087	0.073	0.039
0.4	0.782	0.054	0.075	0.062	0.033
0.5	0.812	0.049	0.065	0.052	0.028
0.6	0.838	0.045	0.056	0.044	0.024
0.7	0.860	0.041	0.048	0.037	0.020
0.8	0.878	0.037	0.042	0.031	0.017
0.9	0.894	0.034	0.037	0.026	0.015
1.0	0.907	0.031	0.032	0.022	0.013

Table S.3.7.9: Shares of alternatives for car users based on MNP-WS(AI) model

MOD price per km (€)	Car at reported 15 mins departure window	MOD 30 mins earlier	MOD 15 mins earlier	MOD at reported 15 mins departure window	MOD 15 mins later
0.1	0.353	0.141	0.178	0.182	0.147
0.2	0.393	0.133	0.167	0.170	0.138
0.3	0.436	0.124	0.155	0.157	0.130
0.4	0.482	0.115	0.142	0.144	0.120
0.5	0.530	0.105	0.128	0.130	0.109
0.6	0.578	0.095	0.114	0.116	0.098
0.7	0.624	0.085	0.101	0.104	0.088
0.8	0.665	0.077	0.090	0.092	0.078
0.9	0.702	0.069	0.080	0.082	0.069
1.0	0.734	0.062	0.071	0.073	0.061

Table S.3.7.10: Shares of alternatives for train/metro users based on MNP-WS(AI) model

MOD price per km (€)	Train/metro at reported 15 mins departure window	MOD 30 mins earlier	MOD 15 mins earlier	MOD at reported 15 mins departure window	MOD 15 mins later
0.1	0.470	0.141	0.186	0.095	0.108
0.2	0.493	0.135	0.176	0.091	0.105
0.3	0.516	0.128	0.167	0.087	0.101
0.4	0.539	0.122	0.157	0.083	0.098
0.5	0.562	0.116	0.148	0.080	0.094
0.6	0.584	0.110	0.140	0.076	0.091
0.7	0.606	0.104	0.131	0.073	0.087
0.8	0.627	0.098	0.123	0.069	0.083
0.9	0.647	0.092	0.115	0.066	0.080
1.0	0.667	0.086	0.108	0.063	0.076

Table S.3.7.11: Shares of alternatives for bus/tram/light-rail users based on MNP-WS(AI) model

MOD price per km (€)	Bus/tram/light-rail at reported 15 mins departure window	MOD 30 mins earlier	MOD 15 mins earlier	MOD at reported 15 mins departure window	MOD 15 mins later
0.1	0.135	0.132	0.217	0.118	0.398
0.2	0.180	0.124	0.205	0.112	0.380
0.3	0.235	0.114	0.190	0.105	0.356
0.4	0.301	0.102	0.172	0.096	0.328
0.5	0.372	0.091	0.154	0.087	0.297
0.6	0.445	0.079	0.135	0.077	0.264
0.7	0.515	0.068	0.117	0.068	0.232
0.8	0.580	0.058	0.100	0.059	0.202
0.9	0.639	0.050	0.086	0.051	0.175
1.0	0.689	0.042	0.073	0.044	0.151

Table S.3.7.12: Shares of alternatives for bike users based on MNP-WS(AI) model

MOD price per km (€)	Bike at reported 15 mins departure window	MOD 30 mins earlier	MOD 15 mins earlier	MOD at reported 15 mins departure window	MOD 15 mins later
0.1	0.634	0.080	0.118	0.112	0.061
0.2	0.693	0.072	0.098	0.091	0.051
0.3	0.746	0.064	0.081	0.072	0.043
0.4	0.791	0.057	0.066	0.056	0.035
0.5	0.828	0.051	0.054	0.044	0.029
0.6	0.858	0.045	0.044	0.035	0.024
0.7	0.882	0.040	0.037	0.028	0.019
0.8	0.902	0.035	0.030	0.022	0.016
0.9	0.918	0.031	0.026	0.018	0.013
1.0	0.931	0.028	0.022	0.014	0.011

Chapter 4 - A General Framework to Forecast the Adoption of Novel Products: A Case of Autonomous Vehicles

Individual's preference for novel products (e.g., autonomous vehicles) with limited or no available prototypes and rapidly growing services (e.g., mobility-on-demand/ride-hailing) is continuously shaped by the information obtained from multiple sources (e.g., media and social networks). The information obtained from such sources are used to evaluate the risk associated with the adoption/usage of the product/service. The existing behavior models not only fail to capture the information propagation within the individual's social network, but also they do not incorporate the impact of such word-of-mouth (WOM) dissemination on the consumer's risk preferences. This chapter contributes to the growing literature on preference evolution by formulating and validating a framework (discrete choice model) to capture the effect of social-network represented through WOM dissemination.

The framework is based on integrated choice and latent variable (ICLV) approach. The WOM and risk are represented as latent variables with explicit information exchange based on interpersonal network. Specifically, we extend the ICLV framework to estimate consumer behavior, which incorporates social network effects and interplay between WOM and risk aversion. The model is calibrated using stated preference survey data of 1,495 Nashville residents on adoption of autonomous vehicles (AVs). Further, the calibrated consumer behavior model and synthetic population are passed through the agent-based model for forecasting the product market share. The output of the agent-based model provides the effect of the purchase price, post-purchase satisfaction, and safety measures/regulations on the forecasted AV market share. These findings are crucial for policymakers to develop infrastructure plans and manufacturers to conduct an after-sales cost-benefit analysis.

This chapter is based on the following article:

Dubey, S., Sharma, I., Mishra, S., Cats, O., & Bansal, P. (2022). A general framework to forecast the adoption of novel products: A case of autonomous vehicles. *Transportation research part B: methodological*, *165*, 63-95.

4.1 Introduction

Capturing consumers' intention to adopt/use a novel product/service is vital for multiple disciplines such as transportation, marketing, sales, technology, economics, finance, human-machine interaction, and social behavior, among others. We contribute to this interdisciplinary literature by providing a general framework to elicit consumers' preferences and forecasting their adoption of "really new products" (i.e., innovative products with entirely new or different attributes from any existing products) (Gregan-Paxton and John, 1997). Autonomous vehicle (AV) – a fully-automated self-driving privately-owned vehicle – is a case in point, which falls under this product category with recent innovations in technology-assisted motorized driving. Understanding consumer preferences and forecasting adoption rates of AVs are crucial for policymakers to devise a plan to meet infrastructure needs and make regulatory decisions to manage a mixed fleet of AVs and conventional vehicles (CVs). At the same time, quantifying the effect of the purchase price and marketing strategies on AV adoption rate is equally critical for manufacturers to conduct an after-sales cost-benefit analysis.

4.1.1 Background and Motivation

Potential consumers can state their intentions to adopt an existing product based on the attributes of interest, by means of trial periods and test drives. In contrast, capturing consumer's intention to purchase a futuristic product is challenging due to the unavailability of accessible prototypes for first-hand experience. Therefore, early adopters actively search for information about the anticipated attributes, benefits, and barriers associated with novel products to minimize associated risks and maximize post-purchase satisfaction (Dholakia, 2001; Dowling and Staelin, 1994; Liu, 2013; Manning et al., 1995; Mosley and Verschoor, 2005).

With recent technological advancements in smartphones and ubiquitous internet connectivity, potential consumers are increasingly exchanging their opinions and recommendations about innovations through electronic media, social media, blogs, and peer-to-peer communication, among other communication channels and informational sources (Gupta and Harris, 2010; Ha, 2002). The information obtained from such channels is commonly referred to as *word-of-mouth* (WOM). In this era of a digital revolution, the influence of the product-related information through WOM on consumer preferences has become substantial enough to be carefully accounted for in econometric models (Huete-Alcocer, 2017). Due to the inability to experience the product, WOM plays an even more vital role in alleviating or increasing risks associated with the adoption of novel product (Hirunyawipada and Paswan, 2006; Hussain et al., 2018, 2017; Krishnamurthy, 2001; Manning et al., 1995; Tan, 1999). Such differences in product information transmission and its effect on the consumers' risk perception call for specific consumer behavior models for novel products.

We envision that an ideal econometric model to elicit the consumers' preferences for novel products should have five components: consumer's risk preferences, WOM through offline social networks and online channels, the interplay between consumer's risk preferences and WOM, adoption level of the product in social network/city, and the influence of key product attributes such as purchase price on consumer's preferences. Followed by generating a synthetic population, such a consumer preference model can be integrated into an agent-based model to forecast the adoption of the novel product under different scenarios (e.g., purchase price reduction or changes in risk preferences due to technological improvements such as reduction in AV crash rate).

4.1.2 Research Gap

The literature on capturing the impact of WOM on consumer preferences is prolific (see Table S.4.1.1 in the Supplement-4 of 40+ such studies at th end of the chapter). Specific to the transportation sector, structural equation models (Kwon et al., 2020; Thøgersen and Ebsen, 2019), discrete choice models (He et al., 2014; Helveston et al., 2015; Jansson et al., 2017), agent-based models (Kieckhäfer et al., 2017), exploratory factor analysis (Ozaki and Sevastyanova, 2011), regression analysis (Barth et al., 2016; Du et al., 2018; Moons and De Pelsmacker, 2012), text mining (Ma et al., 2019), theory of reasoned action (Alzahrani et al., 2019), and Bass model (Hong et al., 2020) have been used to model WOM and social network effects in the adoption of green or electric vehicles (EVs). Specific to AVs, Ghasri and Vij (2021) explored the influence of WOM on the consumer preferences using discrete choice. Most past studies could only quantify consumers' preferences to adopt EVs or AVs, but failed to translate the estimated preferences into a forecasting model. For instance, the results of structural equation models on *consumers' intention to purchase* are not adequate for forecasting the adoption of novel products. Only He et al. (2014) and Kieckhäfer et al. (2017) extended the analysis to incorporate the effect of WOM in forecasting the adoption of EVs, and Talebian and Mishra (2018) did the same for AVs. However, these studies lack the underlying consumer behaviour model.

Similarly, only a handful of previous studies used structural equation models (Chikaraishi et al., 2020), the technology acceptance model (Zhang et al., 2019), or discrete choice models (Bansal et al., 2021b; Wang and Zhao, 2019) to understand consumers' risk preferences in the adoption of EVs and AVs. However, none of these studies forecasted the market penetration of new technologies. A similar pattern was observed in modeling risk preferences for other novel products such as farming techniques (Barham et al., 2014; Brick and Visser, 2015). To substantiate our claim, we summarize the related literature in Table A.4.1 in the appendix. There are also many studies in the literature, which completely ignored WOM and risk preferences, and relying exclusively on product attributes (such as purchase price) in agent-based models to forecast the adoption of novel products such as EVs and AVs (e.g. Bansal and Kockelman, 2017; Musti and Kockelman, 2011).

In summary, numerous studies modeled WOM and risk preferences in eliciting consumers' inclination towards novel products, but they have three main shortcomings. First, previous studies fail to explicitly incorporate the social network effect. A handful of studies have modeled the effect of information from internal or external sources on consumer preferences (for example, Ghasri and Vij, 2021; Sharma and Mishra, 2020) but have failed to model *information propagation* within the social network. Therefore, these consumer behavior models cannot be used to forecast the adoption of novel products. Second, none of the previous studies has simultaneously accounted for the effect of WOM and risk aversion on consumer behavior. Third, while only a handful of studies have gone beyond consumer behavior analysis and forecasted the adoption of the novel product, forecasting models rely on simplistic (mostly synthetic, i.e., not calibrated with the contextual data) consumer behavior models.

4.1.3 Word-of-mouth and Perceived Risks in Mobility-on-demand Services

The choice/usage of new services such as mobility-on-demand (MOD) may also be affected by the WOM. Factors such as perceived service features (app quality (Nguyen-Phuoc et al., 2021a)), company work ethics (Sthapit and Björk, 2019), etc., can impact the intention of service usage through WOM. Similarly, perceived risk (security and safety) (Nguyen-Phuoc et al., 2021b; Jing et al., 2021), and trust (Wu and Neil, 2021; Jiang et al., 2022) can directly impact the intention of service usage.

Similar to the studies discussed in section 4.1.2, studies on WOM and risk in the context of MOD services have failed to explicitly incorporate the social network effect. These studies typically use structural equation modeling (SEM) approach to identify effects with the assumption of independence between observations. Further, these studies do not have a stated-preference component and hence the developed models cannot be used to predict the choice of MOD services.

4.2 Contributions

We propose a comprehensive framework to forecast the adoption of the novel product where a well-calibrated new consumer behavior model is integrated into a population-based agent-based model. Specifically, the consumer behavior model follows the specification of the integrated choice and latent variable (ICLV) model (also known as the hybrid choice model), where WOM and risk aversion are considered as latent variables. The proposed model – interdependent ICLV – extends the ICLV model (Bhat et al., 2016b) by incorporating cross-loading of latent variables and panel effects in the discrete choice component. In this specification, autoregressive structure in the latent construct of ICLV captures social network effects, and cross-loading WOM on risk aversion accounts for their interaction effects. The indirect utility of the choice model captures the effect of the purchase price and adoption rates of the product within the social network and the city. We derive the maximum likelihood estimator of the interdependent ICLV model and calibrate it with stated preference data. The calibrated consumer behavior model, synthetic population, and individual-level social network are passed through an agent-based simulation model to predict individual's preferences to buy the novel product in each time step. The individual-level preferences are aggregated to find the adoption rate in each time step. We also highlight the implications of neglecting the information propagation effect in the agent-based simulation. The proposed framework is general enough to be applied for forecasting the adoption of any novel product. However, to make the discussion contextual, we demonstrate its capabilities in forecasting the adoption of AVs.

The remainder of the chapter is organized as follows: Section 4.3 discusses the design of stated choice experiments to collect the preferences of Nashville (Tennessee, USA) residents for AV adoption. Sub-section 4.3.2 provides specific details of the considered aspects of WOM and risk preferences and the details of data collection and summary statistics are provided in sub-section 4.3.3 and 4.3.4. Section 4.4 presents the contextual and mathematical representation of the interdependent ICLV model. Section 4.5 summarizes the results of the ICLV model. Section 4.6 details the synthetic population generation, the agent-based simulation framework, and scenario-based analysis of the forecasted adoption rates of AVs in Nashville. Conclusions and avenues of future research are discussed in the final section 4.7.

4.3 Survey Design and Data Collection

4.3.1 Discrete Choice Experiment Design

We designed and conducted a stated preference survey with a discrete choice experiment (DCE). In the DCE, respondents were asked to choose between a CV and an AV during their next car purchase. They needed to make choices based on the purchase prices of both cars and the adoption of AVs in their social network and city. Before the experiment, respondents were informed about the differences between AVs and CVs using infographics. To ensure that respondents do not find automation very futuristic, we also mentioned that Google's AV has driven more than 20 million miles on public roads. We communicated that Level 4 AVs are slightly more expensive than CVs because they need additional accessories to operate without a human driver, but both cars are equivalent in all other attributes (e.g., engine power, fuel economy, body type, and aesthetics). Attribute levels of both alternatives in the DCE are presented in Table 4.1. The purchase price of AV was pivoted on the purchase price of the CV, which was asked in a question preceding the DCE.

Four attribute levels for the purchase price and three attribute levels for each social network and city level AV adoption lead to a total of thirty-six choice scenarios. We used the full factorial design and presented each respondent with three randomly selected scenarios out of thirty-six choice scenarios. An example of the choice scenario presented to respondents is shown in Figure 4.1.

Table 4.1: Attribute levels in the discrete choice experiment and experiment design to capture word of mouth (WOM) effect related to the adoption of autonomous cars

	Alternatives	
Attribute	**Conventional car** 	**Autonomous car** 
Discrete choice experiment		
Purchase price (US$)	Reported by the respondent	1. 20% higher than the cost of conventional car 2. 30% higher than the cost of conventional car 3. 40% higher than the cost of conventional car 4. 50% higher than the cost of conventional car
% of people in **respondent's social network** who adopted autonomous cars	Not applicable	1. 30% 2. 60% 3. 90%
% of people in **respondent's city** who adopted autonomous cars	Not applicable	1. 30% 2. 60% 3. 90%
WOM Experiment 1: safety aspects of autonomous cars		
Source of information	1. Friend 2. Car dealer 3. Colleague 4. Media	Same as the one for conventional car
Vehicle crashes per 100 million miles	1,090	1. 415 2. 290 (30% less than 415) 3. 207 (50% less than 415)
Crashes with no clarity on responsibility/liability	Not applicable	1. 10% 2. 30%
WOM Experiment 2: environmental friendliness, travel time savings, and safety aspects of autonomous cars		
Source of information	1. Friend 2. Car dealer 3. Colleague 4. Media	Same as the one for conventional car
Travel time reduction in autonomous cars	Not applicable	1. 20% less than conventional cars 2. 40% less than conventional cars
CO_2 emissions reduction in autonomous cars	Not applicable	1. 30% less than conventional cars 2. 50% less than conventional cars
Crashes with no clarity on responsibility/liability	Not applicable	1. 10% 2. 30%

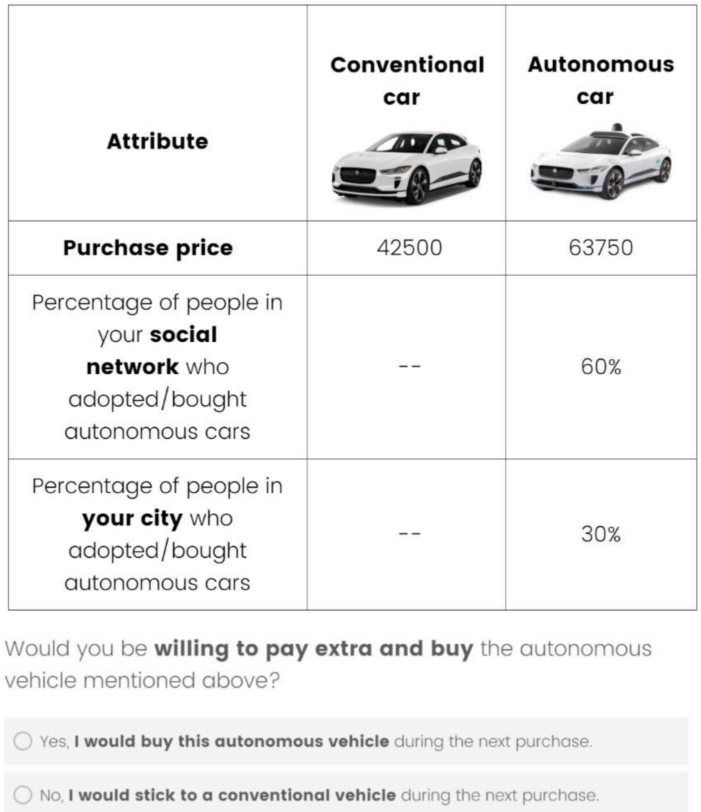


Figure 4.1: An example of a choice situation presented to respondents

4.3.2 WOM Experiments

Apart from the DCE, the survey also had two experiments to capture the type and magnitude of the WOM transmitted by respondents based on the source of information and AV attributes. In both experiments, we used four information sources: friend, car dealer, colleague, and media. All the attribute levels of both experiments are tabulated in Table 4.1.

In experiment 1, we provided information about vehicle crashes and fatality rates for CVs and AVs, and the percentage of AV crashes with no clarity about who is responsible for the crash. Following Blanco et al. (2016), we used 1,090 and 415 vehicle crashes per 100 million miles as crash rates for CVs and AVs, respectively. Assuming a potential reduction of 30-50% in the number of AV crashes, we considered 415, 290, and 207 as the three levels of the AV crash rate. Whereas we used 1.13 fatalities per 100 million miles for CVs (IIHS, 2020), it was considered to be zero for AVs because Google's AV did not report any fatality in the year 2018 and 2019 (Waymo, 2020). We also assumed that making anyone accountable or responsible for the crash might be challenging in 10-30% of AV crashes. Therefore, we considered 10% and 30% as two levels for this attribute. Experiment 2 is similar to experiment 1, but crash rates and fatalities were replaced with reductions in travel time and CO_2 emissions due to automation. The past findings suggest that AVs are expected to reduce travel time and CO_2 emissions by 37% and 30%, respectively, at 50% market penetration (Olia et al., 2016). Based on this information, we used attribute levels of 20% and 40% for travel time reduction and 30% and 50% for CO_2 emission reduction.

The full factorial designs of experiments 1 and 2 have (4x3x2) 24 and (4x2x2x2) 32 choice scenarios. One randomly selected scenario was presented to each respondent for one of the two experiments. Readers will note that both experiments ensure a trade-off between the benefits of automation (crash/fatality reduction in experiment 1, and travel time and emissions reduction in experiment 2) and the associated risks (AV crashes with no clarity on responsibility). Considering these trade-offs, the respondent was asked to rate three statements, each corresponding to positive, neutral, and negative WOM, on a five-point Likert scale (from strongly disagree to strongly agree) in each experiment. Specifically, based on the presented information in the experiment, the respondents were asked how likely they would positively, neutrally, or negatively communicate their opinion about AV adoption to their close social ties. The narratives of both experiments 1 and 2, along with the WOM statements, are shown in example scenarios presented in Figure 4.1 and Figure 4.2, respectively.

Suppose **your friend** provides you with the following information on the **crash and fatality rates** of conventional and autonomous cars if both vehicles are driven for **100 million miles:**

Conventional cars		**Autonomous cars**	
Crashes	**Fatalities**	**Crashes**	**Fatalities**
1,090	*1.13*	*290*	0.00

The above table indicates that autonomous cars have a much lower crash and fatality rates, but **your friend** also informs that it is not clear who is responsible for the crash in **30%** of crashes encountered by **autonomous cars**.

Assume people in your close social network ask about your opinion on buying an **autonomous car over a conventional car.** Based on the information presented above, t**o what extent do you agree the following statements:**

	Strongly agree	Somewhat agree	Neutral	Somewhat disagree	Strongly disagree
I will suggest them to **consider buying an autonomous car** over a conventional car because the former is much **safer**.	○	○	○	○	○
I will be **neutral** in my recommendation.	○	○	○	○	○
I will suggest them to **consider buying a conventional car** over an autonomous car because at least one knows who is **responsible for a crash** in a conventional car.	○	○	○	○	○

Figure 4.1: An example scenario that captures WOM related to the safety of autonomous cars (experiment 1)

Suppose **a print or electronic media channel** provides you with the following information on the travel time and emission reduction in autonomous cars as compared to conventional cars if both vehicles have **an equal market share** (i.e., 50% market penetration of autonomous cars):

Autonomous cars	
Reduction in travel time	**Reduction in CO_2 emissions**
20%	30%

But **the media channel** also informs you that there are two potential limitations of autonomous cars:

1. Whereas you can accelerate the conventional car to reach on time for important meetings or flights, you will not have such flexibility to make the last moment decision while riding autonomous cars.
2. During an accident, about **30%** of the time it will not be clear who is responsible for the crash encountered by autonomous cars.

Assume people in your close social network ask about your opinion on buying an **autonomous car over a conventional car.** Based on information presented above, **to what extent do you agree to the following statements:**

	Strongly agree	Somewhat agree	Neutral	Somewhat disagree	Strongly disagree
I will suggest them to **consider buying an autonomous car** over a conventional car because the former is more **reliable and environmental-friendly**.	○	○	○	○	○
I will be **neutral** in my recommendation.	○	○	○	○	○
I will suggest them to **consider buying a conventional car** over an autonomous car because at least one can **make last-moment decisions to accelerate and who is responsible for a crash** in a conventional car.	○	○	○	○	○

Figure 4.2: An example scenario that captures WOM related to environmental friendliness, travel time savings, and safety aspects of autonomous cars (experiment 2)

4.3.3 Data Collection

The web-based stated preference survey was hosted on Qualtrics and was disseminated among Nashville residents between August and November 2020. Survey participants were recruited with the help of an online market research firm. The participants were asked screening questions regarding age and the city of residence to ensure that only Nashville residents with age over 18 years participate in the survey. The respondents were also asked about the five-digit ZIP code of the home location, which was subsequently used to generate synthetic population and social networks (see Sections 4.4.3.6 and 4.6.1 for details). To ask for such detailed residential information, we had to take approval from the Institutional Review Board (IRB) at the University of Memphis under the "*Expedited*" track. The Zipcode-level spatial distribution of the respondents in Nashville is displayed in Figure 4.3.

Apart from the DCE and two WOM experiments, the survey asked respondents about their socioeconomic characteristics, accident history, and social ties (see Figure S.4.3.1 in the Supplement-4 for the definition of a close social tie). We also asked respondents to report their perceptions about independent statements on the five-point Likert scale – the indicators of the respondent's anticipated risk in adopting AVs (exact question wording is provided in Figure 4.5). To maintain the sample quality, participants with a response time below 50% of the median response time were removed - a standard practice in the marketing literature (Callegaro et al., 2014; Greszki et al., 2015; Roßmann, 2010). We removed 106 fast responses, and the final sample had 1,495 complete responses. The marginal distributions of sample and population (as per American Community Survey 2017 obtained from Manson et al., 2019) across ethnicity, gender, and age are shown in Figure 4.4. The overall sampling distribution across all demographic levels is comparable to the population distribution.

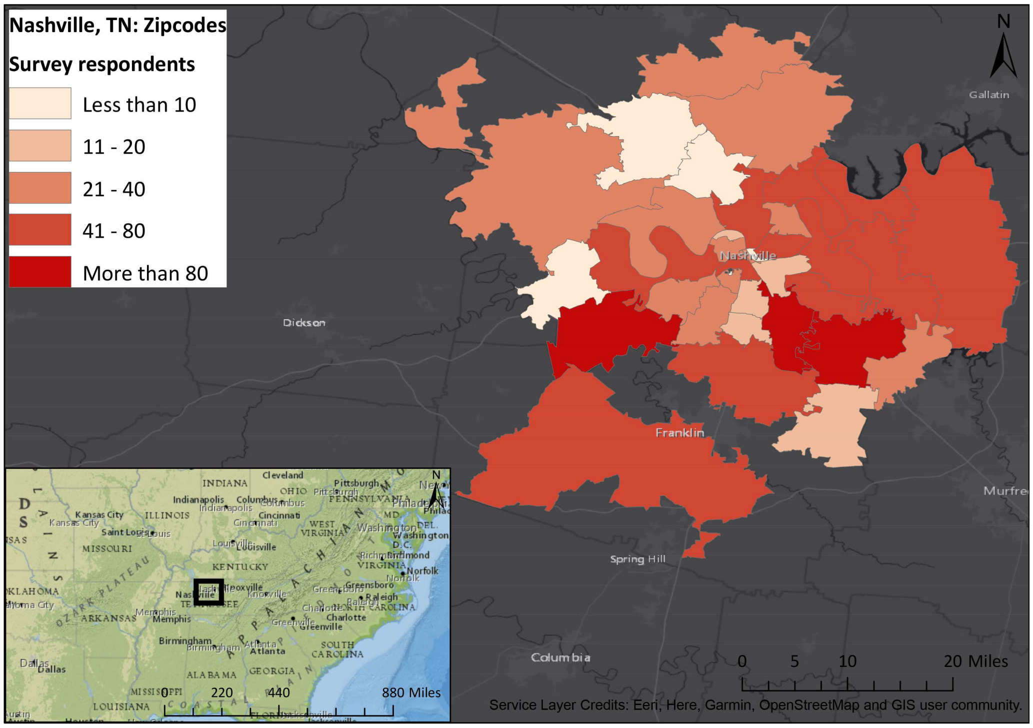


Figure 4.3: Spatial distribution of survey respondents in Nashville

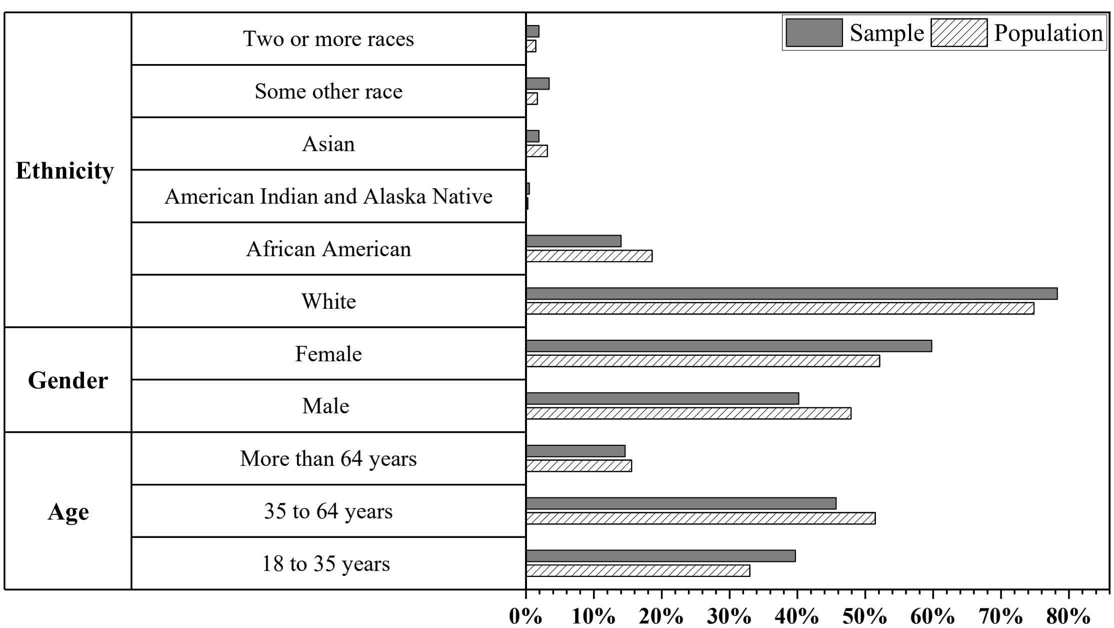


Figure 4.4: Marginal distribution of sample and population across demographics

4.3.4 Summary Statistics

Table 4.1: summarizes the descriptive statistics of the survey sample. From a social network perspective, respondents have about 12 close social ties. Among the individuals with accident history, most of them incurred minor damages, and a minority of the sample (6%) suffered from severe injuries.

The distributions of responses to the statements indicating the risk perception of the respondent on the five-point Likert scale are shown in Figure 4.5. Over half of respondents are worried about the value-for-money in an AV purchase (Ind01). Only 27% of the respondents are willing to take a risk of purchasing an AV to have an exciting experience (Ind02). 58% of the respondents indicated that they would be uncomfortable in switching to AVs (Ind03), but this might not be specific to automation technology because around 45% of respondents generally struggle with such risky decisions (Ind04).

Table 4.1: Descriptive statistics of the sample

Categorical variables			
Variable	**Percentage**	**Variable**	**Percentage**
Gender		Any kind disability undermining ability to drive	
Male	40%	Yes	11%
Female	60%	No	89%
Age		Ethnicity	
18 to 35 years	40%	White	78%
35 to 65 years	46%	African American	14%
more than 65 years	15%	Others	8%
Educational Attainment		Annual household income	
High school or below	20%	less than $25,000	16%
Some College or College graduate	61%	$25,000-$35,000	11%
Master's (MS) or Doctoral Degree (Ph.D.)	15%	$35,000-$75,000	35%
Professional Degree (MD, JD, etc.)	4%	$75,000-$125,000	22%
		More than $125,000	16%
Willingness to pay to purchase a new car		Number of children in household	
less than $15,000	31%	Zero	65%
$15,000-$30,000	40%	One or more	35%
more than $30,000	29%		
Involve in accidents where vehicle incurred minor damages		Involved in accidents where vehicle incurred major damages	
Yes	56%	Yes	36%
No	44%	No	64%
Involved in accidents and suffered from minor injuries		Involved in accidents and suffered from severe injuries	
Yes	24%	Yes	6%
No	76%	No	94%
Continuous variables			
Number of vehicles in the household		Number of workers in the household	
Mean	2.82	Mean	1.58
Standard deviation	0.93	Standard deviation	0.66
Household members		Number of social ties	
Mean	2.53	Mean	11.66
Standard deviation	1.03	Standard deviation	61.22
Household’s frequency of purchasing a car (in years)			
Mean	6.98		
Standard deviation	4.47		

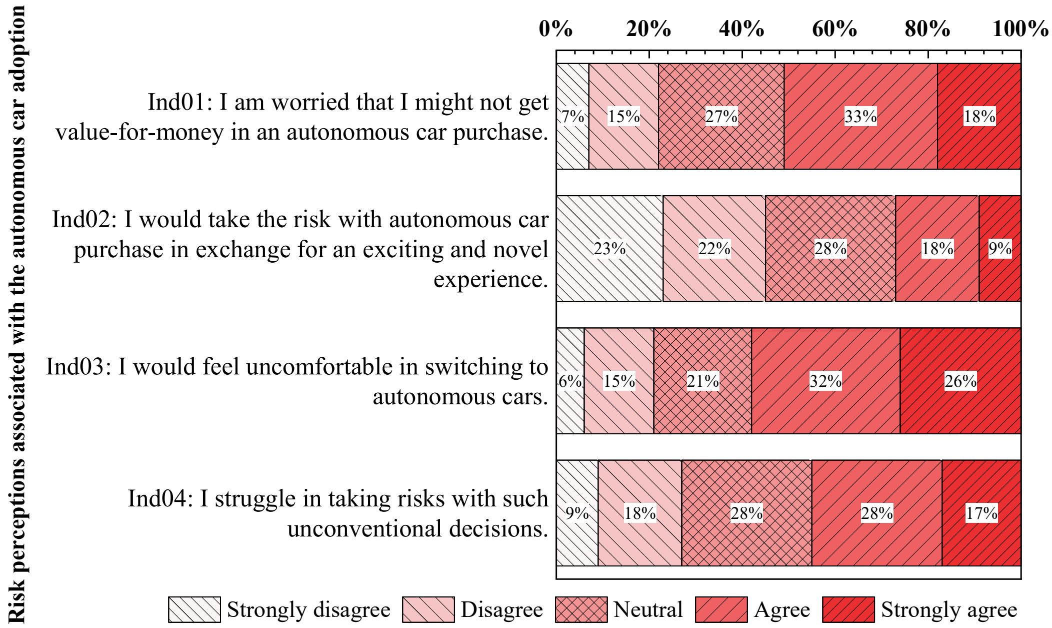


Figure 4.5: Descriptive statistics of statements related to risk perception associated with the autonomous car adoption

4.4 Consumer Behavior Model

4.4.1 Word of Mouth (WOM)

There is well-documented evidence of social influence in the purchase of ice cream (Richards et al., 2014), electronic equipment (Narayan et al., 2011), smartphone (Park and Chen, 2007), organic food items (Chen, 2007), and automobile (Grinblatt et al., 2008). The literature classifies social influence into three major outcomes – conformity, compliance, and obedience (Maness et al., 2015). Conformity is the most common social influence that occurs when an individual changes the behavior to gain acceptance in a group or improve social status by impressing others. Compliance and obedience occur in situations where an individual is *requested* and *ordered* to change the behavior, respectively. Conformity is the most plausible form of social influence in the context of AVs and other novel products. Our review suggests that there could be four ways to model information transfer through WOM and conformity behavior.

The *first* approach is based on the threshold-based specification, which defines a threshold on the proportion of population and friends who must adopt the product before the individual does so (Granovetter, 1978). Such effects need to be incorporated in AV adoption because previous studies on EVs have found the presence of threshold effects. For instance, Mau et al. (2008) observed a significant increase in the individual's willingness to pay for EVs as a function of overall market share. Threshold effects can be incorporated by explicitly modeling a willingness to adopt innovation as a function of market share (Zhang et al., 2011), or an additive utility component can be added based on the choice of others in the network (He et al., 2014; Hsu et al., 2013; Kim et al., 2014; Rasouli and Timmermans, 2016). The *second* approach considers that the exact nature of social influence is unknown, and the total utility of the product is comprised of an individual's utility plus a weighted sum of utilities of others in the social network (see Anselin, 2013 and Bhat, 2014 for applications in spatial econometrics). The *third* and *fourth* approaches assume that individuals revise their attribute importance weight and attribute value itself as a function of preferences of others in their interpersonal network (Narayan et al., 2011).

While threshold-based specification is straightforward to incorporate, they mask the propagation of information in the social network and only offer an aggregate behavioral effect. In the absence of such micro-level dynamics, the interplay between WOM and risk preferences is difficult to model. From the econometric perspective, this approach could lead to biased parameter estimates as it ignores the spatial/social-network-level correlations among individuals. The last two approaches are information hungry as they require precise information about attribute level communication within the social network. Therefore, we mainly rely on the second approach to model social network effects and capture aggregate threshold effects by controlling for the adoption rates of AVs within the individual's social network and the city.

Generally, the exact nature of social influence is not discernable in the second approach, especially when the social network effect is directly incorporated in the utility equation of a choice model (Bhat et al., 2015; Sidharthan and Bhat, 2012). Moreover, such specification does not offer any means for information propagation without directly including several information-related indicators in the utility equation. These additional indicators could induce measurement error and increase the number of covariates substantially. On the other hand, applying the second approach through the latent construct of the ICLV structure has two advantages. First, the essential information related to social influence (i.e., attitudes such as risk-aversion and positive WOM dissemination) can be encapsulated in a low-dimensional vector of latent variables. This specification is also much less vulnerable to measurement errors. Second, the analyst can incorporate the social network effect on latent variables to enable the exchange of information between consumers, a critical trait of a consumer behavior model that makes it useful for forecasting the adoption of novel products (Bhat et al., 2016b). Thus, the ICLV model helps open the black box by putting a structure on the information dissemination (see Bhat et al., 2015, 2016b for ICLV applications). Such behavioral insights derived from ICLV make it an attractive alternative to model social influence. In this study, the information spread by an individual is characterized by the WOM latent variable, which is a function of the WOM of individuals in the social network (see mathematical details in Section 4.4.3). WOM is measured using responses to indicator questions presented in the WOM experiments (see Figure 4.1 and Figure 4.2).

4.4.2 Risk Preference

Risk can be broadly classified into seven types – financial, performance, physical, time, social, psychological, and network externality (see Dholakia, 2001; Hirunyawipada and Paswan, 2006 for a detailed review). By measuring the *risk aversion* latent variable through the responses to four risk-related statements summarized in Figure 4.5, ICLV accounts for *psychological* risks associated with AV adoption. By directly incorporating AV adoption rates at the social network and city level in the utility equation of ICLV, we implicitly model the perceived *time* risk. The information provided in WOM experiments regarding the lack of liability in AV crashes accounts for *performance* risk, and dependence of an individual's WOM on the WOM of social network captures *social* risk. Thus, the proposed interdependent ICLV model could capture *performance* and *social* risks with the cross-loading of WOM on the risk aversion latent variable.

4.4.3 Interdependent Integrated Choice and Latent Variable Model (ICLV)

Figure 4.6 details the three components of the interdependent ICLV model – structural equation model, measurement equation model, and discrete choice model. The figure highlights how the WOM of decision-makers is affected by the information obtained from external sources and their interpersonal network. The combined information (represented by WOM) is considered to influence the risk-aversion behavior of decision-makers. Finally, information and risk-aversion attitude, along with product attributes, determine the AV adoption behavior.

We provide a general formulation of all three components of the model and discuss them in the context of the empirical study. Subsequently, we write the joint likelihood function and discuss the estimation details. The methodology is based on the ICLV model of Bhat et al. (2016b), but we make two extensions to the existing model. First, we capture the moderation effect between attitudes in the structural equation through cross-loading of latent variables. Second, the discrete choice component of the ICLV model is adjusted to account for panel effects. We write our own code in GAUSS, a matrix programming language, to estimate the interdependent ICLV model.

4.4.3.1 Latent Variable Structural Equation Model

Let l and q be the indexes for latent variables $l = (1, 2, ..., L)$ and individuals $q = (1, 2, ..., Q)$. In the empirical study, we consider WOM $(l = 1)$ and risk aversion $(l = 2)$ as two latent variables $(\text{i.e., } L = 2)$. The latent variable (z^*_{ql}) is written as a linear function of covariates:

$$z^*_{ql} = \boldsymbol{\alpha}_l{}' \boldsymbol{s}_{ql} + \eta_{ql} \tag{4.1}$$

Eq. (4.1) assumes that the individual's latent attitude is independent of other individuals. To incorporate the effect of interpersonal network, Eq. (4.1) is modified as follows:

$$z^*_{ql} = \boldsymbol{\alpha}_l{}' \boldsymbol{s}_{ql} + \eta_{ql} + \delta_l \sum_{q'=1}^{Q} w_{qq'} z^*_{q'l} \tag{4.2}$$

where $\boldsymbol{s}_{ql}$ is a $(F \times 1)$ vector of observed covariates, $\boldsymbol{\alpha}_l$ is the corresponding vector of coefficients, η_{ql} is a normally distributed error term, δ_l $(0 \le \delta_l \le 1)$ is the autoregressive parameter which captures the interdependence effect across individuals in the interpersonal network, and $w_{qq'}$ is a weight matrix with $w_{qq} = 0$ and $\sum_{q' \ne q}^{Q} w_{qq'} = 1 \;\; \forall q$. Essentially, Eq. (4.2) is a spatial auto-correlation regression (Anselin, 2013). In this study, $\boldsymbol{s}_{ql}$ consists of socio-economic characteristics, information variables (both type and source of) and accident history variables. The variables presented in the WOM experiments are only included in equation corresponding to WOM (i.e., $\boldsymbol{s}_{q1}$). We estimate δ_1 and set δ_2 to zero because social network effects in risk aversion are transmitted through cross-loading of WOM. We define the following notations to write Eq. (4.2) in matrix form for all Q individuals:

$z_q^* = \left(z_{q1}^*, z_{q2}^*, ..., z_{qL}^*\right)'$ $\left[L \times 1 \text{ vector}\right]$,

$z^* = \left(\left(z_1^*\right)', \left(z_2^*\right)', ..., \left(z_Q^*\right)'\right)'$ $\left[QL \times 1 \text{ vector}\right]$,

$\tilde{s}_q = \begin{pmatrix} s'_{q1} & & 0 \\ & \ddots & \\ 0 & & s'_{qL} \end{pmatrix}$ $\left[L \times LF \text{ matrix}\right]$,

$\tilde{s} = \left(\tilde{s}'_1, \tilde{s}'_2, ..., \tilde{s}'_Q\right)'$ $\left[QL \times LF \text{ matrix}\right]$,

$\boldsymbol{\alpha} = \left(\boldsymbol{\alpha}'_1, \boldsymbol{\alpha}'_2, ..., \boldsymbol{\alpha}'_L\right)'$ $\left[LF \times 1 \text{ vector}\right]$,

$\boldsymbol{\eta}_q = \left(\eta_{q1}, \eta_{q2}, ..., \eta_{qL}\right)'$ $\left[L \times 1 \text{ vector}\right]$,

$\boldsymbol{\eta} = \left(\boldsymbol{\eta}'_1, \boldsymbol{\eta}'_2, ..., \boldsymbol{\eta}'_Q\right)'$ $\left[QL \times 1 \text{ vector}\right]$,

$\boldsymbol{\delta} = \left(\delta_1, \delta_2, ..., \delta_L\right)'$ $\left[L \times 1 \text{ vector}\right]$,

$\tilde{\boldsymbol{\delta}} = \mathbf{1}_Q \otimes \boldsymbol{\delta}$ $\left[QL \times 1 \text{ vector}\right]$,

where " $\otimes$ " represents the Kronecker product, $\mathbf{IDEN}_L$ is an identity matrix of size $(L \times L)$, and $\mathbf{1}_Q$ is a vector of size $(Q \times 1)$ with all its elements equal to 1. To allow for correlation among the latent variables of an individual, $\boldsymbol{\eta}_q$ is assumed to follow a multivariate normal (MVN) distribution $\boldsymbol{\eta}_q \sim \text{MVN}_L[\mathbf{0}_L, \boldsymbol{\Gamma}]$, where $\mathbf{0}_L$ is an $(L \times 1)$ column vector of zeros, and $\boldsymbol{\Gamma}$ is the correlation matrix of size $(L \times L)$. Considering $L = 2$ in this study only Γ_{12} is estimable.

We assume $\boldsymbol{\eta}_q$ to be independent across individuals $\left(\text{i.e., Cov}\left(\boldsymbol{\eta}_q, \boldsymbol{\eta}_{q'}\right) = 0, \forall q \neq q'\right)$. Thus, Eq. (4.2) can be written in matrix form for all Q individuals as follows:

$$z^* = \mathbf{S}\left[\tilde{s}\boldsymbol{\alpha} + \boldsymbol{\eta}\right] \tag{4.3}$$

where $\mathbf{S} = \left[\mathbf{IDEN}_{QL} - \tilde{\delta}.*\left(\mathbf{W} \otimes \mathbf{IDEN}_L\right)\right]^{-1}$ is a matrix of size $(QL \times QL)$, " .* " represents the product of each element of a vector with the corresponding row of a matrix, $\mathbf{IDEN}_{QL}$ is an identity matrix of size $(QL \times QL)$, and $\mathbf{W}$ is a $(Q \times Q)$ row normalized weight matrix.

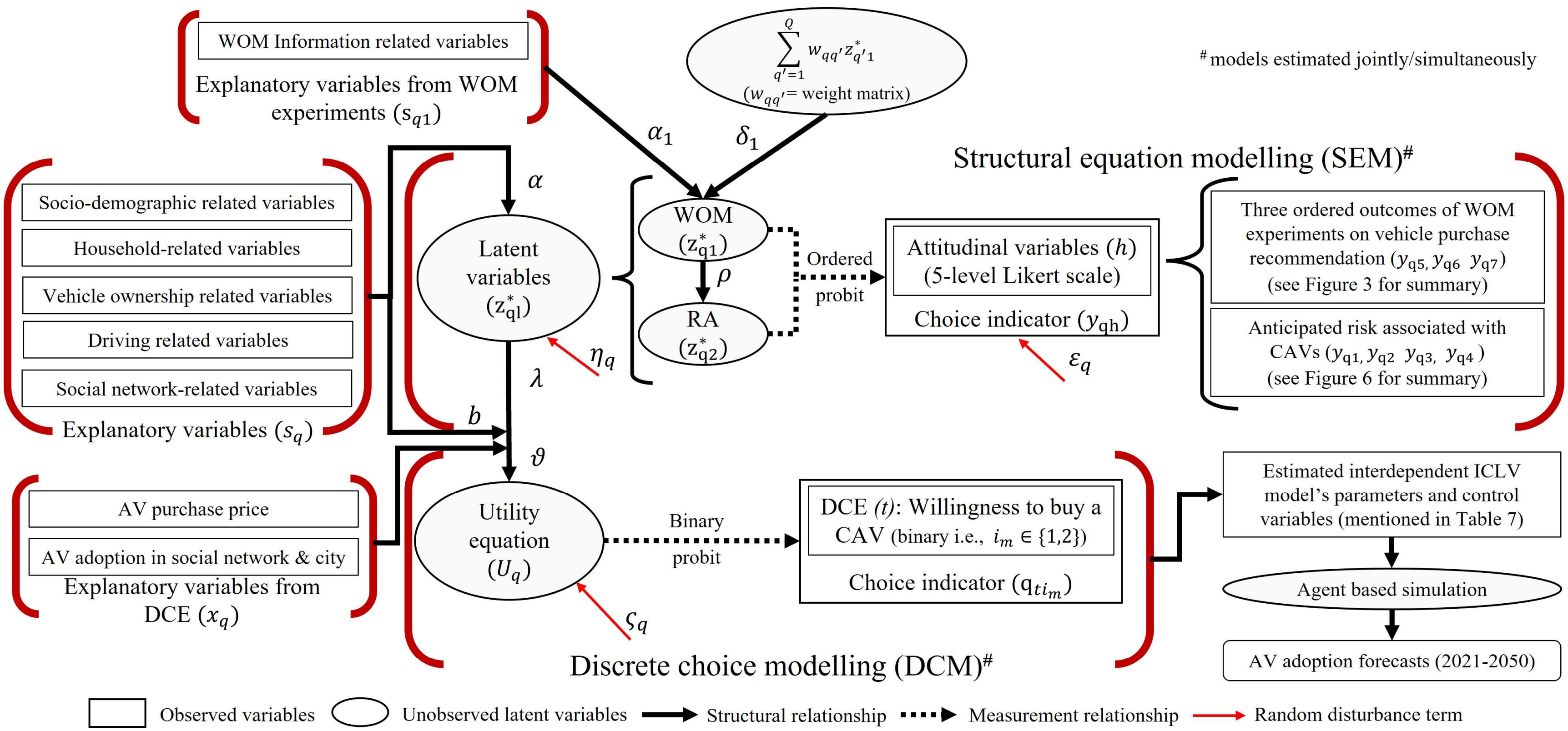


Figure 4.6: Modeling framework of the Interdependent ICLV model

While the attitude of individuals is affected by their interpersonal/spatial network, there may also be a moderation effect across different types of attitudes. For example, if an individual has a strong sense of duty towards the environment (pro-environment), he/she may also exhibit a strong attitude towards trying new environmental-friendly products even if they are novel in the market (risk-taking behavior). Similarly, in the context of this study, WOM can alleviate or augment the risk aversion. Therefore, we extend Eq. (4.3) to accommodate moderation effect as follows:

We define an indicator matrix $\mathbf{I\_mat}$ of size $(L \times L)$ with zeros in all cells. If the analyst wishes to load latent variable l'' on l', a value of "1" is inserted in the cell (l', l'') of the matrix $\mathbf{I\_mat}$. For two latent variables in the current study where WOM $(l=1)$ is loaded on the risk aversion $(l=2)$, the matrix $\mathbf{I\_mat}$ can be written as follows: $\mathbf{I\_mat} = \begin{bmatrix} 0 & 0 \\ 1 & 0 \end{bmatrix}$. Next, we define a matrix $\mathbf{R}$ of size $(L \times L)$ with zeros in all cells and place the corresponding cross-loading parameter $\left[\boldsymbol{\rho} = \left(\rho_1, \rho_2, ..., \rho_{(L*(L-1)*0.5)-L}\right)' \left[\left\{(L*(L-1)*0.5)-L\right\} \times 1 \text{ vector}\right]\right]$ in the cells of matrix $\mathbf{R}$ based on the following pseudocode:

$$
\begin{aligned}
&\boldsymbol{R} = zeros(L, L) \\
&count = 0 \\
&for\ i = 1\ to\ L \\
&\quad for\ j = 1\ to\ L \\
&\quad\quad if\ (i \neq j) \\
&\quad\quad\quad if\ (\mathbf{I\_mat}[i, j] = 1) \\
&\quad\quad\quad\quad count = count + 1 \\
&\quad\quad\quad\quad \boldsymbol{R}[i, j] = \boldsymbol{\rho}[count]
\end{aligned}
$$

The matrix $\mathbf{R}$ for the case study has the following configuration: $\mathbf{R} = \begin{bmatrix} 0 & 0 \\ \rho_1 & 0 \end{bmatrix}$[25]. With this information, we extend Eq. (4.3) to account for moderation effects along with spatial effects:

$$
\boldsymbol{z}^* = \mathbf{DS}\left[\tilde{\boldsymbol{s}}\boldsymbol{\alpha} + \boldsymbol{\eta}\right] \tag{4.4}
$$

where $\mathbf{D} = \mathbf{IDEN}_Q \otimes \left[\mathbf{IDEN}_L - \mathbf{R}\right]^{-1}$. Thus, $\boldsymbol{z}^* \sim \text{MVN}_{QL}(\tilde{\boldsymbol{\theta}}, \tilde{\boldsymbol{\Xi}})$, where mean is $\tilde{\boldsymbol{\theta}} = \mathbf{DS}\tilde{\boldsymbol{s}}\boldsymbol{\alpha}$ and correlation matrix is $\tilde{\boldsymbol{\Xi}} = \mathbf{D}\left(\mathbf{S}\left[\mathbf{IDEN}_Q \otimes \boldsymbol{\Gamma}\right]\mathbf{S}'\right)\mathbf{D}'$.

4.4.3.2 Latent Variable Measurement Equation Model

Since all indicators to capture the underlying attitudes are measured on Likert scale, we only present the measurement equation system corresponding to ordinal variables. Readers are

[25] The loading matrix would be a lower-triangular matrix to ensure one-way cross-loading/structural effect.

referred to Bhat et al. (2016a) for a comprehensive measurement equation system with a combination of continuous, ordinal, count, and nominal outcomes.

Let h be the index for ordinal variables $h = (1, 2, \ldots, H)$ and $j = (1, 2, \ldots, J)$ be the number of categories for ordinal outcomes. In this study, $H = 7$ (3 for WOM [see Figure 4.2] and 4 for risk aversion [see Figure 4.5]) and $J = 5$. Let y^*_{qh} be the latent variable which leads to the observed outcome y_{qh} for individual q and ordinal variable h. Following the usual ordered response formulation, we can write the link function:

$$y^*_{qh} = \boldsymbol{\gamma}'_h \boldsymbol{x}^*_{qh} + \boldsymbol{d}'_h \boldsymbol{z}^*_q + \varepsilon_{qh}, \qquad \psi_{h,y_{qh}-1} < y^*_{qh} < \psi_{h,y_{qh}}, \tag{4.5}$$

where $\boldsymbol{x}^*_{qh}$ is a $(K \times 1)$ vector of observed covariates (including the constant), $\boldsymbol{\gamma}_h$ is the corresponding vector of coefficients, $\boldsymbol{d}_h$ is a $(L \times 1)$ vector of latent variable loadings on the ordinal variable h, ε_{qh} is a normally distributed random error term, and $\psi_{h,y_{qh}}$ is the threshold. For each ordinal variable, the thresholds should be in ascending order and should cover the real line, i.e. $\psi_{h,0} < \psi_{h,1} < \psi_{h,2} \ldots < \psi_{h,J-1} < \psi_{h,J}$, where $\psi_{h,0} = -\infty$ and $\psi_{h,J} = \infty$. To set the origin of the ordinal variable, one can either set the second threshold $\left(\psi_{h,1}\right)$ or the intercept to zero. Here, we choose to do the former: $\psi_{h,1} = 0$. In the empirical study, $\boldsymbol{x}^*_{qh}$ only has a constant $(K = 1)$. Next, we define the following notations to write Eq. (4.5) in a matrix form.

$$\boldsymbol{y}_q^* = \left(y_{q1}^*, y_{q2}^* \ldots, y_{qH}^*\right)' \qquad \left[H \times 1 \text{ vector}\right],$$

$$\boldsymbol{y}^* = \left(\left(y_1^*\right)', \left(y_2^*\right)' \ldots, \left(y_Q^*\right)'\right)' \qquad \left[QH \times 1 \text{ vector}\right],$$

$$\boldsymbol{x}_q^* = \begin{pmatrix} \left(\boldsymbol{x}_{q1}^*\right)' & & 0 \\ & \ddots & \\ 0 & & \left(\boldsymbol{x}_{qH}^*\right)' \end{pmatrix} \qquad \left[H \times HK \text{ matrix}\right],$$

$$\tilde{\gamma} = \left(\gamma_1', \gamma_2', \ldots, \gamma_H'\right)' \qquad \left[HK \times 1 \text{ vector}\right],$$

$$\boldsymbol{d} = \begin{pmatrix} \boldsymbol{d}_1' \\ \boldsymbol{d}_2' \\ \vdots \\ \boldsymbol{d}_H' \end{pmatrix} \qquad \left[H \times L \text{ matrix}\right],$$

$$\boldsymbol{\varepsilon}_q = \left(\varepsilon_{q1}, \varepsilon_{q2}, \ldots, \varepsilon_{qH}\right)' \qquad \left[H \times 1 \text{ vector}\right],$$

$$\boldsymbol{\psi}_h = \left(\psi_{h,0}, \psi_{h,1}, \ldots, \psi_{h,J}\right)' \qquad \left[J \times 1 \text{ vector}\right],$$

$$\boldsymbol{\psi}_{q,low} = \left(\psi_{1,y_{q1}-1}, \psi_{2,y_{q2}-1}, \ldots, \psi_{H,y_{qH}-1}\right)' \qquad \left[H \times 1 \text{ vector}\right],$$

$$\boldsymbol{\psi}_{q,up} = \left(\psi_{1,y_{q1}}, \psi_{2,y_{q2}}, \ldots, \psi_{H,y_{qH}}\right)' \qquad \left[H \times 1 \text{ vector}\right],$$

Eq. (4.5) can be written in matrix form for individual q as follows:

$$\boldsymbol{y}_q^* = \boldsymbol{x}_q^* \tilde{\boldsymbol{\gamma}} + \boldsymbol{d}\boldsymbol{z}_q^* + \boldsymbol{\varepsilon}_q, \quad \boldsymbol{\psi}_{q,low} < \boldsymbol{y}_q^* < \boldsymbol{\psi}_{q,up} \tag{4.6}$$

To reduce the model complexity, $\boldsymbol{\varepsilon}_q$ is assumed to follow a standard MVN distribution: $\boldsymbol{\varepsilon}_q \sim \text{MVN}_{H\times H}(\boldsymbol{0}_H, \textbf{IDEN}_H)$ because the latent variables $\left(\boldsymbol{z}_q^*\right)$ loadings naturally generate the correlation across ordinal variables.

4.4.3.3 Discrete Choice Model

Let $t = (1, 2, \ldots, T)$ be the index for choice occasion and $i = (1, 2, \ldots, I)$ be the index for alternative. In the case study, $T = 3$ and $I = 2$.The indirect utility of individual q due to choosing alternative i during choice occasion t is:

$$U_{qti} = \boldsymbol{b}_i' \boldsymbol{x}_{qti} + \boldsymbol{\lambda}_i' \boldsymbol{z}_q^* + \boldsymbol{\vartheta}'(\mathbf{A}_{qti} \boldsymbol{z}_q^*) + \varsigma_{qti} \tag{4.7}$$

where $\boldsymbol{x}_{qti}$ is an $(M\times1)$ vector of attributes (including the constant), $\boldsymbol{b}_i$ is a vector of corresponding marginal utilities, $\boldsymbol{\lambda}_i$ is a $(L\times1)$ vector of coefficients of latent variables for alternative i, and ς_{qti} is a normally-distributed error term. In the empirical study, $\boldsymbol{x}_{qti}$ consists of alternative-specific constant, socio-demographic variables, purchase price, percentage adoption in the social network, and percentage adoption in the city. Note that $\boldsymbol{\lambda}_i$ for one alternative is normalized to zero for identification. $\mathbf{A}_{qti}$ is a $(LM \times L)$ matrix of altenative-specific attributes $\left(\boldsymbol{x}_{qti}\right)$ that interact with latent variables, and $\boldsymbol{\vartheta}$ is the corresponding $(LM \times 1)$ column vector of marginal utilities. We define the following notations to convert Eq. (4.7) into matrix form:

$$\boldsymbol{U}_{qt} = \left(U_{qt1}, U_{qt2}, ..., U_{qtI}\right)' \quad \left[I \times 1 \text{ vector}\right],$$

$$\boldsymbol{U}_{q} = \left(\boldsymbol{U}'_{q1}, \boldsymbol{U}'_{q2}, ..., \boldsymbol{U}'_{qT}\right)' \quad \left[TI \times 1 \text{ vector}\right],$$

$$\boldsymbol{U} = \left(\boldsymbol{U}'_{1}, \boldsymbol{U}'_{2}, ..., \boldsymbol{U}'_{Q}\right)' \quad \left[QTI \times 1 \text{ vector}\right]$$

$$\boldsymbol{x}_{qt} = \begin{pmatrix} \boldsymbol{x}_{qt1}' & & 0 \\ & \ddots & \\ 0 & & \boldsymbol{x}_{qtI}' \end{pmatrix} \quad \left[I \times IM \text{ matrix}\right],$$

$$\boldsymbol{x}_{q} = \begin{pmatrix} \boldsymbol{x}_{q1} \\ \boldsymbol{x}_{q2} \\ \vdots \\ \boldsymbol{x}_{qT} \end{pmatrix} \quad \left[TI \times IM \text{ matrix}\right],$$

$$\tilde{\boldsymbol{b}} = \left(\boldsymbol{b}_1', \boldsymbol{b}_2', ..., \boldsymbol{b}_I'\right)' \quad \left[IM \times 1 \text{ vector}\right],$$

$$\tilde{\boldsymbol{\lambda}} = \begin{pmatrix} \boldsymbol{\lambda}_1' \\ \boldsymbol{\lambda}_2' \\ \vdots \\ \boldsymbol{\lambda}_I' \end{pmatrix} \quad \left[I \times L \text{ matrix}\right],$$

$$\tilde{\boldsymbol{\lambda}} = \mathbf{1}_T \otimes \tilde{\boldsymbol{\lambda}} \quad \left[TI \times L \text{ matrix}\right],$$

$$\boldsymbol{\varpi}_{qti} = (\boldsymbol{\vartheta}' \mathbf{A}_{qti}) \quad \left[1 \times L \text{ vector}\right],$$

$$\boldsymbol{\varpi}_{qt} = \begin{pmatrix} \boldsymbol{\varpi}_{qt1} \\ \boldsymbol{\varpi}_{qt2} \\ \vdots \\ \boldsymbol{\varpi}_{qtI} \end{pmatrix} \quad \left[I \times L \text{ matrix}\right],$$

$$\boldsymbol{\varpi}_{q} = \begin{pmatrix} \boldsymbol{\varpi}_{q1} \\ \boldsymbol{\varpi}_{q2} \\ \vdots \\ \boldsymbol{\varpi}_{qT} \end{pmatrix} \quad \left[TI \times L \text{ matrix}\right],$$

$$\varsigma_{qt} = \left(\varsigma_{qt1}, \varsigma_{qt2}, ..., \varsigma_{qtI}\right) \quad \left[1 \times I \text{ vector}\right],$$

$$\varsigma_{q} = \left(\varsigma_{q1}, \varsigma_{q2}, ..., \varsigma_{qT}\right)' \quad \left[TI \times 1 \text{ vector}\right],$$

Let $\mathbf{\Lambda}$ be the covariance matrix of ς_{qt}, which we assume to be independent across choice occasions to reduce the model complexity because latent variable $\left(z_q^*\right)$ loadings generate the correlations across choice occasions. Thus, Eq. (4.7) for individual q can be written as follow:

$$\boldsymbol{U}_q = \boldsymbol{x}_q \tilde{\boldsymbol{b}} + \left(\tilde{\lambda} + \boldsymbol{\varpi}_q\right) \boldsymbol{z}_q^* + \varsigma_q, \tag{4.8}$$

where $\varsigma_q \sim MVN_{TI \times TI}\left(\mathbf{0}, \mathbf{IDEN}_T \otimes \mathbf{\Lambda}\right)$.

4.4.3.4 Joint Likelihood

Note that obtaining the marginal distribution of $\boldsymbol{U}_q$ and $\boldsymbol{y}_q^*$ is not straighford due to spatial correlation in the latent variable ($\boldsymbol{z}_q^*$) across individuals. Therefore, we work with the joint distribution of all individuals to write the model likelihood:

$$\boldsymbol{y}^* \boldsymbol{U} \sim MVN_{\left[Q(H+TI)\right] \times \left[Q(H+TI)\right]}\left(\mathbf{B} = \boldsymbol{\mu}_1 + \boldsymbol{\mu}_2 \tilde{\boldsymbol{\theta}}, \mathbf{\Omega} = \boldsymbol{\mu}_2 \tilde{\mathbf{\Xi}} \boldsymbol{\mu}_2' + \mathbf{IDEN}_Q \otimes \mathbf{\Sigma}\right), \tag{4.9}$$

where

$$\boldsymbol{\mu}_{1q} = \left(\left[\boldsymbol{x}_q^* \tilde{\boldsymbol{\gamma}}\right]', \left[\boldsymbol{x}_q \tilde{\boldsymbol{b}}\right]'\right)' \qquad \left[(H+TI) \times 1 \text{ vector}\right],$$

$$\boldsymbol{\mu}_1 = \left(\boldsymbol{\mu}_{11}', \cdots, \boldsymbol{\mu}_{1Q}'\right)' \qquad \left[Q(H+TI) \times 1 \text{ vector}\right],$$

$$\boldsymbol{\mu}_{2q} = \left(\boldsymbol{d}', \left(\tilde{\lambda} + \boldsymbol{\varpi}_q\right)'\right)' \qquad \left[(H+TI) \times L \text{ matrix}\right],$$

$$\boldsymbol{\mu}_2 = \begin{pmatrix} \boldsymbol{\mu}_{21} & & 0 \\ & \ddots & \\ 0 & & \boldsymbol{\mu}_{2Q} \end{pmatrix} \qquad \left[Q(H+TI) \times QL \text{ matrix}\right],$$

$$\mathbf{\Sigma} = \begin{pmatrix} \mathbf{IDEN}_H & \mathbf{0}_{H \times TI} \\ \mathbf{0}_{TI \times H} & \mathbf{IDEN}_T \otimes \mathbf{\Lambda} \end{pmatrix} \qquad \left[(H+TI) \times (H+TI) \text{ matrix}\right],$$

Since, only the difference in utility matters, we work with utility differences in the discrete choice part. We specifically subtract the utility of the chosen alternative from utilities of all non-chosen alternatives. Moreover, top left element of the differenced error covariance matrix ($\tilde{\mathbf{\Lambda}}$) is fixed to 1 to set the utility scale for identifiability (Keane, 1992). Thus, for I alternatives case, only $\left\{I * \left(I-1\right) * 0.5\right\} - 1$ covariance elements are identifiable. Further, since all the differenced error covariance matrices must originate from the same undifferenced error covariance matrix ($\mathbf{\Lambda}$), we specify matrix $\mathbf{\Lambda}$ as follows (Sidharthan and Bhat, 2012): $\mathbf{\Lambda} = \begin{bmatrix} 0 & 0 \\ 0 & \tilde{\mathbf{\Lambda}} \end{bmatrix}$. We also had to transform Eq. (4.9) in the utility-difference space using a matrix $\mathbf{M\_Diff}$ of size $\left[Q(H + T(I-1)) \times Q(H + TI)\right]$ as shown in Eq. (4.10). The procedure to compute $\mathbf{M\_Diff}$ is provided in Algorithm A.4.1 in Appendix-4. The resulting joint distribution in the utility differenced space is:

$$\bar{\boldsymbol{y}}^{*}\bar{\boldsymbol{U}} \sim MVN_{[Q(H+T(I-1))]\times[Q(H+T(I-1))]}\left(\bar{\mathbf{B}} = \mathbf{M\_Diff} * \mathbf{B}, \bar{\boldsymbol{\Omega}} = \mathbf{M\_Diff} * \boldsymbol{\Omega} * \mathbf{M\_Diff}'\right) \tag{4.10}$$

4.4.3.5 Estimation

To evaluate the joint likelihood presented in Eq. (4.10), we need to compute a $Q(H+T(I-1))$ dimensional integral involved in the multivariate normal cumulative distribution function (MVNCDF). Despite several advancements in quasi-Monte Carlo (Bhat, 2003), quadrature (Bansal et al., 2021b), analytical methods (Bhat, 2018) to evaluate high-dimensional integrals, computing such a high-dimensional integral at the desired accuracy remains infeasible. Therefore, we make use of the composite marginal likelihood (CML) approach, which define a surrogate likelihood function by taking the product of low dimensional MVNCDF. The surrogate function for Eq. (4.10) is as follows:

$$\begin{aligned} L_{CML}(\boldsymbol{\Theta}) = & \left\{\left[\prod_{q=1}^{Q}\prod_{h=1}^{H}\prod_{q'=q}^{Q}\prod_{h'=1}^{H}\Pr\left[y_{qh}, y_{q'h'}\right]\right]\forall\left\{\begin{matrix} q \neq q' \\ or \\ q = q' \ and \ h' > h \end{matrix}\right\}\right\} \\ & \times\left\{\left[\prod_{q=1}^{Q}\prod_{q'=1}^{Q}\prod_{h=1}^{H}\prod_{t=1}^{T}\Pr\left[y_{qh}, q'_{ti_m}\right]\right]\right\} \\ & \times\left\{\left[\prod_{q=1}^{Q}\prod_{t=1}^{T}\prod_{q'=q}^{Q}\prod_{t'=1}^{T}\Pr\left[q_{ti_m}, q'_{t'i_m}\right]\right]\forall\left\{\begin{matrix} q \neq q' \\ or \\ q = q' \ and \ t' > t \end{matrix}\right\}\right\} \end{aligned} \tag{4.11}$$

where $\boldsymbol{\Theta} = [Vech(\boldsymbol{\alpha}), Vech(\boldsymbol{\Gamma}), \boldsymbol{\delta}, \boldsymbol{\rho}, Vech(\tilde{\boldsymbol{\gamma}}), Vech(\boldsymbol{d}), \boldsymbol{\psi}, \tilde{\boldsymbol{b}}, Vech(\boldsymbol{\lambda}), \boldsymbol{\vartheta}, Vech(\boldsymbol{\Lambda})]$, "$Vech(.)$" vectorizes all the elements of the matrix, y_{qh} indicates the observed scale for the ordinal variable h by the individual q, and q_{ti_m} indicates the chosen alternative i_m at the choice occasion t by the individual q. In Eq. (4.11), for each pair of individuals q and q', the first, second, and third terms correspond to the pairing of ordinal variables, pairing of ordinal variables with nominal variables, and pairing of nominal variables, respectively. Please note that the highest dimensionality of integration in Eq. (4.11) is $(I-1)*2$ as compared to $Q(H+T(I-1))$ in Eq. (4.10). The explicit form of CML function (Eq. 4.11) for a pair of individuals q and q' can be written with the help of additional matrices.

Create a selection matrix $\mathbf{D}_{qq'}$ of size $\left[2(H+T(I-1))\times Q(H+T(I-1))\right]$ to extract the mean $\left(\bar{\boldsymbol{B}}_{qq'}\right)$ and covariance matrix $\left(\bar{\Omega}_{qq'}\right)$ for the pair of individuals q and q', such that $\bar{\mathbf{B}}_{qq'} = \mathbf{D}_{qq'}\bar{\mathbf{B}}$, $\bar{\Omega}_{qq'} = \mathbf{D}_{qq'}\bar{\Omega}\mathbf{D}_{qq'}'$. To create $\mathbf{D}_{qq'}$, we create a matrix of zeros of the same size and insert two identity matrices of size $(H+T(I-1))$. The first identify matrix is inserted in the first $(H+T(I-1))$ rows and columns $\left[(q-1)*(H+T(I-1))+1\right]$ to $\left[q*(H+T(I-1))\right]$

of $\mathbf{D}_{qq'}$. The second identity matrix is insered in rows $\left(H+T(I-1)+1\right)$ to $\left[2\left(H+T(I-1)\right)\right]$, and columns $\left[(q'-1)*\left(H+T(I-1)\right)+1\right]$ to $\left[q'*\left(H+T(I-1)\right)\right]$.

Next, to explicitely write the *first term* (pairing of ordinal variables) of the CML expression in Eq. (4.11), we create a selection matrix $\mathbf{V}_{qq'}$ of size $\left(2H\times 2\left(H+T(I-1)\right)\right)$. Specifically, we create a matrix of zeros of the same size as of $\mathbf{V}_{qq'}$ and insert two identity matrices of size $(H\times H)$. The first identity matrix is inserted in first H rows and columns of $\mathbf{V}_{qq'}$ and insert another identity matrix in rows $(H+1)$ to $2H$ and columns $\left[H+T(I-1)+1\right]$ to $\left[2H+T(I-1)\right]$.

$$\bar{\mathbf{B}}_{\mathbf{V},qq'}=\mathbf{V}_{qq'}\bar{\mathbf{B}}_{qq'},\ \bar{\mathbf{\Omega}}_{\mathbf{V},qq'}=\mathbf{V}_{qq'}\bar{\mathbf{\Omega}}_{qq'}\mathbf{V}_{qq'}{}',$$
$$\boldsymbol{\psi}_{low}=\left(\boldsymbol{\psi}'_{low}\left[\left\{(q-1)*H+1\right\}:\left\{(q-1)*H+H\right\}\right],\boldsymbol{\psi}'_{low}\left[\left\{(q'-1)*H+1\right\}:\left\{(q'-1)*H+H\right\}\right]\right)',$$
$$\boldsymbol{\psi}_{up}=\left(\boldsymbol{\psi}'_{up}\left[\left\{(q-1)*H+1\right\}:\left\{(q-1)*H+H\right\}\right],\boldsymbol{\psi}'_{up}\left[\left\{(q'-1)*H+1\right\}:\left\{(q'-1)*H+H\right\}\right]\right)',$$
$$\boldsymbol{\mu}_{\mathbf{V},low}=\frac{\boldsymbol{\psi}_{low}-\bar{\mathbf{B}}_{\mathbf{V},qq'}}{\sqrt{diag\left(\bar{\mathbf{\Omega}}_{\mathbf{V},qq'}\right)}},\boldsymbol{\mu}_{\mathbf{V},up}=\frac{\boldsymbol{\psi}_{up}-\bar{\mathbf{B}}_{\mathbf{V},qq'}}{\sqrt{diag\left(\bar{\mathbf{\Omega}}_{\mathbf{V},qq'}\right)}}$$

To explicitely write the *second term* (pairing of ordinal variables with nominal variables) of the CML expression in Eq. (4.11), we create a rearrangement matrix $\mathbf{\Delta}_{qq'}$ of size $\left[2\left(H+T(I-1)\right)\times 2\left(H+T(I-1)\right)\right]$ that brings together ordinal and nominal responses together for simplicity. We create a matrix of zeros of the same size as of $\mathbf{\Delta}_{qq'}$ and insert four identity matrices, two of size $(H\times H)$ and the remaining two of size $\left[T(I-1)\times T(I-1)\right]$. The first identity matrix of size $(H\times H)$ is inserted in the first H rows and columns, and the second identity matrix in rows $(H+1)$ to $2H$ and columns $\left[H+T(I-1)+1\right]$ to $\left[2H+T(I-1)\right]$ of $\mathbf{\Delta}_{qq'}$. Similarly, the first identity matrix of size $\left[T(I-1)\times T(I-1)\right]$ in inserted in rows $(2H+1)$ to $\left[2H+T(I-1)\right]$ and columns $(H+1)$ to $\left[H+T(I-1)\right]$ and the second identity matrix in rows $\left[2H+T(I-1)+1\right]$ to $\left[2\left(H+T(I-1)\right)\right]$ and columns $\left[2H+T(I-1)+1\right]$ to $2\left(H+T(I-1)\right)$ of $\mathbf{\Delta}_{qq'}$. A selection matrix $\mathbf{H}_{ht}$ of size $\left[I\times 2\left(H+T(I-1)\right)\right]$ is also defined. To create $\mathbf{H}_{ht}$, we start with a matrix of zeros of the same size. Subsequently, the cell $(1,h)$ is filled with value of 1 and an identity matrix of size $(I-1)\times(I-1)$ is inserted in rows 2 to I and columns $\left[2H+(t-1)(I-1)+1\right]$ through $\left[2H+t(I-1)\right]$. Then we define the following notations:

$$\bar{\mathbf{B}}_{\mathbf{\Delta},qq'}=\mathbf{\Delta}_{qq'}\bar{\mathbf{B}}_{qq'},\ \bar{\mathbf{\Omega}}_{\mathbf{\Delta},qq'}=\mathbf{\Delta}_{qq'}\bar{\mathbf{\Omega}}_{qq'}\mathbf{\Delta}'_{qq'},$$
$$\boldsymbol{\psi}^{h}_{low}=\left(\boldsymbol{\psi}_{low}[h],\mathbf{0}_{I-1}\right),\ \boldsymbol{\psi}^{h}_{up}=\left(\boldsymbol{\psi}_{up}[h],\mathbf{0}_{I-1}\right).$$

Finally, to write the *third term* (pairing of nominal variables) in Eq. (4.11) explicitly, we create a matrix $\mathbf{E}_{tt'}$ of size $\left[2\left(I-1\right)\times 2\left(H+T(I-1)\right)\right]$. Specifically, we create a matrix of zeros of the same size as of $\mathbf{E}_{tt'}$ and insert two identity matrices of size $\left[(I-1)\times(I-1)\right]$. The first identity matrix is inserted in first $\left(I-1\right)$ rows and columns $\left[2H+\left(t-1\right)\left(I-1\right)+1\right]$ through $\left[2H+t\left(I-1\right)\right]$. The second identity matrix is inserted in the last $\left(I-1\right)$ rows and columns $\left[2H+\left(t'-1\right)\left(I-1\right)+1\right]$ through $\left[2H+t'\left(I-1\right)\right]$. The surrogate likelihood function a pair of individuals q and q' is:

$$
\begin{aligned}
L_{CML}^{qq'}(\mathbf{\Theta}) = & \left(\prod_{h=1}^{2H-1} \prod_{h'=h+1}^{2H} \begin{bmatrix} \Phi_2\left(\left\{\boldsymbol{\mu}_{\mathbf{V},up}[h], \boldsymbol{\mu}_{\mathbf{V},up}[h']\right\}, \bar{\mathbf{\Omega}}_{\mathbf{V},qq'}^{hh'}\right) - \Phi_2\left(\left\{\boldsymbol{\mu}_{\mathbf{V},up}[h], \boldsymbol{\mu}_{\mathbf{V},low}[h']\right\}, \bar{\mathbf{\Omega}}_{\mathbf{V},qq'}^{hh'}\right) \\ -\Phi_2\left(\left\{\boldsymbol{\mu}_{\mathbf{V},low}[h], \boldsymbol{\mu}_{\mathbf{V},up}[h']\right\}, \bar{\mathbf{\Omega}}_{\mathbf{V},qq'}^{hh'}\right) + \Phi_2\left(\left\{\boldsymbol{\mu}_{\mathbf{V},low}[h], \boldsymbol{\mu}_{\mathbf{V},low}[h']\right\}, \bar{\mathbf{\Omega}}_{\mathbf{V},qq'}^{hh'}\right) \end{bmatrix} \right) \times \\
& \left(\prod_{h=1}^{2H} \prod_{t=1}^{2T} \Phi_I\left[\left(\boldsymbol{\psi}_{up}^{h} - \mathbf{H}_{ht}\bar{\mathbf{B}}_{\Delta,qq'}\right), \mathbf{H}_{ht}\bar{\mathbf{\Omega}}_{\Delta,qq'}\mathbf{H}_{ht}'\right] - \Phi_I\left[\left(\boldsymbol{\psi}_{low}^{h} - \mathbf{H}_{ht}\bar{\mathbf{B}}_{\Delta,qq'}\right), \mathbf{H}_{ht}\bar{\mathbf{\Omega}}_{\Delta,qq'}\mathbf{H}_{ht}'\right] \right) \times \\
& \left(\prod_{t=1}^{2T-1} \prod_{t'=t+1}^{2T} \Phi_{2(I-1)}\left[-\mathbf{E}_{tt'}\bar{\mathbf{B}}_{qq'}, \ \mathbf{E}_{tt'}\bar{\mathbf{\Omega}}_{qq'}\mathbf{E}_{tt'}'\right] \right).
\end{aligned}
\tag{4.12}
$$

where $\bar{\mathbf{\Omega}}_{\mathbf{V},qq'}^{hh'}$ is a $\left(2\times 2\right)$ submatrix of $\bar{\mathbf{\Omega}}_{\mathbf{V},qq'}$ corresponding to h and h' ordinal indicators, and $\Phi_{2(I-1)}\left[-\mathbf{E}_{tt'}\bar{\boldsymbol{B}}_{qq'}, \ \mathbf{E}_{tt'}\bar{\mathbf{\Omega}}_{qq'}\mathbf{E}_{tt'}'\right]$ is a cummulative distribution function of $2\left(I-1\right)$ dimensional MVN with mean $\left(-\mathbf{E}_{tt'}\bar{\boldsymbol{B}}_{qq'}\right)$ and covariance $\left(\mathbf{E}_{tt'}\bar{\mathbf{\Omega}}_{qq'}\mathbf{E}_{tt'}'\right)$.

The maximum dimension of integration in Eq. (4.12) is $\left(I-1\right)*2$. We use GHK- simulator with quasi-random draws to evaluate MVNCDF accurately. Readers are referred to Train (2000) and Bhat (2003) for a detailed discussion on benefits of using quasi-random draws. The asymptotic covariance matrix of the model parameters is obtained by inverting Godambe's (1960) sandwich information matrix, which requires Hessian and Jacobian matrices of the loglikelihood function at the convergence. The Jacobian matrix for models with spatial dependencies is computed using window sampling approach. Readers are referred to Zhao and Joe (2005), Bhat (2014), and Sidharthan and Bhat (2012) for more details on the calculations of the Hessian and the Jacobian matrix.

4.4.3.6 Spatial Weight Matrix Computation

All the data required to estimate the interdependent ICLV model can be obtained from a stated preference survey, except the weight matrix used in Eq. (4.2). Essentially, the weight matrix determines the un-moderated weights assigned by individuals to others in their interpersonal network. The weight matrix can be constructed in two ways. The first method relies on the concept that “everything is related to everything else, but near things are more related than distant things” (Tobler, 1970). This concept has been extensively used in spatial econometrics to construct the weight matrix as a function of spatial distance, such as the inverse of distance (Anselin, 2010). On the other hand, the second method uses the concept of homophilic – similarity in terms of socio-demographic attributes, proximity, attitudes, and other behavioral characteristics. This concept is often used in social sciences to model information propagation and online interactions (Bhattacharya and Sarkar, 2021; David-Barrett, 2020).

In the current study, we construct weight matrices using both methods – i) geographical distance (inverse of distance) and ii) homophilic based weight matrices. For the geographical distance-based weight matrix, the strength of a tie between two individuals is negatively proportional to the Euclidian distance between their residential locations. We use the R package "geosphere" to calculate the shortest pair-wise distance between five-digit zip codes of home locations (Hijmans et al., 2017). We compute the homophilic-based index using the Gower dissimilarity index because it can handle both continuous and categorical data on socio-demographic characteristics (Gower, 1971). The Gower dissimilarity index $w_{qq'}$ is given by:

$$w_{qq'} = \frac{\sum_{k=1}^{K} \omega_k s_{qq'k}}{\sum_{k=1}^{K} \omega_k} \tag{4.13}$$

where $s_{qq'k}$ is the contribution of the variable k in the similarity between individuals q and q' $\left(q \neq q'; q, q' \in Q\right)$ and ω_k is the corresponding weight. For the continuous and categorical variables, contributions are calculated using normalized Manhattan and Dice distances, respectively. A value of $w_{qq'}$ close to zero indicates a strong tie. We consider socio-demographic characteristics like age, gender, ethnicity, educational attainment, and household income to generate the Gower-distance-based weight matrix. The contribution weight ω_k for each variable is assumed to be the same. One may improve the construction of the weight matrix and estimation of Eq. (4.14) by utilizing additional information such as information about social network composition such as the types of members in the network (friends, family, and peers), and channel of interaction (face-to-face, email, or cellphone) to construct richer Gower dissimilarity index (Carrasco and Miller, 2006).

The autoregressive parameter δ_l is bounded between 0 and 1. Therefore, the sum of elements of any row of weight matrix **W** cannot exceed a value greater than 1. Further, the weights should be the higher between individuals of similar socio-economic and demographic characteristics. Therefore, the weight matrix constructed using Gower index is modified as 1 – **W** before performing row normalization.

Further, a closer look at Eq. (4.11) indicates that the likelihood computation requires the joint probability calculation for all pairs of individuals. Assuming that each individual is connected with every other individual is unrealistic and computationally prohibitive. To make the likelihood estimation tractable, one can either follow Tobler's law (i.e., weight beyond a certain distance is zero) or put constraints on the number of effective social ties in an individual's interpersonal network. In this study, we use the latter and consider two configurations with five and ten social ties, i.e., we determine the nearest/closet five and ten ties/individuals based on Euclidian distance and Gower-similarity index (1- $w_{qq'}$). Thus, we estimate the interdependent ICLV model with four specifications of the weight matrix and ties -- spatial distance with five ties, spatial distance with ten ties, Gower distance with five ties, and Gower distance with ten ties. Eq. (4.11) can be modified to restrict likelihood computation based on individual's social network as follows:

$$L_{CML}(\boldsymbol{\Theta}) = \underbrace{\left\{\left[\prod_{q=1}^{Q}\prod_{h=1}^{H}\prod_{q'=q_s\{1\}}^{q_s\{|q_s|\}}\prod_{h'=1}^{H}\Pr\left[y_{qh}, y_{q'h'}\right]\right]\forall\left\{\begin{matrix} q \neq q' \\ or \\ q = q' \text{ and } h' > h \end{matrix}\right\}\right\}}_{L_{CML}(1)}$$
$$\times \underbrace{\left[\prod_{q=1}^{Q}\prod_{q'=q_s\{1\}}^{q_s\{|q_s|\}}\prod_{h=1}^{H}\prod_{t=1}^{T}\Pr\left[y_{qh}, q'_{ti_m}\right]\right]}_{L_{CML}(2)} \tag{4.14}$$
$$\times \underbrace{\left\{\left[\prod_{q=1}^{Q}\prod_{t=1}^{T}\prod_{q'=q_s\{1\}}^{q_s\{|q_s|\}}\prod_{t'=t+1}^{T}\Pr\left[q_{ti_m}, q'_{t'i_m}\right]\right]\forall\left\{\begin{matrix} q \neq q' \\ or \\ q = q' \text{ and } t' > t \end{matrix}\right\}\right\}}_{L_{CML}(3)}$$

where $|q_s|$ indicates the cardinality of set q_s, q_s contains the neighbors/closet ties of individual q including q, and $q_s\{1\}$ indicates the first element of the social network. In the current empirical application, a $|q_s| = 6(self + 5\ ties)$ corresponding to five ties entails computation of 455 $(5\ ties * 91)$, 140 $(5\ ties * 28)$, and 75 $(5\ ties * 15)$ two-dimensional MVNCDF per individual for expression $L_{CML}(1)$, $L_{CML}(2)$, and $L_{CML}(3)$, respectively.

4.4.3.7 Computational Challenges of the Interpersonal ICLV Model

There are a few points which warrant further discussion related to model complexity. First, due to the use of probit kernel, the dimension of integration does not increase due to an increase in number of latent variables as is the case in logit kernel-based models. The final dimension of integration is solely a function of the number of nominal and non-nominal variables. Second, the use of a probit kernel also allows for the seamless inclusion of structural endogeneity between latent variables. Incorporating structural endogeneity between latent variables in a logit-kernel-based ICLV framework will involve several conditional draws which may cause instability in the estimation. Third, the assumption of normal distribution can be relaxed through the use of skew-normal distribution (Bhat et al., 2015) in the structural equation leading to an overall non-normal distribution in the variables of measurement and choice model. However, the parameter obtained from the skew-distribution-based ICLV model tends to have a high bias as compared to the normal distribution-based ICLV model due to the highly non-linear model. This can further impact the recoverability of parameters in the presence of endogenous social-network effect. Recently, Bhat and Mondal (2002) proposed a copula-based framework to introduce non-normal error distribution in the structural equation. They do not report any simulation exercise and hence the parameters bias between skew-normal-based ICLV to copula-based ICLV cannot be quantified. Future works can explore the feasibility of a copula framework to allow for non-normal error structure. Finally, the assumption of a known weight matrix is a major limitation which plagues both latent-variable-based social-network models and error-covariance-based social-network models. There are few notable works where attempts have been made to turn the weight matrix endogenous (Ahrens and Bhattacharjee, 2015; Lam and Souza, 2020; Krisztin and Piribauer, 2023). However, the LASSO-based approaches (Ahrens and Bhattacharjee, 2015; Lam and Souza, 2020) essentially end up solving a least-square problem. This approach is not feasible in a maximum likelihood-based approach. A possible middle ground could be to iterate between two approaches in the case of continuous dependent variables. The Bayesian framework approach (Krisztin and Piribauer, 2023) can overcome the LASSO approach but the authors report the simulation for a 100 individual/grid configuration possibly due to scaling issues associated with a large number of parameters in a highly non-linear model. A practical approach to estimating the endogenous weight matrix could be to employ a two-step approach similar to the expectation-maximization approach where one can iterate between estimating a parametrized weight matrix based on Gower distance in the first step and estimating the other parameters in the second step. The Gower distance approach results in the estimation of way few parameters (equal to the number of attributes used to calculate the Gower distance) as compared to $N*\left(N-1\right)*0.5$ (assuming a symmetric weight matrix). Of course, the approach needs to be tested in detail to understand its implications related to bias and coverage probability.

4.5 Results of Consumer Behavior Model

4.5.1 Statistical Model fit assessment

As we estimate the ICLV model using the CML approach, we adopt composite likelihood information criterion (CLIC) to compare non-nested models, i.e. models with the same number of ties but different weight matrix configurations (Varin and Vidoni, 2005). CLIC is computed using the following expression: $\left[\log L_{CML}\left(\boldsymbol{\Theta}\right)-\text{tr}\left(J\left(\boldsymbol{\Theta}\right)H\left(\boldsymbol{\Theta}\right)^{-1}\right)\right]$, where $\left[\log L_{CML}\left(\boldsymbol{\Theta}\right)\right]$ is the composite log-likelihood and $\text{tr}\left[J\left(\boldsymbol{\Theta}\right)H\left(\boldsymbol{\Theta}\right)^{-1}\right]$ is the penalty term (trace of the product of Jacobian and Hessian inverse). The model with higher CLIC is preferred. Table 4.2 provides the CLIC statistics and other relevant statistics for all the four weight matrix specifications.

Table 4.2: Summary of model fit statistics

Specification		**Composite Log-likelihood**	**Composite likelihood information criterion (CLIC)**	**Choice model Composite log-likelihood**	**Average probability of correct prediction (standard deviation in brackets)**
Distance measure	**Number of ties**				
Gower	5	-2,730,103.1	-2,734,658.1	-1,32,048.8	0.581 (0.097)
Spatial	5	-2,738,108.8	-2,741,157.9	-1,32,557.8	0.544 (0.058)
Gower	10	-5,440,721.0	-5,458,700.8	-2,64,773.9	0.581 (0.098)
Spatial	10	-5,457,718.3	-5,464,455.8	-2,64,932.6	0.548 (0.060)

The CLIC statistics suggest that the Gower-similarity-based weight matrix configuration better explains the AV preferences. However, a close look at the average probability of correct prediction suggests that the model fit is only marginally sensitive to the configuration of the spatial weight matrix.

4.5.2 Structural Equation Model Results

Table 4.3 provides the parameter estimates of the structural equation for latent variables. Since the direction of effects does not change much across weight matrix specifications, we present and discuss results for the weight matrix based on Gower distance with five ties. The results of the other three weight matrix configurations (Table S.4.2.1 to S.4.2.6 in Supplement-4 Section S.4.2) and the non-spatial model (Table S.4.2.7 to S.4.2.9 in Supplement-4 Section S.4.2) are provided in the Supplement-4.

Several demographic characteristics, type and source of information, and accident history have a statistically significant effect on WOM dissemination. For instance, bachelor's degree holders are more likely to spread positive information about AVs than those with lower education levels, ceteris paribus. The positive effect of education could be attributed to the fact that highly educated individuals can process more information and thereby be more certain about the long-term benefits of AVs, such as lower accident rates and emissions (Golbabaei et al., 2020; Haboucha et al., 2017; Han et al., 2011; Jansson et al., 2011; Jerit et al., 2006; Knight et al., 2010; Liljamo et al., 2018). Individuals living in high-income households tend to be more active in disseminating positive information than their low-income counterparts (Bansal et al., 2016). The effect of income on spreading positive WOM could be related to hedonic experience (Paridon et al., 2006). In terms of household configurations, three demographic variables have a positive effect on WOM dissemination. The number of workers in the household has a positive impact on WOM communication. One possible reason for such positive WOM communication could be the self-relocation and parking capability of the AVs, a trait beneficial for large working households (Baron et al., 2021). The number of children in the household is also linked to the positive dissemination of WOM. The results also suggest that male decision-makers are more likely to spread positive WOM compared to their female counterparts (Kim et al., 2019; Liljamo et al., 2018; Zoellick et al., 2019). A higher propensity of men towards AVs could be attributed to status symbols. Owning an AV can convey a sense of symbol or power manifested through a willingness to pay a premium price for new innovative car technology (Wadud and Chintakayala, 2021).

Vehicle ownership (i.e., the number of cars) is negatively related to WOM dissemination (Liljamo et al., 2018). Since vehicle ownership is generally a proxy for driving propensity (Kaneko and Kagawa, 2021), households with higher vehicle ownership may not want to relinquish the pleasure derived from manual driving. Two of the four information variables are found to be statistically significant in explaining the WOM, namely the number of AV-involved crashes and the proportion of such crashes with the lack of liability. Both covariates have an intuitive sign. We include informational variables in the structural equation part of the model so that their propagation effect through the social network can be explicitly captured. This structural relationship also leads to an elegant top-down propagation of the effect of information from latent variables to observed indicators and choices.

Among information sources, information received from friends, colleagues, and media has a positive influence on WOM compared to that of the car dealer. This result might be a consequence of relatively lesser trust in the information provided by dealers. Finally, the severity of injury/damage in accidents has a stimulating effect on WOM dissemination. In the event of minor injury/damage to the individual/vehicle, the effect is negative. However, the effect turns out to be positive in the event of major injury/damage. The results indicate that people with the worst experience of manual driving are more likely to realize the benefits of automated driving from the safety perspective (Menon et al., 2019).

We now discuss the parameter estimates of the structural equation for the second latent variable – risk aversion. Bachelor's degree holders exhibit higher risk aversion compared to their counterparts with lower education (Jung, 2015), perhaps because they are more aware of the risks associated with the adoption of nascent AV technology. Moreover, females with a higher number of workers and children in the household are likely to be highly risk-averse compared to their counterparts. The cross-loading parameter (ρ) (i.e., loading of WOM on risk aversion) is negative and statistically significant, suggesting that the increase in positive WOM reduces risk aversion. The result is aligned with intuition. Note that the actual association of demographic characteristics and risk-averse behavior should be derived after considering the indirect effect of these variables on risk aversion through WOM.

Table 4.3: Structural equation model parameter estimates for interdependent ICLV model with weight matrix based on Gower distance with five ties

Explanatory Variables		**Coefficient (t-stat)**	
		Word of Mouth (WOM)	**Risk Aversion**
Education Status	Some college degree or below	-0.101 (-1.90)	---
	Professional degree (MD, JD, etc.)	-0.198 (-2.50)	---
	College Graduate	---	0.239 (3.25)
	MS, PhD or Doctoral degree	---	0.239 (3.25)
Household Income Base: >75K	<=35K	-0.280 (-1.66)	---
	36K - 75K	-0.150 (-3.36)	---
Household Configuration	Number of Workers	0.266 (3.59)	0.055 (1.21)
	Number of Children	0.304 (3.58)	0.074 (1.80)
	Respondent Male (Base: Female)	0.010 (1.18)	-0.256 (-2.29)
Vehicle Ownership	Number of Vehicles	-0.132 (-3.37)	---
Information Variables	Number of crashes in AV	-0.046 (-3.36)	---
	Reduction in travel time in AV	---	---
	Reduction in CO2 emission in AV	---	---
	Unclear liability in x% of AV-involved crashes.	-0.637 (-3.07)	---
Information Source Base: Car Dealer	Friend	0.010 (1.04)	---
	Colleague at work	0.028 (1.15)	---
	Media	0.092 (2.81)	---
Past One year accident involvement. Number of accidents where…	Vehicle incurred minor damages.	-0.062 (-1.98)	---
	Vehicle incurred major damages.	0.043 (1.65)	---
	I suffered from minor injuries.	-0.143 (-3.05)	---
	I suffered from severe injuries.	0.087 (2.62)	---
Cross Loading (ρ)	WOM		-1.049 (-5.12)
Spatial Parameter (δ)		0.247 (18.77)	0 (fixed)
Correlation between WOM and Risk Aversion (Γ_{12})		0.369 (1.53)	

'---' indicates that the parameter was not significant at a significance level of 0.2 and hence removed

The social network effect is captured through an autoregressive parameter (δ) in the structural equation of WOM. The autoregressive parameter is significant and has a value of 0.25. This parameter estimate can be interpreted as the weight given by individuals to the information received from their social network. As discussed earlier, we do not estimate the autoregressive parameter for risk aversion because cross-loading of WOM (ρ) implicitly captures social network effect. Finally, the error correlation (Γ_{12}) between WOM and risk aversion is 0.37. Its interpretation is much more nuanced than it appears. A closer look at Eq. (4.4) reveals that the correlation matrix of latent variables is $\tilde{\boldsymbol{\Xi}} = \mathbf{D}\left(\mathbf{S}\left[\mathbf{IDEN}_Q \otimes \boldsymbol{\Gamma}\right]\mathbf{S}'\right)\mathbf{D}'$. Since all the elements of matrix $\mathbf{S}$ are positive by being auto-regressive parameter boundness, the inner expression $\mathbf{S}\left[\mathbf{IDEN}_Q \otimes \boldsymbol{\Gamma}\right]\mathbf{S}'$ remains positive as the error-correlation matrix $\boldsymbol{\Gamma}$ has positive elements, i.e., (Γ_{12}). The off-diagonal elements of matrix $\mathbf{D}$ are non-positive numbers since the cross-loading of WOM on risk aversion (ρ) is negative. Thus, all the cells representing correlation between WOM and risk aversion for both inter and intra individual have negative entries. Therefore, the implied correlation ($\tilde{\Xi}$) between WOM and risk aversion is negative, suggesting that the aggregate effect of unobserved variables on the latent variables is in the opposite direction. Further, a negative implied correlation suggests that WOM and risk aversion are not-orthogonal (not-independent) latent variables. Non-orthogonality implies that a certain amount of common behavioural traits (attitudes) is measured by both latent variables.

4.5.3 Measurement Equation Model Results

The parameter estimates for the measurement equation of latent variables are provided in Table 4.4. Two out of three measurement indicators of WOM and all four measurement indicators of risk aversion show association. All the loading parameters have the expected signs. For example, WOM has positive loading on the statement "I will suggest them to consider buying an AV over a CV because the former is much safer" measured on a five-point Likert scale going from strongly disagree to strongly agree. Other loading parameters can be interpreted similarly. Table 4.4 also provides the estimates for the intercept and thresholds of ordered indicators. Very small standard errors of thresholds indicate that cut-off values are statistically separated from each other at a significance level of 0.05.

4.5.4 Choice Model Results

Table 4.5 summarizes the parameter estimates of the utility equation of the binary choice variable – whether to buy an AV or not. Aligned with the intuition, the effects of social and city-level adoption rates on the individual's likelihood to adopt an AV are positive and statistically significant (Bansal et al., 2016; Bansal and Kockelman, 2018; Sharma and Mishra, 2020). The effect of price also exhibits the expected trend, as the likelihood of buying an AV decrease with an increase in the AV price relative to the CV price. We consider a non-linear specification with an estimable power parameter on the ratio of AV price and CV price. However, the price effect turns out to be linear because the power parameter is not statistically different from 1 (at a significance level of 0.2).

A few socioeconomic variables directly affect the likelihood of choosing an AV. The likelihood of purchasing an AV increases with the number of workers, possibly due to self-relocation and increased productivity during work-related trips (Lavieri et al., 2017; Saeed et al., 2020; Wadud et al., 2016). An increase in the number of children reduces the likelihood of owning an AV. The indirect effect of the number of children on latent variables explains this direct effect. It is interesting to note that while those with the higher number of children are likely to disseminate positive WOM (Sinha et al., 2020), they also have higher risk aversion. Perhaps, the latter effect dominates in direct effect due to severe concerns related to children's safety (Haboucha et al., 2017). Finally, males are more likely to purchase an AV than their female counterparts because females may be more concerned about the negative aspects of self-driving technology (Kyriakidis et al., 2015).

Table 4.4: Measurement equation model parameter estimates for interdependent ICLV model with weight matrix based on Gower distance with five ties, $\psi_1 = -\infty, \psi_2 = 0, \psi_6 = \infty$

Statement (Five-point Likert scale with labels strongly disagree to strongly agree)	Coefficient (t-stat)		Coefficient (standard error)			
	Word of Mouth (WOM)	Risk Aversion	Intercept	ψ_3	ψ_4	ψ_5
I will suggest them to consider buying an autonomous car over a conventional car because the former is much safer.	1.16 (3.46)		1.562 (6.42)	0.986 (0.142)	2.400 (0.324)	3.856 (0.514)
I will suggest them to consider buying a conventional car over an autonomous car because at least one knows who is responsible for a crash in a conventional car.	-0.335 (-3.56)		1.950 (10.63)	0.974 (0.051)	2.007 (0.069)	2.886 (0.087)
I am worried that I might not get value-for-money in an autonomous car purchase.		0.277 (2.61)	1.519 (16.69)	0.667 (0.038)	1.429 (0.055)	2.431 (0.081)
I would take the risk with autonomous car purchase in exchange for an exciting and novel experience.		-0.560 (-3.42)	0.800 (6.71)	0.761 (0.052)	1.686 (0.100)	2.566 (0.145)
I would feel uncomfortable in switching to autonomous cars.		1.052 (21.27)	2.630 (10.14)	1.155 (0.154)	2.078 (0.270)	3.491 (0.452)
I struggle in taking risks with such unconventional decisions.		0.616 (7.40)	1.790 (7.49)	0.942 (0.081)	1.866 (0.149)	2.899 (0.227)

Table 4.5: Choice model parameter estimates for interdependent ICLV model with weight matrix based on Gower distance with five ties (base: will not buy an AV)

Explanatory Variables		Coefficient (t-stat)
Price and adoption variables	Constant	1.000 (31.03)
	Percentage adoption in social ties	1.081 (4.68)
	Percentage adoption in city/community	0.523 (1.98)
	Ratio of AV to CV price	-2.547 (-3.56)
Household Configuration	Number of workers	0.041 (1.96)
	Number of children	-0.088 (-7.08)
	Respondent Male (Base: Female)	0.129 (11.30)
Latent Variable Loading	WOM	0.605 (12.15)
	Risk Averse	-0.612 (-9.81)
Latent Variable Interaction	WOM * Percentage adoption in social ties	---
	Risk Aversion * Percentage adoption in social ties	1.121 (5.43)
	WOM * Percentage adoption in city/community	0.408 (2.37)
	Risk Aversion * Percentage adoption in city/community	---
	WOM * Ratio of AV to CV price	0.663 (9.26)
	Risk Aversion * Ratio of AV to CV price	---

'---' indicates that the parameter is not significant at a significance level of 0.2.

The effect of latent variables on the likelihood of buying an AV has an intuitive sign. For instance, individuals with positive WOM dissemination and lower risk aversion have a higher inclination toward buying AVs. Further, we also explore the interaction effects of latent variables and the adoption rates at both social network and city levels. The interaction parameter estimates indicate that the effect of positive WOM dissemination increases with the increase in city-level AV adoption, whereas the negative effect of risk aversion is pacified by the AV adoption in the social network. Finally, the WOM latent variable also has a statistically significant interaction effect with the ratio of AV price to CV price. The positive interaction effect parameter indicates that the negative effect of AV price decreases with the increase in positive WOM dissemination.

While the parameter estimates of the consumer behavior model provide the directional effect of several variables on the likelihood of AV adoption, they cannot be translated into analytical expressions of the forecasted market share of AVs. To this end, we use these parameter estimates and perform an agent-based simulation to understand the market evolution of AV under various scenarios (e.g., change in AV price and reduction in AV-involved crash rates).

4.6 Agent-Based Model: simulation

4.6.1 Synthetic Population Generation

To run an agent-based simulation for the entire household population of Nashville (Davidson County), we expand the survey sample to the household-level synthetic population using an iterative proportional updating (IPU) algorithm. The algorithm adjusts and reallocates weights among households until household- and person-level attributes are both matched with the marginal distributions of attributes in the population (Konduri et al., 2016). We obtain population-level marginal distribution (at household- and person-level) for Nashville from American Community Survey 2013-2017 (Manson et al., 2019). We consider household size, income, and the number of workers, children, and vehicles as the household-level control variables. In addition, age, gender, ethnicity, educational attainment, and disability are used as person-level control variables. To match the spatial distribution of the population, we utilize the five-digit ZIP code of the survey respondent's home location and census tract from the population using their crosswalk (Din and Wilson, 2020). We apply the IPU algorithm through open-source Python software, PopGen (Konduri et al., 2016). The survey sample of 1,495 respondents is thus expanded to a synthetic population of 421,223 households.

4.6.2 Agent-Based Simulation Framework

Figure 4.7 presents the agent-based simulation (ABM) framework, which takes the estimated consumer behavior model, synthetic population, agent-level social network, and the control variables mentioned in Table 4.6 as inputs. The ABM is run for 50 iterations where the iteration corresponds to one year. The AV price at time t is obtained using the following discounting equation: starting price × (1 – yearly discount rate)$^{(t-1)}$. The two variables related to AV safety and regulation – the number of AV-involved crashes and the proportion of AV-involved crashes with unknown liability – are generated based on their range in the WOM choice experiment. The magnitude of both variables is iteratively reduced to represent the expectations of experts that AV-involved crashes would reduce with the advancement in the automation technology and stronger laws will be developed to ensure liability of AV-involved crashes. Specifically, we adopt the following quadratic function to find the value of these variables at time t (see Table 4.1 for upper limits): $\text{Upper limit} - \left(\sqrt{\text{Upper limit}}\right) * \left(t/\text{Curvature}\right) - 1$. Moreover, the percentage of the population receiving the information about the above-discussed two information variables through media in year t is determined by the following function: $2\sqrt{t} + 2t + 1$. This function ensures an increase in media exposure over time. For example, the function implies that 5% of people receive information through media in the first year, but the proportion jumps to 15% in the fifth year and 72% in the thirtieth year. Finally, an agent also gets information from a *friend* when the AV adoption in his/her social network exceeds 40%.

Table 4.6: Control variables and their description

Variable	Description
Starting price	Starting market price of AVs
Yearly discount rate	Discount rate which determines the annual reduction in the AV price
Proportion of satisfied agents	Percentage of agents who are satisfied with the purchase of AV
Curvature crash	Curvature value used in the function to determine the rate of reduction in AV-involved crashes
Curvature legal	Curvature value used in the function to determine the rate of reduction in legal issues related to AV-involved crashes

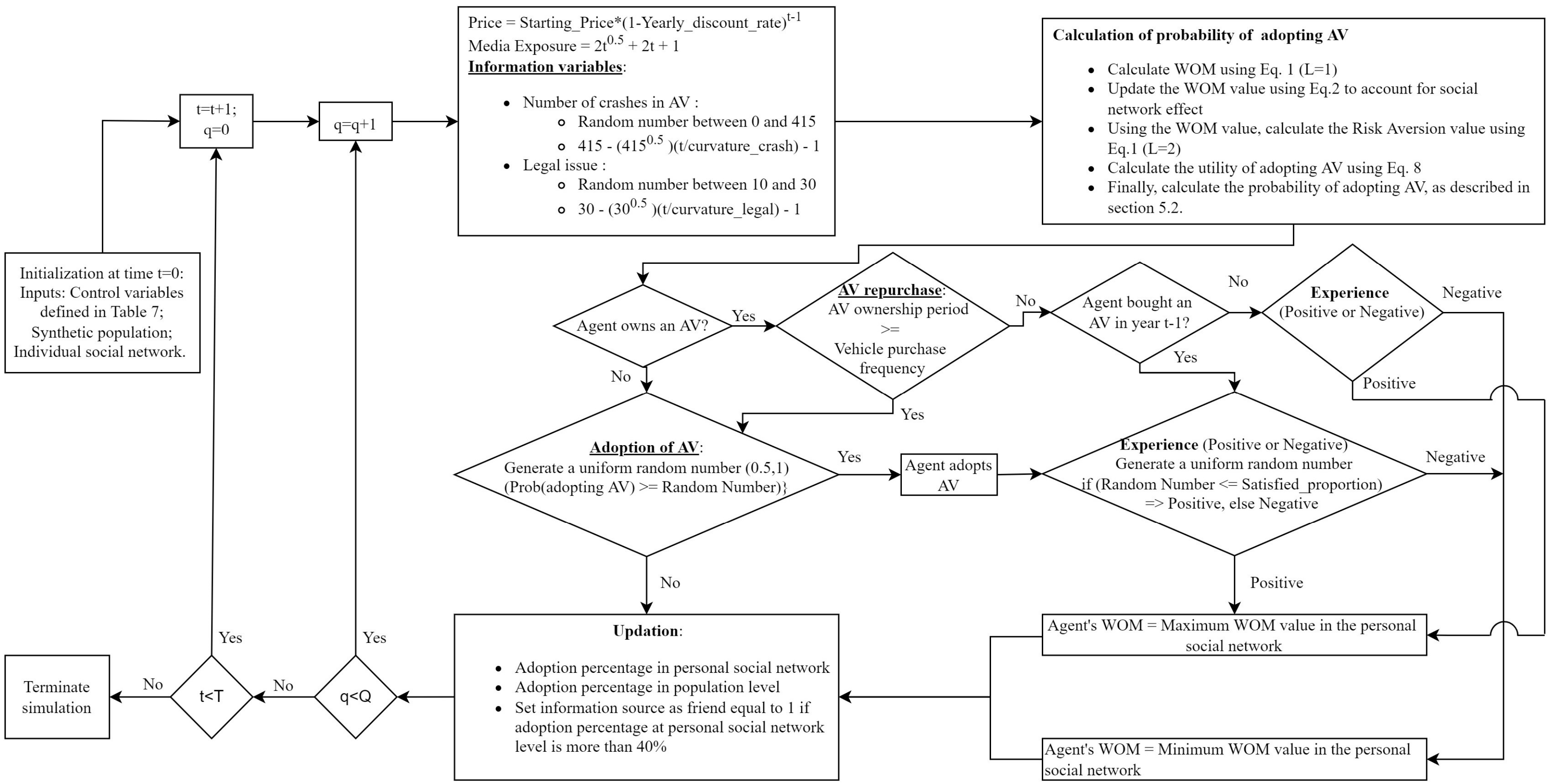


Figure 4.7: Agent-Based Simulation framework using Interdependent ICLV model

By inserting the above-discussed inputs, spatial weight matrix, agent's social network, and other characteristics of agents in Eq. (4.4), we calculate the values of both latent variables – WOM and risk aversion – for each agent in a year. While applying Eq. (4.4), we calculate WOM followed by risk aversion to ensure the loading of WOM on risk aversion is explicitly accounted. By plugging in latent variable values, the purchase price, and city-level and social-network-level AV adoption in Eq. (4.8), we compute the systematic part of utility. Subsequently, the probability of choosing the AV by each agent in a year is obtained. The probability calculation involves the computation of the cumulative distribution function of normal distribution. The *probability* of adopting an AV is translated into the *decision to buy* an AV if the probability is greater than the random number drawn from a uniform distribution with a range (0.5, 1).

Once an agent purchases an AV, the decision to replace the AV is determined probabilistically based on the user-reported value in the survey. Specifically, if the duration of AV ownership exceeds the user-reported vehicle purchase frequency, the decision to replace the AV (or re-enter the AV market) is determined probabilistically based on a uniform random number (re-enter the market of random number is greater than 0.5). The density plot of the user-reported vehicle replacement time period is shown in Figure 4.8. The plot indicates a high level of heterogeneity in vehicle purchase frequency of the individuals with a substantial mass concentrated in the region of 2-13 years.

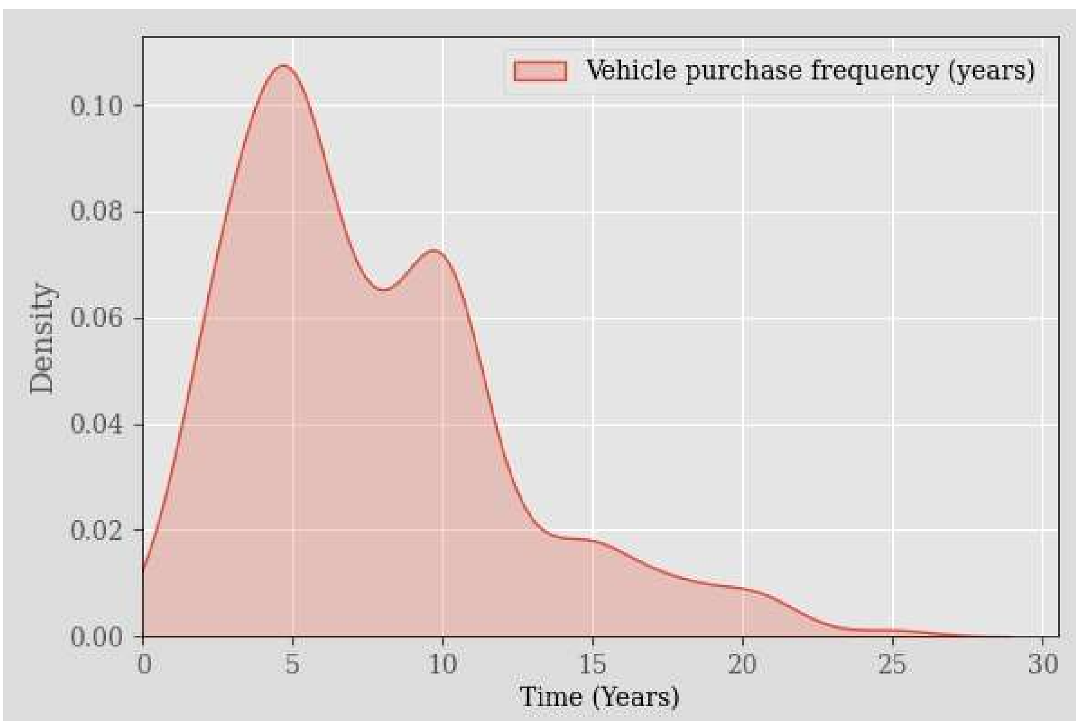


Figure 4.8: Probability density function of vehicle purchase frequency

Upon agents' purchases of AV, their post-purchase AV experience (positive/negative) is updated only once in the subsequent year after the purchase. Since there is no systematic way to capture post-purchase experiences of novel products like AVs, we use a random number generation approach. Specifically, we fix the proportion of agents with post-purchase satisfaction at the beginning of the simulation (see the variable *proportion of satisfied agents* in Table 4.6). We draw a random number from standard uniform distribution and assign positive experience to an agent if the random number is below the pre-specified proportion of satisfied agents, else negative experience is assigned. Depending upon the type of experience (positive or negative), an agent is assigned with a maximum or a minimum of her social network's WOM value. This WOM updating ensures that the type of post-purchase experience is fixed for an agent, but the WOM value (a proxy for the extent of positive/negative experience) may evolve over years.

Finally, social network- and city-level AV adoption levels are updated at the end of each year. The entire simulation is repeated for 50 iterations (i.e., 2021-2070) for any given scenario using fifteen different starting values (i.e., random seeds). We observed that the standard deviations of the forecasted market shares across different starting values were small, we only show the average of the city-level AV adoption across different starting values. Multiple simulation scenarios are considered by varying control variable values in Table 4.7.

4.6.3 Agent-Based Simulation Results

We forecast the market share of AVs on a fifty-year horizon (2021-2070) in three scenarios characterized by a combination of i) AV price, ii) the extent of the post-purchase satisfaction of early adopters, iii) reduction in AV-involved crash rates, and clear liability in AV-involved crashes. All three scenarios are simulated for four different social network configurations of social networks, i.e., a combination of the two social distance measures (Euclidian/spatial and Gower) and two values of social ties (five and ten). The value of incorporating information dissemination in forecasting models is also highlighted.

4.6.3.1 Scenario 1: Effect of AV price and post-purchase satisfaction of adopters

We consider the starting price of AVs to be $60,000 and assume it to decrease annually by 1%, 5%, and 10% (Bansal and Kockelman, 2018). Moreover, we forecast AV market share for the proportion of adopters with a positive post-purchase experience being either 30% or 90%. The plots of the forecasted AV adoption are shown in Figure 4.9 (see Figures S.4.4.1 to S.4.4.4 in Supplement-4 for plots with 95% confidence interval). Two main insights can be derived from these plots. First, there is a noticeable difference in the adoption trajectories obtained using spatial-distance- and Gower-similarity-based weight matrices. Second, the spatial-distance-based weight matrix configuration project a higher AV adoption rate than the Gower-similarity configuration across all price reduction rates and proportions of satisfied adopters. A possible explanation for such adoption trajectories lies in the fundamental nature of social network construction. In case of Gower-similarity weight matrix, an individual's social network contains ties which may disseminate very similar WOM (both magnitude and direction), leading to slower increase in overall WOM and slower decrease in risk aversion. These differences in trajectories are much more pronounced at lower price reduction rates (1%). The results indicate that price reduction of AV technology has a strong effect on AV adoption. Whereas a 5% annual reduction in AV price can help achieve a market share of around 75% in the next thirty years, an annual reduction of 1% would lead to an AV market share of only around 16% in 2050 (spatial-distance based social network with 5 ties and 30% satisfaction rate). Consumer satisfaction also plays a critical role in AV adoption. In case of moderate annual reduction of 5% in AV price and the same social network configuration, 50% market share is forecasted to be achieved in 16 years in a 90% post-purchase satisfaction scenario, but the same share would be attained in 18 years if 30% of early adopters are satisfied after buying AVs. The most effective strategy seems to be technological improvements to achieve large price reduction for a steep adoption trajectory.

4.6.3.2 Scenario 2: Effect of interpersonal social network

To capture the impact of the interpersonal social network, we benchmark the forecasting results of ABM by integrating interdependent and independent consumer behavior models. The independent model does not (explicitly) account for the interpersonal network effects (i.e., $\delta = 0$). Even in the absence of network effects, the consumer behavior model captures the direct impact of information sources on consumer uptake but fails to account for the indirect network effects transmitted through the structural equation of the WOM latent variable. The independent model cannot capture explicit WOM dissemination by (dis)satisfied adopters (i.e., the model is insensitive to the proportion of satisfied adopters), but can help capture the aggregate city and social-network adoption rate. We estimated a separate independent ICLV model by setting $\delta = 0$, and the estimation results are available in Tables S.4.2.7 to S.4.2.9 of the Supplement-4. In Figure 4.10 and Figure 4.11, we present the adoption trajectories obtained based on interdependent ICLV models with Gower-similarity and spatial-distance based weight matrix configurations (with five ties), respectively. Similar trajectories based on the independent ICLV model are superimposed in these plots. Please note that the social network is also constructed for independent ICLV model to determine the city and social-network adoption percentages as they are used as explanatory variables in the choice model. These plots suggest that the adoption trajectory of independent ICLV model lies in between those of Gower-similarity (lower end) and spatial-distance (upper end) weight matrix configuration for a given price-rate reduction and proportion of satisfied adopters. The same pattern is also observed for the ten ties case (see Figures S.4.4.5 and S.4.4.6 in the Supplement-4). Overall, the results (Figure 4.10 and Figure 4.11) suggest that ignoring explicit information dissemination may lead to under/over estimation of AV adoption depending on the underlying social-network configuration. These results corroborate our initial assertion that independent model may lead to unreliable forecasts due to its inability to capture the information propagation.

4.6.3.3 Scenario 3: Effect of reduction in AV-involved crashes and related legal issues

In this scenario, we quantify the effect of reduction in AV-involved crashes and the proportion of such crashes with no clear liability. As technology advances, AV-involved crashes and legal issues are likely to decrease, and the reduction is controlled in the ABM by curvature parameters (i.e., curvature crash and curvature legal) in Table 4.6. In particular, we consider four combinations of reductions in AV-involved crashes and legal issues regarding liability: (low, low), (low, high), (high, low), and (high, high) with corresponding curvatures (1.10, 5.00), (1.10, 1.00), (0.30, 5.00), and (0.30, 1.00), respectively. The AV-involved crashes and proportion of such crashes with legal issues in any year *t* can be obtained by plugging these values into the following function: $\text{Upper limit} - \left(\sqrt{\text{Upper limit}}\right) * \left(t/\text{Curvature}\right) - 1$ (as discussed in section 4.6.2). In this scenario, we set an initial AV price to \$60,000, an annual reduction in AV price to 5%, and the proportion of satisfied adopters to 90%.

Figure 4.12 shows the impact of all four possible combinations of curvatures on the adoption of AVs (see Figures S.4.4.7 to S.4.4.10 in Supplement-4 for plots with a 95% confidence interval). Similar to the previous observations, spatial-distance based weight matrix configuration provides a steeper adoption trajectory, *ceteris paribus*. The forecasting results show that the (high, high) scenario takes 25 years to achieve an AV market share of 50%, but the (low, low) scenario would attain the same market share in 27 years (based on ten ties Gower-similarity configuration).

4.6.3.4 AV adoption in Nashville

We apply the ABM to assess the spatial (zip code-level) distribution of AV adoption levels in Nashville. We assume that AVs are introduced in 2021 with an initial price of $60,000. We also consider an annual reduction in AV price by 5% and the proportion of satisfied adopters as 75%. The forecasted AV adoption densities (the number of adopted AVs per square mile) in the years 2030, 2040 and 2050 for Gower distance-based social network with five ties and with and without ($\delta = 0$) explicit information dissemination is shown in Figure 4.13 and Figure 4.14. The plots indicate that, regardless of starting density, all zip codes exhibit marked improvement in AV density with time. Further, similar to the earlier observations, the independent ICLV model ($\delta = 0$) has a higher rate of adoption as compared to the model with explicit information dissemination. In fact, the difference is very pronounced at the end of first 10 years (2030). The spatial adoption distribution for other models are provided in Figures S.4.4.11 to S.4.4.16 of Supplement-4 .

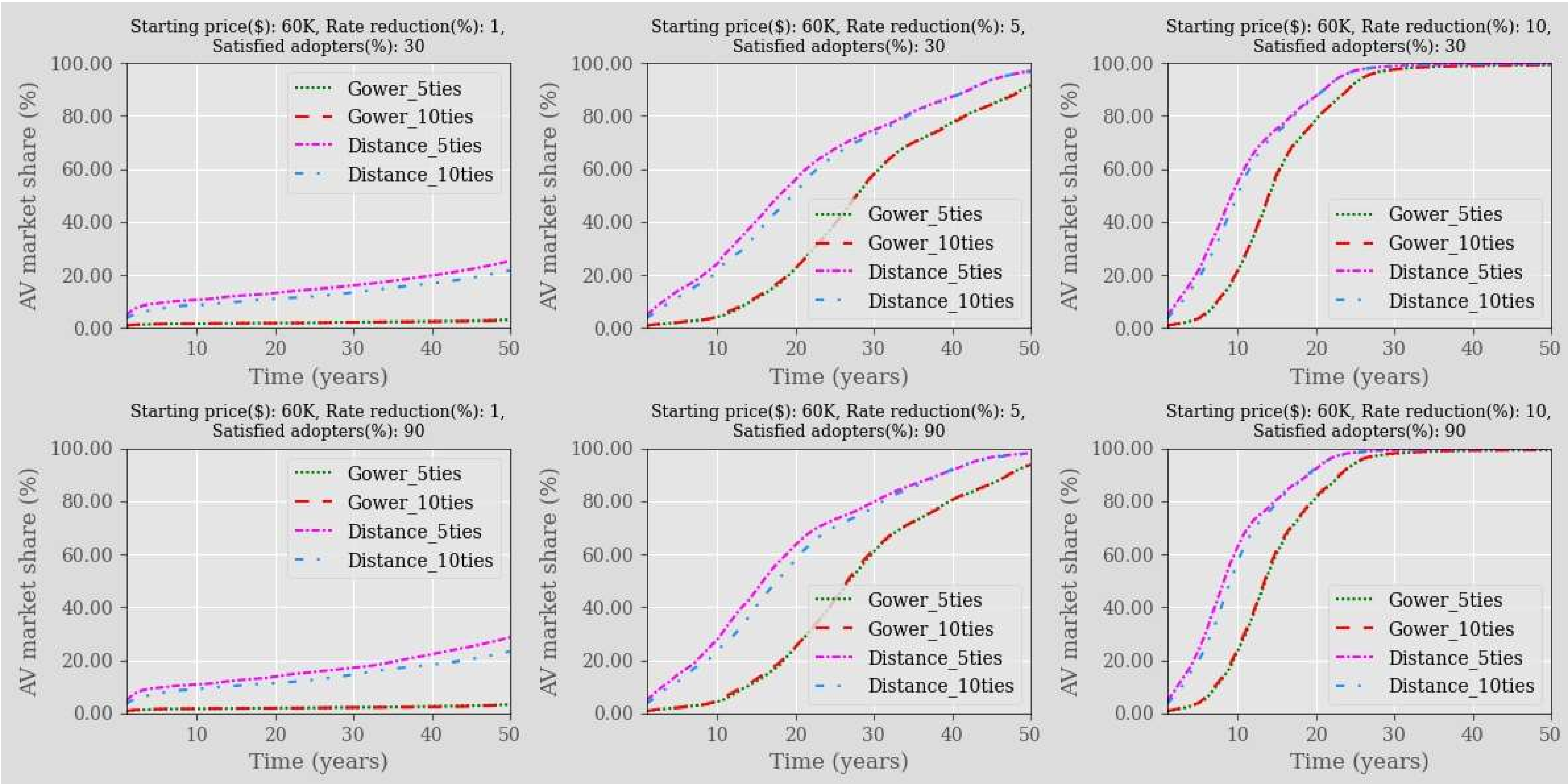


Figure 4.9: Effect of AV price reduction and proportion of AV adopters with post-purchase satisfaction on AV adoption

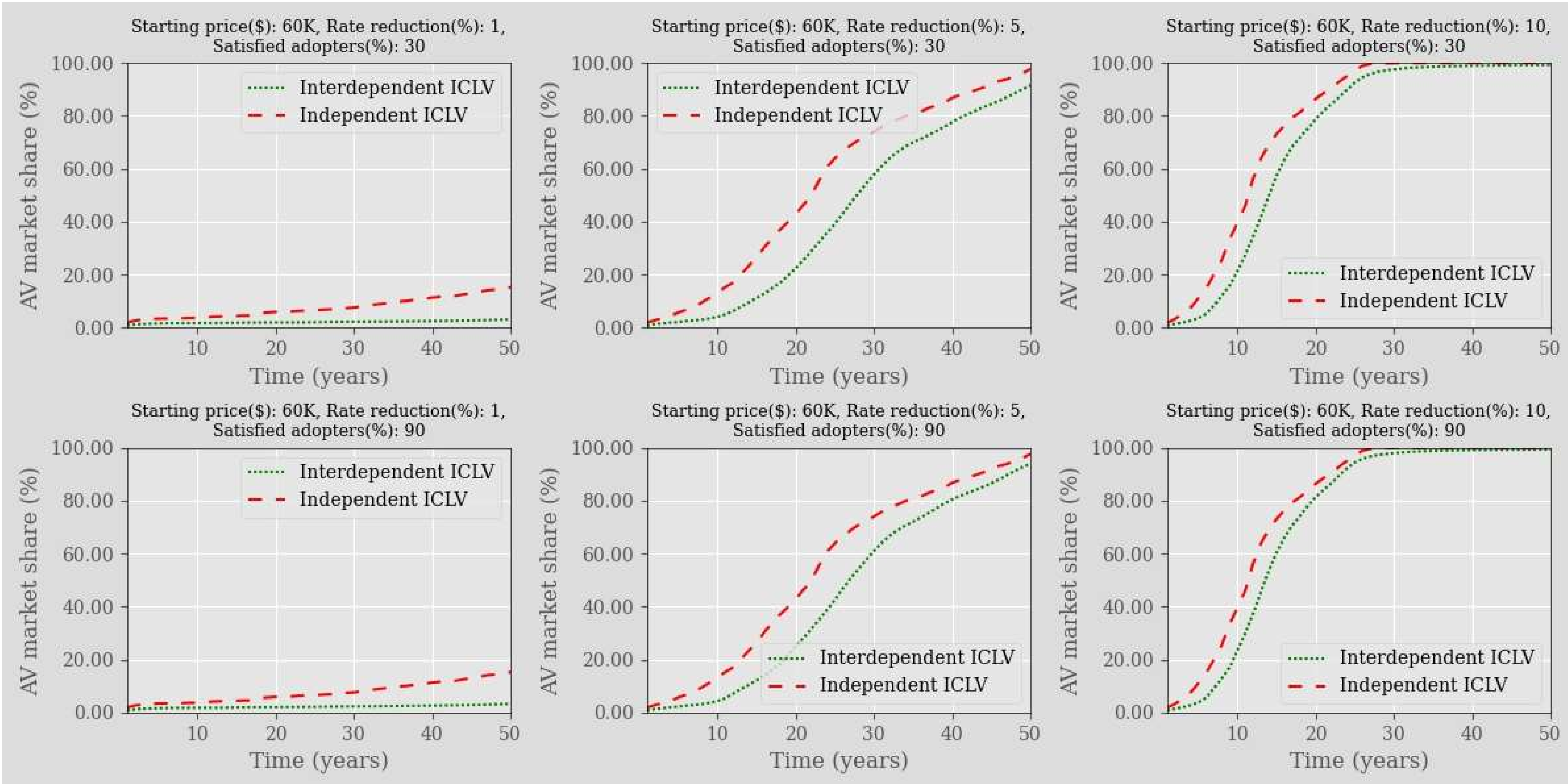


Figure 4.10: Effect of interpersonal social network on AV adoption for 5 ties configuration based on Gower-similarity weight matrix

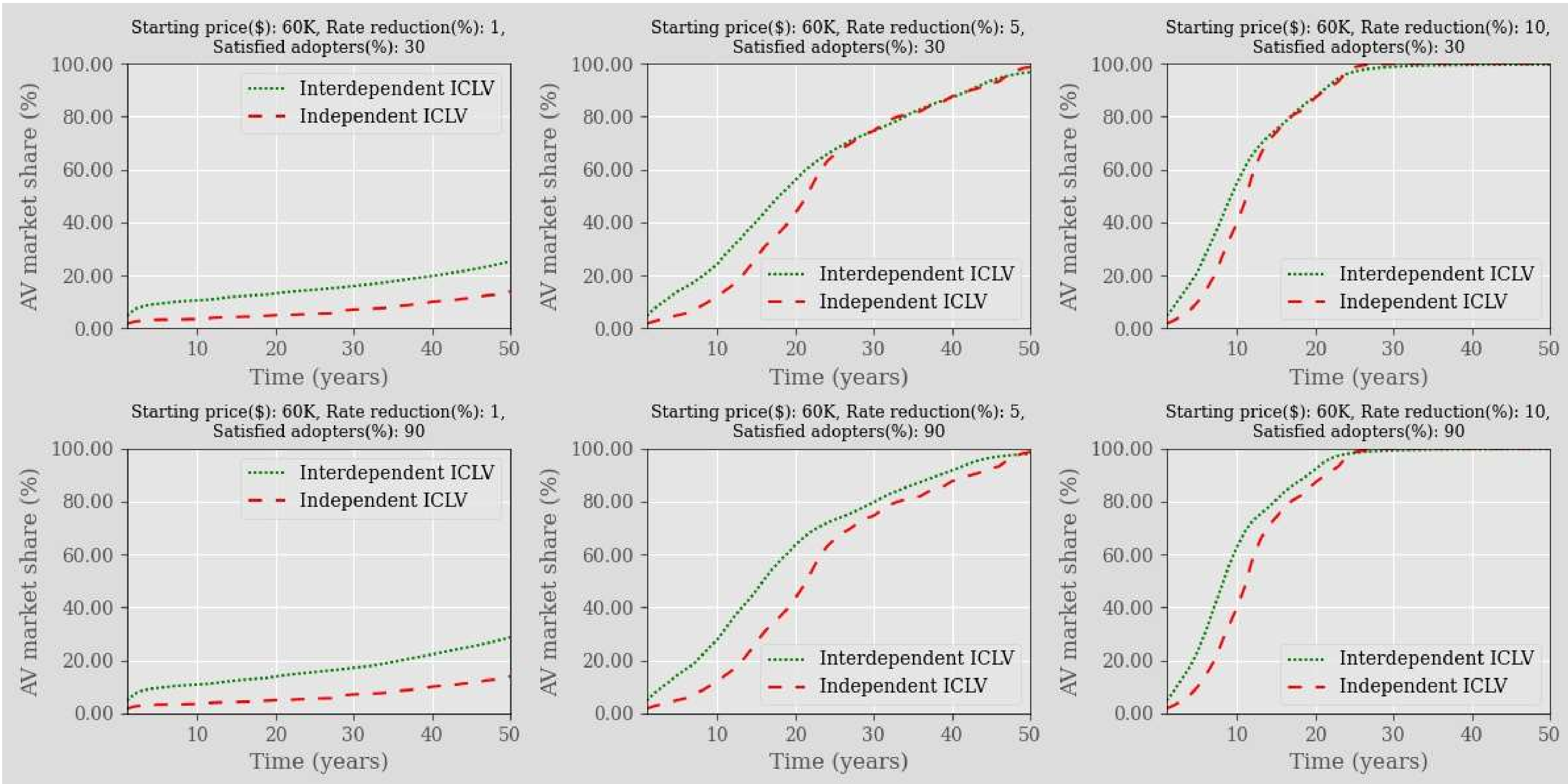


Figure 4.11: Effect of interpersonal social network on AV adoption for 5 ties configuration based on spatial-distance weight matrix

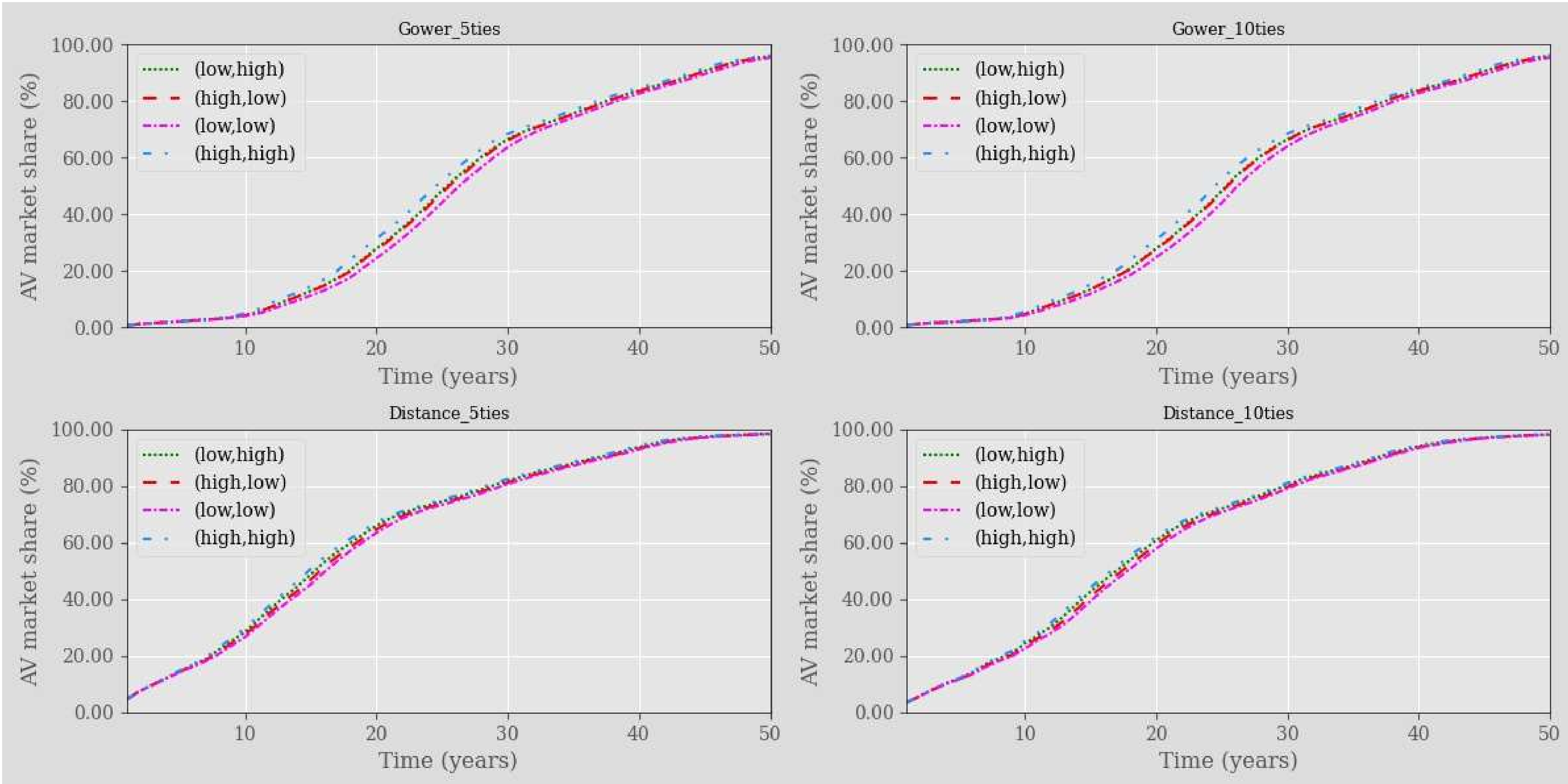


Figure 4.12: Effect of reduction in AV-involved crashes and proportion of such crashes with legal issues on AV adoption

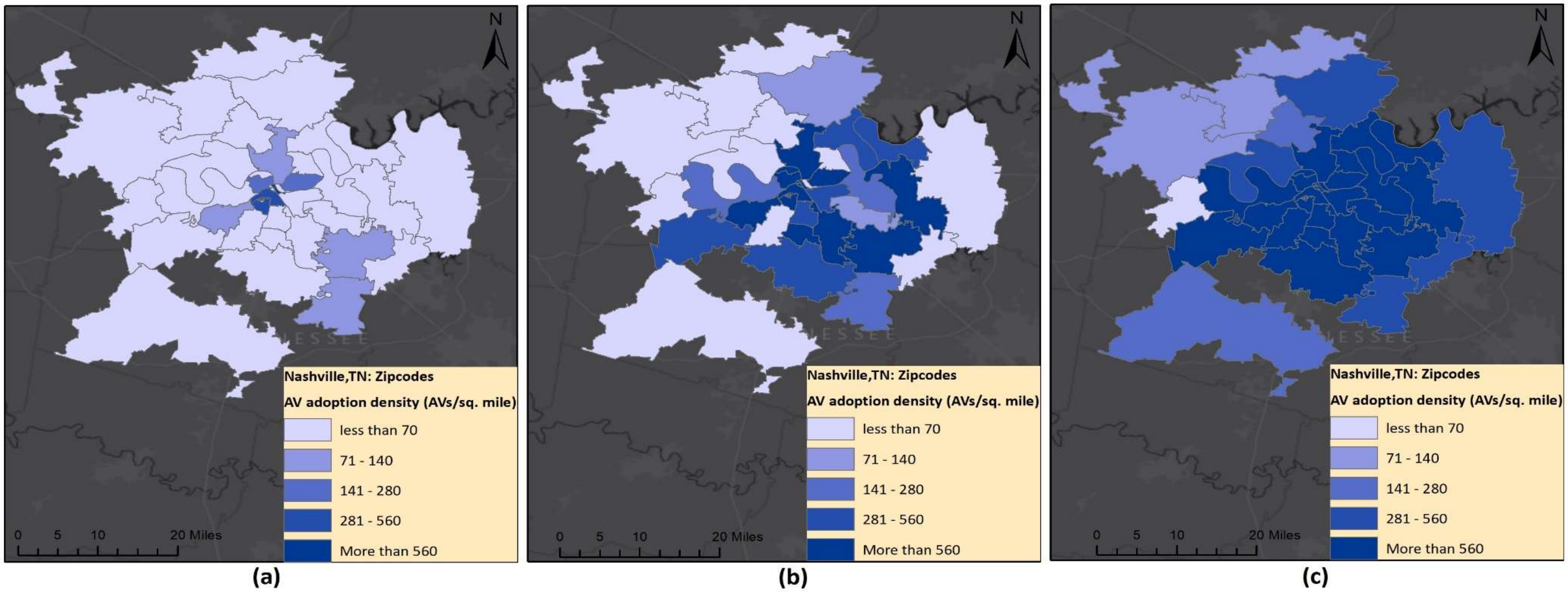


Figure 4.13: AV adoption density in Nashville, TN (a) 2030 (b) 2040 (c) 2050 (weight matrix based on Gower distance with five social ties with information dissemination)

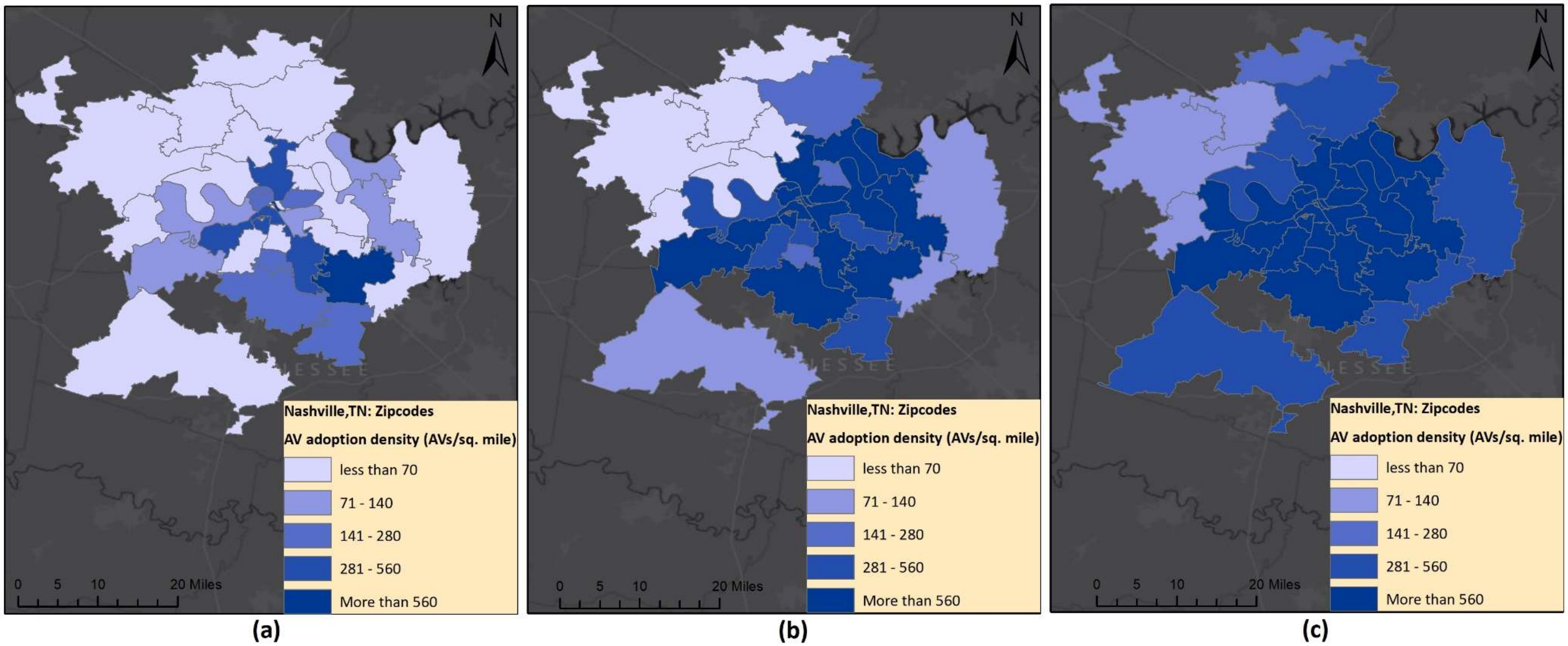


Figure 4.14: AV adoption density in Nashville, TN (a) 2030 (b) 2040 (c) 2050 (weight matrix based on Gower distance with five social ties with no information dissemination)

4.7 Conclusions and Future Work

Forecasting the adoption of the novel or "really new" products is of interest across multiple disciplines. Due to the lack of first-hand experience, potential early adopters of novel products actively expose themselves to word of mouth (WOM) information obtained from multiple sources (e.g., social networks and media) to assuage the potential risks. Not only do the existing consumer behavior models for novel products fail to capture the social network effects and interplay between WOM dissemination and risk aversion of consumers, but even cutting-edge forecasting models for such products also lack the integration of a calibrated consumer behavior model.

This study develops a general framework to forecast the adoption of novel products by combining a consumer behavior model with a population-level agent-based model (ABM). The consumer behavior is estimated using an integrated choice and latent variable (ICLV) model with WOM and risk aversion as two latent variables. The latent construct in ICLV captures spatial effects, i.e., the impact of homophilic peers in consumers' social networks. The discrete choice model in the ICLV accounts for the product's purchase price and adoption rates at individual's social network and city levels. We extend this ICLV model to account for the moderation of risk aversion behavior through WOM and panel effects in the choice component, and derive a maximum likelihood estimator to estimate the extended model. A calibrated consumer behavior model, synthetic population, and social network of all agents are embedded in an agent-based simulation framework to forecast the market share of the novel product. The proposed framework is applied to forecast the future adoption of autonomous vehicles (AV) in Nashville, USA over the next thirty years. The framework (both methodological and stated-preference (SP) survey) can also be used to model the effect of WOM and risk association on the usage of services such as mobility-on-demand (MOD). Depending on the scope of the study, various factors related to WOM and risk association as discussed in section 4.1.3 can be incorporated in the SP survey and accordingly model can be calibrated.

We calibrate the consumer behavior model with the data collected from an online stated preference survey of 1,495 residents from Nashville. The consumer behavior model identifies the risk-averse demographic groups and those with a tendency to spread the positive WOM about AVs. The results also indicate that reduction in AV-involved crashes and clear liability in these crashes is critical for positive WOM dissemination. Positive WOM turns out to be the driving factor in reducing the risk aversion of consumers. The results of the discrete choice component show that lower purchase price and higher social-network- and city-level adoption increase an individual's likelihood to purchase an AV. Whereas results of the consumer behavior model are new additions to the AV literature, the main contribution of this study stems from providing a general framework to quantify the effect of policy interventions on the adoption of AV technology.

The calibrated consumer model and synthetic population of Nashville is passed through the ABM to forecast the market share of AVs over the next 50 years (i.e., 2021-2070) in different scenarios. We quantify the effect of reduction in the purchase price, the extent of the post-purchase satisfaction, the importance of including social network effects, and the improvement in AV safety measures on the market share of AVs. In a moderate scenario – an annual price reduction of 5% at the initial price of $60,000, and 90% of adopters with post-purchase satisfaction, AVs are likely to attain 50% market share in eighteen years and around 80% market share in thirty-one years after their market introduction.

This study could be extended in several empirical and methodological directions. First, the agent-based simulation does not consider the used vehicle market, shared AVs, and comprehensive vehicle transaction mechanisms. The choice experiments also do not consider vehicle-specific attributes such as make, model, and body type. Future studies can conduct new experiments to capture these aspects or use revealed preference data, develop corresponding econometric models, and integrate them into the agent-based model. Second, our study considers that CAVs are likely to reduce travel time and emissions based on the existing literature, but the induced demand could reverse this effect. Exploring such possibilities and their effect on CAV adoption is an important avenue for future research. Third, we do not estimate the weight matrix in the ICLV estimation; instead, it is calculated based on the Euclidian distance or similarity in socio-demographic characteristics. Some studies in spatial statistics have estimated weight matrix elements, but those are not scalable (Bhattacharjee and Jensen-Butler, 2013; Qu and Lee, 2015). Future studies can build upon these studies to find ways to reduce the complexity by assuming zero effect (i.e., fixing the weight matrix element to zero) beyond a certain distance or the number of social ties. Fourth, we consider a fixed number of ties for every individual in the ICLV estimation. Subsequent studies can explore potential ways to estimate the number of ties. The social networks in such subsequent studies can also consider familiarity or experience with AVs to bolster similarity between two consumers. Fifth, while we adopt CML due to its well-established statistical properties, future studies can explore the potential of alternative estimation methods such as the Bayesian Gibbs sampler. Since the model has Gaussian distributions at all levels, sampling from conditional posterior distributions of all model parameters should be straightforward, following the data augmentation techniques adopted by Daziano (2015) and Buddhavarapu et al. (2021). Moreover, emerging approximate Bayesian inference methods could be derived for the computationally efficient estimation of the proposed ICLV model. These methods are generally appropriate for initial specification search because they are around 20-50 times faster than MCMC (see Bansal et al. (2021) for spatial count data models), but underestimate standard errors. Sixth, the simulation framework in our study relies on the synthetic population generated from the survey sample, which very well matches the current population of the study area. However, the temporal evolution of socio-economic variables is limited, leading to small standard errors of the AV adoption trajectories across repeated simulations. Future studies can complement the developed framework with the synthetic population for which several individuals- and household-level socioeconomic characteristics could evolve using underlying econometric models (Eluru et al., 2008; Pinjari et al., 2008).

Appendix-4

Algorithm A.4.1: An algorithm to generate **M_Diff** matrix

M_Diff $= \text{zeros}\left(Q\left(H+T(I-1)\right), Q\left(H+TI\right)\right)$

for q in 1:Q

  row_ms = $(q-1)*\left(H+T(I-1)\right)+1$

  row_me = $q*\left(H+T(I-1)\right)$

  col_ms = $(q-1)*\left(H+TI\right)+1$

  col_me = $q*\left(H+TI\right)$

  $\mathbf{M}_q = \text{zeros}\left(H+T\left(I-1\right), H+TI\right)$

  $\mathbf{M}_q\left[1:H, 1:H\right] = \mathbf{IDEN}_H$

  Iden_mat = $\mathbf{1}_{I-1}$

  O_neg = -1*ones($I-1$,1)

  for t in 1:T

    if($i_q^t == 1$)

      temp = O_neg~Iden_mat

    elseif($i_q^t == I$)

      temp = Iden_mat ~ O_neg

    else

      temp = Iden_mat[.,1:i_q^t-1] ~ O_neg~Iden_mat[.,i_q^t:I-1]

    end

    row_s = $H+(\text{t}-1)*(I-1)+1$

    row_e = $H+\text{t}*(I-1)$

    col_s = $H+(\text{t}-1)*I+1$

    col_e = $H+\text{t}*I$

    $\mathbf{M}_q\left[\text{row\_s} : \text{row\_e}, \text{col\_s} : \text{col\_e}\right] = \text{temp}$

  M_Diff[row_ms : row_me, col_ms : col_me] = $\mathbf{M}_q$

Note: where " ~ " refers to horizontal concatenation and i_q^t is the chosen alternative at time period t by individual q.

Supplement-4

S.4.1 Word-of-mouth studies

Table S.4.1.1: Existing studies on the effect of word of mouth (WOM) and risk preferences on the adoption of novel products

Source	Data	Focus area	Method	Major findings
			Word of Mouth (WOM)	
Alzahrani et al. (2019)	847 Saudi residents	EV adoption	Theory of reasoned action	WOM captured in terms of social norms has a positive influence on the residents' intention to adopt EVs. Also, environmental concerns are positively associated with social norms.
Barth et al. (2016)	548 German residents	EV adoption	Regression analysis	WOM measured through subjective norms has positive influence on residents' intention to buy EVs.
Baber et al. (2016)	251 Internet users in Pakistan	Intention to buy electronic product	SEM	Attitude towards a product mediates the impact of eWOM received from a trustworthy and experienced source on the receiver's intention to buy the product.
Baker et al. (2016)	TalkTrack US database: 186,775 conversations	Purchase intention (multiple brands)	Linear mixed models	Positive WOM and strong ties are positively related with purchase intention, but negative impact of negative WOM is much higher in magnitude. Interpersonal WOM contributes more after purchase.
Belgiawan et al. (2013)	500 Indonesian students	Intention to purchase a car	Principal component analysis	WOM obtained from siblings has a positive impact on intention to buy a new car.
Berger and Schwartz (2011)	Over 1,687 participants (Boston, USA)	Product diffusion (multiple products)	Poisson log-normal model	Interesting products garner more WOM in the beginning but less in later stages. Publicly visible products gather increased WOM in both early and later stages. Promotional product giveaways relate positively with the increased WOM.
Bhandari and Rodgers (2018)	447 US students	Brand trust and purchase intention	Regression analysis	Brand trust has a mediating effect on the positive influence of eWOM on purchase intention.
Bone (1995)	Three studies (N = 144, 115 and 158)	Product judgements	Multivariate analysis of variance	WOM influences both short- & long-term judgments. Influence is greater when consumers face a disconfirmation experience & WOM source is an expert.
Borowski et al. (2020)	Four simulated social network structures	Diffusion of green travel mode	Agent-based model	Increased and frequent WOM encounters have an effect on the long-term market penetration of green travel mode
Chen et al. (2016)	86 Chinese residents	Purchase intention	SEM	eWOM has a positive influence on attitudes towards the brand and intention to purchase. eWOM is more useful for the consumer with high susceptibility to informational influence.
Cheung et al. (2009)	100 students in Hong Kong	Purchase decision	Partial least squares graph	Positive eWOM in terms of consumer reviews strengthens the relationship between consumers' trust and intention to purchase.
Cheung and Thadani (2012)	Literature synthesis	Purchase intention	Social communication framework	The authors identified critical elements like a beneficiary, source, content, and reaction to develop a framework to quantify the impact of eWOM.
Christodoulides et al. (2012)	103 UK and 106 Chinese consumers	Purchase intention	Analysis of variance	After eWOM exposure, UK consumers were less likely to purchase the product than their Chinese counterparts. UK consumers anchored more on negative information.
Du et al. (2018)	811 Chinese residents	Adoption of new energy vehicles	Hierarchical regression analysis	WOM captured through subjective norms (impact of friends and family) is the strongest predictor of the resident's intention of buying a new energy vehicle.
East et al. (2008)	1,905 UK residents	Purchase intention (multiple products)	Juster scale	Positive WOM has higher impact on purchase intention than negative WOM. However, respondents neglected WOM for the brand they were loyal to and the brands they were not interested in.
Ghasri and Vij (2021)	862 Sydney residents	AV adoption	Discrete choice model	Social media sentiment has highest effect on AV consideration (90% of sample).
He et al. (2014)	41,330 Californian residents	EV adoption	Discrete choice model	In the form of social impact, WOM positively influence an individual's inclination to adopt EVs. An increase in the number of social contacts exerts a strong influence on purchasing decisions.
Helveston et al. (2015)	384 American and 572 Chinese car buyers	EV adoption	Discrete choice model	EVs symbolize high social status in the USA, but not in China.

Source	Data	Focus area	Method	Major findings
Hong et al. (2020)	None (Analytical model)	Green product diffusion	Bass model	Consumer's environmental awareness (CEA) influence the diffusion of green products in market share and pricing strategies. CEA coupled with WOM has no significant effect on pricing strategies but affect market share of green products.
Huang et al. (2014)	Simulated	Novel product diffusion	Bass model	Product peak sales rate and cumulative sales at peak time would be highest when the product is only marketed online. However, product peak adoption time is indifferent to online/offline marketing strategy, rather depends upon online/offline imitation effect and the proportion of offline consumers.
Hussain et al. (2017)	300 Chinese consumers	Food product information adoption	SEM	eWOM source credibility in the form of trustworthiness, expertness, and objectivity has a positive influence on perceived risk.
Hussain et al. (2018)	520 Chinese residents	Food product information adoption	SEM	eWOM source credibility is positively related to opinion seeking and self-worth reinforcement and negatively related to product involvement and economic incentives. Perceived risk is positively related with eWOM credibility.
Ismagilova et al. (2019)	Literature synthesis (69 studies)	Purchase intention	Weight and meta-analysis	eWOM credibility, attitude towards the website and online shopping, and emotional trust are likely to be the best predictors of intentions to buy.
Iyer and Griffin (2020)	Two studies (N= 238 and 307 students)	Purchase intention	SEM	Word-of-mouth is positively related to product attitude and purchase intention. Source trustworthiness is positively related to word-of-mouth usage.
Jalilvand and Samiei (2012)	341 Iranian residents	Purchase intention in automobile industry	SEM	eWOM has positive influence on brand image & consumers' purchase intentions.
Jansson et al. (2017)	3,000 Swedish car owners	EV adoption	Binary logit models	WOM measured through social norms is the key predictor of the car owner's intention to adopt EVs.
Jin and Phua (2014)	Two studies (N = 160, US students)	Purchase intention and source credibility perception	Analysis of variance	A higher number of Twitter followers of celebrities makes them more credible source. Prosocial celebrities with a higher number of followers have a higher influence on product involvement and buying intentions of consumers.
Jung and Seock (2017)	368 Qualtrics US panel	Recovery after service failure	Regression	Consumers respond differently to different types of service recovery, but they particularly favor apology among types of service recovery.
Kieckhäfer et al. (2017)	18,834 agents	Diffusion of EVs	Agent-based and system dynamics approach	Owners transmitting positive WOM contribute to an increase in sales and satisfied customers, which contributes to increasing positive WOM. Thus, WOM plays vital role in long-term diffusion of EVs.
Kwon et al. (2020)	152 South Korean residents	Intention to purchase EVs	SEM	Consumers who are satisfied with EV spread positive WOM.
López and Sicilia (2013)	Two studies in Spain (N = 171 and 170)	Novel product adoption	Chi-squared test and Mann-Whitney U test	WOM marketing is more influential than advertising. WOM marketing, followed by advertising, contributes towards higher intention to adopt the novel product.
Ma et al. (2019)	25,070 comments on a Chinese website	EV adoption	Text mining	eWOM suggests that consumers considered appearance, interiors, occupant space, convenience, and maneuverability in purchase decision.
Mahajan et al. (1984)	67 Southern Methodist University students	Novel product adoption (motion picture)	Bass model	The positive and negative information transmitted by current customers directly impacts potential customers. They predicted the audience of a motion picture & showed optimal marketing schemes to pacify the impact of negative WOM.
Marchand et al. (2017)	100 video games	Novel product adoption	Log-transformed regression	The influence of WOM generated from microblogs and consumer reviews on the adoption of a novel product decreases and increases over time, respectively.
Martin and Lueg (2013)	546 students (student referral method)	Purchase intention	SEM	WOM about novel products was proved to be more influential than for existing products. Also, the listeners' trust in the WOM source and expertise of the WOM source have a significant impact on their purchase decisions.

Source	Data	Focus area	Method	Major findings
Meuter et al. (2013)	72 students in California	Purchase intention (Restaurant)	Scale analysis	Traditional (verbal) WOM is more influential than eWOM channels. Independent sources (i.e., Facebook) are more influential than company-controlled sources of eWOM, such as customer testimonials on a website.
Moons and De Pelsmacker (2012)	1,202 participants	Intention to use EVs	Regression analysis	WOM captured in terms of subjective norms from peers and media positively impact individuals' intention to use EVs.
Ozaki and Sevastyanova (2011)	1,263 UK car owners	Hybrid EV adoption	Factor analysis	WOM received from family and social pressure are essential to accelerate the hybrid EV adoption.
Pettifor et al. (2017)	Literature synthesis (N=21)	Diffusion of green vehicles	Meta-analysis	WOM captured in terms of neighborhood effect, interpersonal communication, and social norms have a similar effect on preferences for alternative fuel vehicles, but effect varies across countries.
Prendergast et al. (2010)	150 shopping mall visitors in Hong Kong	Purchase intention	Theory of reasoned action	Source similarity was defined as the online users in an online forum interested to gather information about similar products. Results indicated a direct relationship between source similarity, persuasiveness, and purchase intention.
Rasouli and Timmermans (2016)	726 Dutch residents	EV adoption	Mixed logit model	Social influence (from peers, colleagues, friends, and relatives) has less impact on EV adoption as compared to EV's relative cost and attributes
Roy et al. (2019)	14 Expert interviews in India	Online purchase intention	Content analysis	Both mixed neutral eWOM and rich eWOM content positively affects online purchase intention.
Shepherd et al. (2012)	Multiple sources	Diffusion of EVs	System dynamics model	Market penetration of EVs depends on the WOM generated from CV users instead of existing EV users.
Talebian and Mishra (2018)	2465 employees of the University of Memphis	AV adoption	Agent-based model	AV adoption barriers will be eliminated by communication within individual's social network.
Thøgersen and Ebsen (2019)	248 Danish car owners	EV adoption	SEM	WOM captured in the form of personal norms had a direct influence on intention to adopt EVs.
Torlak et al. (2014)	248 Turkish students	Purchase intention in cell phone industry	SEM	eWOM has positive influence on brand image & consumers' purchase intentions.
Tsiotsou and Alexandris (2009)	354 Greek fans	Merchandise purchase intention	SEM	Highly attached sports fans are more likely to spread positive WOM for the sponsor, recommend sponsor's products, and purchase tickets.
Risk preferences				
Bansal et al. (2021)	1021 Indians	EV adoption	Discrete choice analysis	44% of respondents were not willing to take risk of buying EVs.
Barham et al. (2014)	American farmers (N= 75 and 116)	Genetically modified corn & soy seeds	Survival model	The impact of risk aversion on the adoption timing of a new technology varies based on seeds' attributes. Risk and ambiguity aversion should be differentiated.
Brick and Visser (2015)	Experiment on 82 South African farmers	Modern farming technique	Regression analysis	Risk-averse individuals were less likely to adopt modern farming inputs, and insurance availability had no impact on reducing the risk aversion.
Chikaraishi et al. (2020)	1,442 Hiroshima Prefecture respondents	AV adoption	Factor analysis and Tobit model	The perceived benefits of AVs outweigh the associated perceived risks. The younger generation is more accepting of the risks associated with AVs.
Ha (2002)	124 South Korean respondents	Pre-purchase information	SEM	Pre-purchase information processing is directly related to reducing consumers' risk perception. Brand also has a significant effect upon consumer perceived risk.
Hirunyawipada and Paswan (2006)	746 respondents	Novel product adoption	SEM	Perceived physical and social risk encourage consumers to look for information related to the new product, but financial risk has the opposite effect.
Wang and Zhao (2019)	1142 Singaporeans	AV adoption	Discrete choice models	Elderly, females, and unemployed are more susceptible to the risk, hence less likely to adopt AVs.

Source	Data	Focus area	Method	Major findings
Zhang et al. (2019)	216 drivers from China	AV adoption	Technology acceptance model	Perceived safety risk had a negative effect on AV acceptance through trust.

Note: eWOM: electronic word of mouth; AVs: autonomous vehicles; EVs: electric vehicles; CVs: conventional vehicles; SEM: structural equation model.

S.4.2 Additional model estimates

Table S.4.2.1: Structural equation model parameter estimates for interdependent ICLV model with weight matrix based on Spatial distance and five ties

Explanatory Variables		**Coefficient (t-stat)**	
		Word of Mouth (WOM)	**Risk Aversion**
Education Status	Some college degree or below	-0.066 (-2.780)	---
	Professional degree (MD, JD, etc.)	-0.331 (-11.28)	---
	College Graduate	---	0.371 (8.57)
	MS, PhD or Doctoral degree	---	0.371 (8.57)
Household Income Base: >75K	<=35K	-0.219 (-3.09)	---
	36K - 75K	---	---
Household Configuration	Number of Workers	0.222 (3.18)	0.058 (2.82)
	Number of Children	0.319 (10.36)	-0.046 (23.98)
	Respondent Male (Base: Female)	0.095 (3.54)	-0.189 (-4.44)
Vehicle Ownership	Number of Vehicles	-0.061 (-12.80)	---
Information Variables	Number of crashes in AV	-0.026 (-10.44)	---
	Reduction in travel time in AV	---	---
	Reduction in CO2 emission in AV	---	---
	Unclear liability in x% of AV-involved crashes.	-0.623 (-16.19)	---
Information Source Base: Car Dealer	Friend	-0.134 (-11.38)	---
	Colleague at work	0.016 (6.60)	---
	Media	0.150 (14.24)	---
Past One year accident involvement. Number of accidents where…	Vehicle incurred minor damages.	0.112 (9.15)	---
	Vehicle incurred major damages.	0.179 (16.73)	---
	I suffered from minor injuries.	-0.212 (-18.47)	---
	I suffered from severe injuries.	-0.115 (-10.40)	---
Cross Loading (ρ)	WOM		-1.027 (-8.44)
Spatial Parameter (δ)		0.357 (21.72)	0 (fixed)
Correlation between WOM and Risk Aversion (Γ_{12})		0.121 (5.85)	

---: indicates that the parameter was not significant at a significance level of 0.2.

Table S.4.2.2: Measurement equation model parameter estimates for interdependent ICLV model with weight matrix based on Spatial distance and five ties, $\psi_1 = -\infty, \psi_2 = 0, \psi_6 = \infty$

Statement (Five-point Likert scale with labels strongly disagree to strongly agree)	Coefficient (t-stat)		Coefficient (standard error)			
	Word of Mouth (WOM)	Risk Aversion	Intercept	ψ_3	ψ_4	ψ_5
I will suggest them to consider buying an autonomous car over a conventional car because the former is much safer.	1.001 (11.18)		1.393 (6.28)	1.031 (0.16)	2.342 (0.11)	3.726 (0.17)
I will suggest them to consider buying a conventional car over an autonomous car because at least one knows who is responsible for a crash in a conventional car.	-0.223 (-6.72)		1.865 (6.22)	0.915 (0.19)	1.901 (0.23)	2.794 (0.30)
I am worried that I might not get value-for-money in an autonomous car purchase.		0.277 (14.48)	1.706 (7.79)	0.71 (0.16)	1.521 (0.18)	2.544 (0.24)
I would take the risk with autonomous car purchase in exchange for an exciting and novel experience.		-0.457 (42.75)	0.692 (7.03)	0.757 (0.13)	1.709 (0.23)	2.619 (0.26)
I would feel uncomfortable in switching to autonomous cars.		0.856 (22.73)	2.852 (4.17)	1.170 (0.09)	2.089 (0.11)	3.506 (0.19)
I struggle in taking risks with such unconventional decisions.		0.472 (12.36)	1.812 (14.81)	0.889 (0.16)	1.721 (0.14)	2.811 (0.11)

Table S.4.2.3: Choice model parameter estimates for interdependent ICLV model with weight matrix based on spatial distance and five ties (base: will not buy an AV)

Explanatory Variables		Coefficient (t-stat)
Price and adoption variables	Constant	1.249 (30.57)
	Percentage adoption in social ties	1.783 (3.45)
	Percentage adoption in city/community	0.018 (31.31)
	Ratio of AV to CV price	-3.145 (-3.62)
Household Configuration	Number of Workers	0.071 (3.79)
	Number of Children	0.240 (2.61)
	Respondent Male (Base: Female)	-0.052 (-3.94)
Latent Variable Loading	WOM	0.991 (22.15)
	Risk Averse	-0.636 (-17.22)
Latent Variable Interaction	WOM * Percentage adoption in social ties	---
	Risk Averse * Percentage adoption in social ties	1.388 (17.50)
	WOM * Percentage adoption in city/community	0.751 (2.15)
	Risk Averse * Percentage adoption in city/community	---
	WOM * Ratio of AV to CV price	0.494 (15.86)
	Risk Averse * Ratio of AV to CV price	---

---: indicates that the parameter was not significant at a significance level of 0.2

Table S.4.2.4: Structural equation model parameter estimates for interdependent ICLV model with ten ties

Explanatory Variables		**Coefficient (t-stat)**			
		Gower distance-based weight matrix		**Spatial distance-based weight matrix**	
		Word of Mouth (WOM)	**Risk Aversion**	**Word of Mouth (WOM)**	**Risk Aversion**
Education Status	Some college degree or below	-0.120 (-3.11)	---	-0.105 (-11.53)	---
	Professional degree (MD, JD, etc.)	-0.212 (-3.35)	---	-0.284 (-21.10)	---
	College Graduate	---	0.233 (6.15)	---	0.279 (20.89)
	MS, PhD or Doctoral degree	---	0.233 (6.15)	---	0.279 (20.89)
Household Income Base: >75K	<=35K	-0.276 (-2.63)	---	-0.134 (-4.63)	---
	36K - 75K	-0.135 (-3.71)	---	-0.031 (-10.65)	---
Household Configuration	Number of Workers	0.260 (3.73)	0.020 (6.17)	0.253 (3.01)	0.009 (2.81)
	Number of Children	0.308 (3.76)	0.047 (10.44)	0.341 (27.63)	-0.036 (-2.12)
	Respondent Male (Base: Female)	0.005 (4.69)	-0.288 (-4.80)	0.058 (5.52)	-0.226 (-13.68)
Vehicle Ownership	Number of Vehicles	-0.122 (-3.67)	---	-0.092 (-2.14)	---
Information Variables	Number of crashes in AV	-0.049 (-3.71)	---	-0.023 (-21.39)	---
	Reduction in travel time in AV	---	---	---	---
	Reduction in CO2 emission in AV	---	---	---	---
	it is not clear who is responsible for the crash in x% of crashes encountered by autonomous cars.	-0.632 (-3.51)	---	-0.596 (-32.52)	---
Information Source Base: Car Dealer	Friend	-0.011 (-0.96)	---	-0.081 (-16.83)	---
	Colleague at work	0.028 (1.99)	---	0.042 (10.09)	---
	Media	0.075 (3.31)	---	0.136 (32.38)	---
Past One year accident involvement. Number of accidents where…	Vehicle incurred minor damages.	-0.028 (-1.86)	---	0.104 (21.16)	---
	Vehicle incurred major damages.	0.052 (2.80)	---	0.136 (32.63)	---
	I suffered from minor injuries.	-0.153 (-3.56)	---	-0.243 (-2.37)	---
	I suffered from severe injuries.	0.062 (3.07)	---	-0.035 (-8.04)	---
Cross Loading (ρ)	WOM		-0.998 (-3.92)		-0.899 (-3.80)
Spatial Parameter (δ)		0.245 (3.63)	0 (fixed)	0.305 (3.03)	0 (fixed)
Correlation between WOM and Risk Aversion (Γ_{12})		0.311 (2.32)		0.112 (2.26)	

---: indicates that the parameter was not significant at a significance level of 0.2

Table S.4.2.5: Measurement equation model parameter estimates for interdependent ICLV model with 10 ties, $\psi_1 = -\infty, \psi_2 = 0, \psi_6 = \infty$

Statement (Five-point Likert scale with labels strongly disagree to strongly agree)	Gower distance-based weight matrix						Spatial distance-based weight matrix					
	Coefficient (t-stat)		Coefficient (standard error)				Coefficient (t-stat)		Coefficient (standard error)			
	Word of Mouth (WOM)	Risk Aversion	Intercept	ψ_3	ψ_4	ψ_5	Word of Mouth (WOM)	Risk Aversion	Intercept	ψ_3	ψ_4	ψ_5
I will suggest them to consider buying an autonomous car over a conventional car because the former is much safer.	1.195 (4.98)		1.579 (6.51)	1.016 (0.08)	2.451 (0.18)	3.942 (0.28)	1.06 (21.20)		1.425 (3.23)	0.995 (0.14)	2.365 (0.05)	3.801 (0.08)
I will suggest them to consider buying a conventional car over an autonomous car because at least one knows who is responsible for a crash in a conventional car.	-0.335 (-5.33)		1.965 (9.38)	0.991 (0.03)	2.02 (0.04)	2.907 (0.04)	-0.179 (-13.33)		1.824 (7.69)	0.924 (0.14)	1.907 (0.16)	2.782 (0.20)
I am worried that I might not get value-for-money in an autonomous car purchase.		0.243 (1.88)	1.527 (12.66)	0.67 (0.02)	1.433 (0.03)	2.424 (0.04)		0.266 (2.31)	1.664 (7.24)	0.696 (0.11)	1.491 (0.14)	2.461 (0.18)
I would take the risk with autonomous car purchase in exchange for an exciting and novel experience.		-0.562 (-4.16)	0.756 (4.61)	0.765 (0.03)	1.697 (0.05)	2.595 (0.08)		-0.471 (-3.94)	0.664 (3.24)	0.729 (0.15)	1.656 (0.38)	2.526 (0.52)
I would feel uncomfortable in switching to autonomous cars.		0.987 (8.93)	2.646 (9.32)	1.112 (0.07)	2.028 (0.13)	3.412 (0.22)		0.929 (3.76)	2.926 (3.90)	1.157 (0.22)	2.088 (0.32)	3.484 (0.51)
I struggle in taking risks with such unconventional decisions.		0.604 (6.99)	1.840 (9.95)	0.924 (0.04)	1.856 (0.07)	2.899 (0.11)		0.559 (2.46)	1.971 (3.24)	0.944 (0.20)	1.831 (0.36)	2.910 (0.71)

Table S.4.2.6: Choice model parameter estimates for interdependent ICLV model with ten ties (base: will not buy an AV)

	Explanatory Variables	Coefficient (t-stat) Gower distance-based weight matrix	Spatial distance-based weight matrix
Price and adoption variables	Constant	0.951 (1.31)	0.825 (2.01)
	Percentage adoption in social ties	1.153 (4.44)	1.390 (9.34)
	Percentage adoption in city/community	0.499 (2.52)	0.347 (2.44)
	Ratio of AV to CV price	-2.507 (-5.85)	-2.681 (-4.25)
Household Configuration	Number of Workers	0.046 (2.86)	0.052 (7.83)
	Number of Children	-0.096 (-1.38)	0.190 (5.68)
	Respondent Male (Base: Female)	0.135 (1.61)	0.139 (4.90)
Latent Variable Loading	WOM	0.534 (11.33)	0.623 (19.52)
	Risk Averse	-0.624 (-33.88)	-0.534 (-2.64)
Latent Variable Interaction	WOM * Percentage adoption in social ties	---	---
	Risk Averse * Percentage adoption in social ties	1.049 (4.78)	1.139 (3.41)
	WOM * Percentage adoption in city/community	0.419 (5.80)	0.400 (2.64)
	Risk Averse * Percentage adoption in city/community	---	---
	WOM * Ratio of AV to CV price	0.640 (9.71)	0.797 (2.57)
	Risk Averse * Ratio of AV to CV price	---	---

---: indicates that the parameter was not significant at a significance level of 0.2

Table S.4.2.7: Structural equation model parameter estimates for independent ICLV model

Explanatory Variables		Coefficient (t-stat)	
		Word of Mouth (WOM)	**Risk Aversion**
Education Status	Some college degree or below	-0.013 (-2.53)	---
	Professional degree (MD, JD, etc.)	-0.084 (-8.65)	---
	College Graduate	---	0.134 (13.55)
	MS, PhD or Doctoral degree	---	0.134 (13.55)
Household Income Base: >75K	<=35K	-0.363 (-12.70)	---
	36K - 75K	-0.134 (-37.63)	---
Household Configuration	Number of Workers	0.309 (85.25)	0.020 (2.40)
	Number of Children	0.382 (33.87)	0.095 (2.57)
	Respondent Male (Base: Female)	0.027 (2.82)	-0.653 (-8.53)
Vehicle Ownership	Number of Vehicles	-0.142 (-60.58)	---
Information Variables	Number of crashes in AV	-0.042 (-38.79)	---
	Reduction in travel time in AV	---	---
	Reduction in CO_2 emission in AV	---	---
	it is not clear who is responsible for the crash in x% of crashes encountered by autonomous cars.	-0.714 (-41.89)	---
Information Source Base: Car Dealer	Friend	-0.075 (-15.73)	---
	Colleague at work	-0.020 (-4.29)	---
	Media	0.046 (9.83)	---
Past One year accident involvement. Number of accidents where…	Vehicle incurred minor damages.	0.097 (18.56)	---
	Vehicle incurred major damages.	0.104 (22.82)	---
	I suffered from minor injuries.	-0.161 (-34.59)	---
	I suffered from severe injuries.	-0.077 (-15.92)	---
Cross Loading (ρ)	WOM		-2.477 (-9.90)
Spatial Parameter (δ)		0 (fixed)	0 (fixed)
Correlation between WOM and Risk Aversion (Γ_{12})		0.166 (4.28)	

---: indicates that the parameter was not significant at a significance level of 0.2

Table S.4.2.8: Measurement equation model parameter estimates for independent ICLV model

Statement (Five-point Likert scale with labels strongly disagree to strongly agree)	Coefficient (t-stat)		Coefficient (standard error)			
	Word of Mouth (WOM)	Risk Aversion	Intercept	ψ_3	ψ_4	ψ_5
I will suggest them to consider buying an autonomous car over a conventional car because the former is much safer.	1.001 (34.25)		1.512 (51.67)	0.949 (0.02)	2.239 (0.03)	3.584 (0.05)
I will suggest them to consider buying a conventional car over an autonomous car because at least one knows who is responsible for a crash in a conventional car.	-0.214 (-26.01)		1.842 (182.37)	0.927 (0.01)	1.915 (0.01)	2.795 (0.01)
I am worried that I might not get value-for-money in an autonomous car purchase.		0.080 (8.54)	1.552 (184.3)	0.682 (0.01)	1.446 (0.01)	2.416 (0.01)
I would take the risk with autonomous car purchase in exchange for an exciting and novel experience.		-0.282 (-8.65)	0.659 (44.68)	0.760 (0.01)	1.714 (0.02)	2.622 (0.03)
I would feel uncomfortable in switching to autonomous cars.		0.267 (8.43)	2.113 (80.59)	0.877 (0.01)	1.599 (0.02)	2.652 (0.03)
I struggle in taking risks with such unconventional decisions.		0.188 (8.70)	1.700 (110.21)	0.813 (0.01)	1.667 (0.01)	2.579 (0.02)

Table S.4.2.9: Choice model parameter estimates for independent ICLV model (base: will not buy an AV)

Explanatory Variables		Coefficient (t-stat)
Price and adoption variables	Constant	2.032 (8.15)
	Percentage adoption in social ties	0.944 (13.45)
	Percentage adoption in city/community	0.612 (7.68)
	Ratio of AV to CV price	-3.519 (-17.97)
Household Configuration	Number of Workers	0.060 (8.87)
	Number of Children	0.197 (3.23)
	Respondent Male (Base: Female)	0.873 (6.89)
Latent Variable Loading	WOM	2.553 (4.63)
	Risk Averse	-1.005 (-11.89)
Latent Variable Interaction	WOM * Percentage adoption in social ties	---
	Risk Averse * Percentage adoption in social ties	0.211 (5.08)
	WOM * Percentage adoption in city/community	0.353 (3.24)
	Risk Averse * Percentage adoption in city/community	---
	WOM * Ratio of AV to CV price	1.284 (5.48)
	Risk Averse * Ratio of AV to CV price	---

---: indicates that the parameter was not significant at a significance level of 0.2

S.4.3 Close social tie

Figure S.4.3.1: Definition of "close social tie" shown to survey participants

S.4.4 Additional adoption graphs

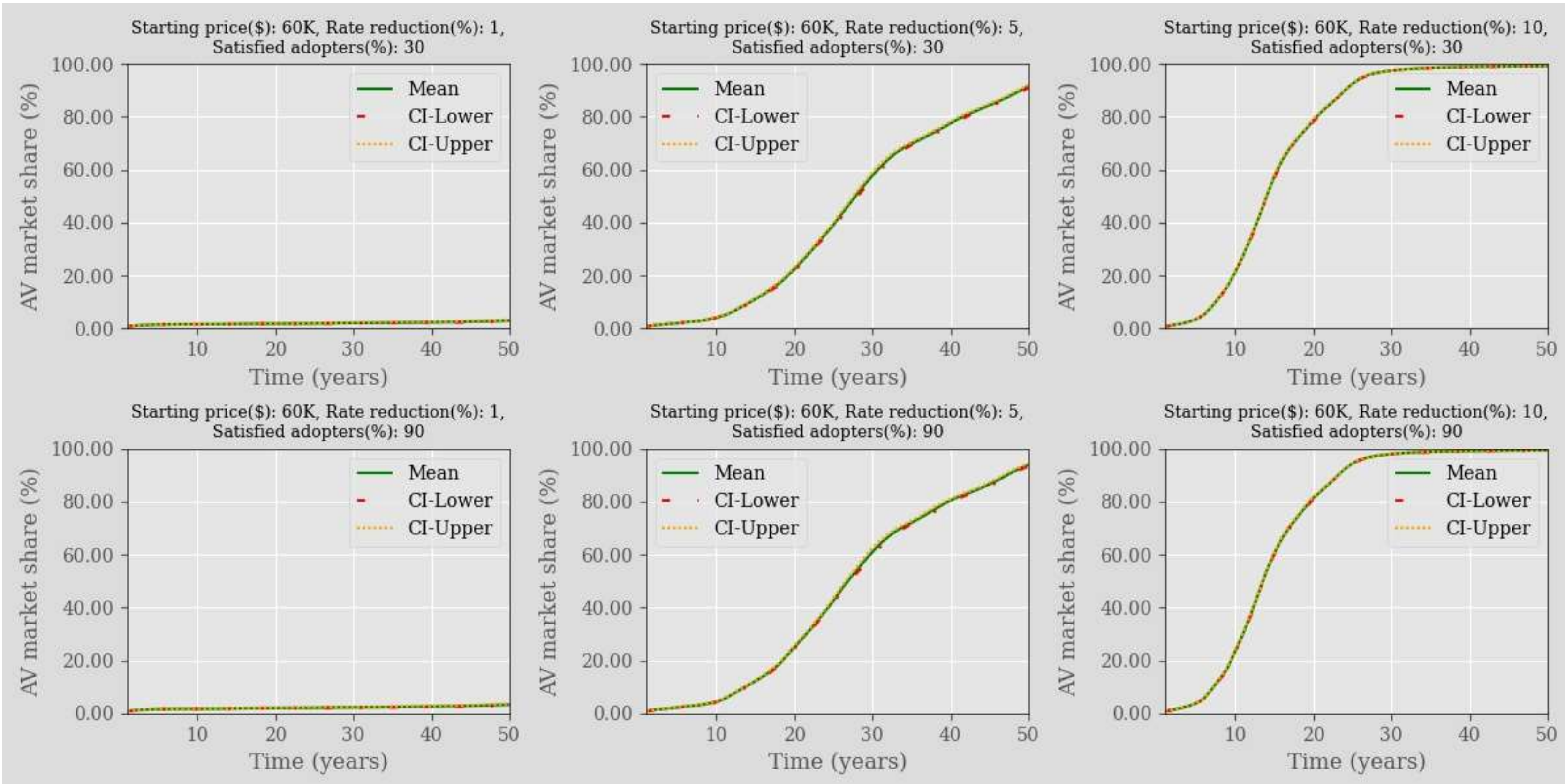


Figure S.4.4.1: Effect of AV price reduction and proportion of AV adopters with post-purchase satisfaction on AV adoption (Weight matrix based on Gower distance with five social ties)

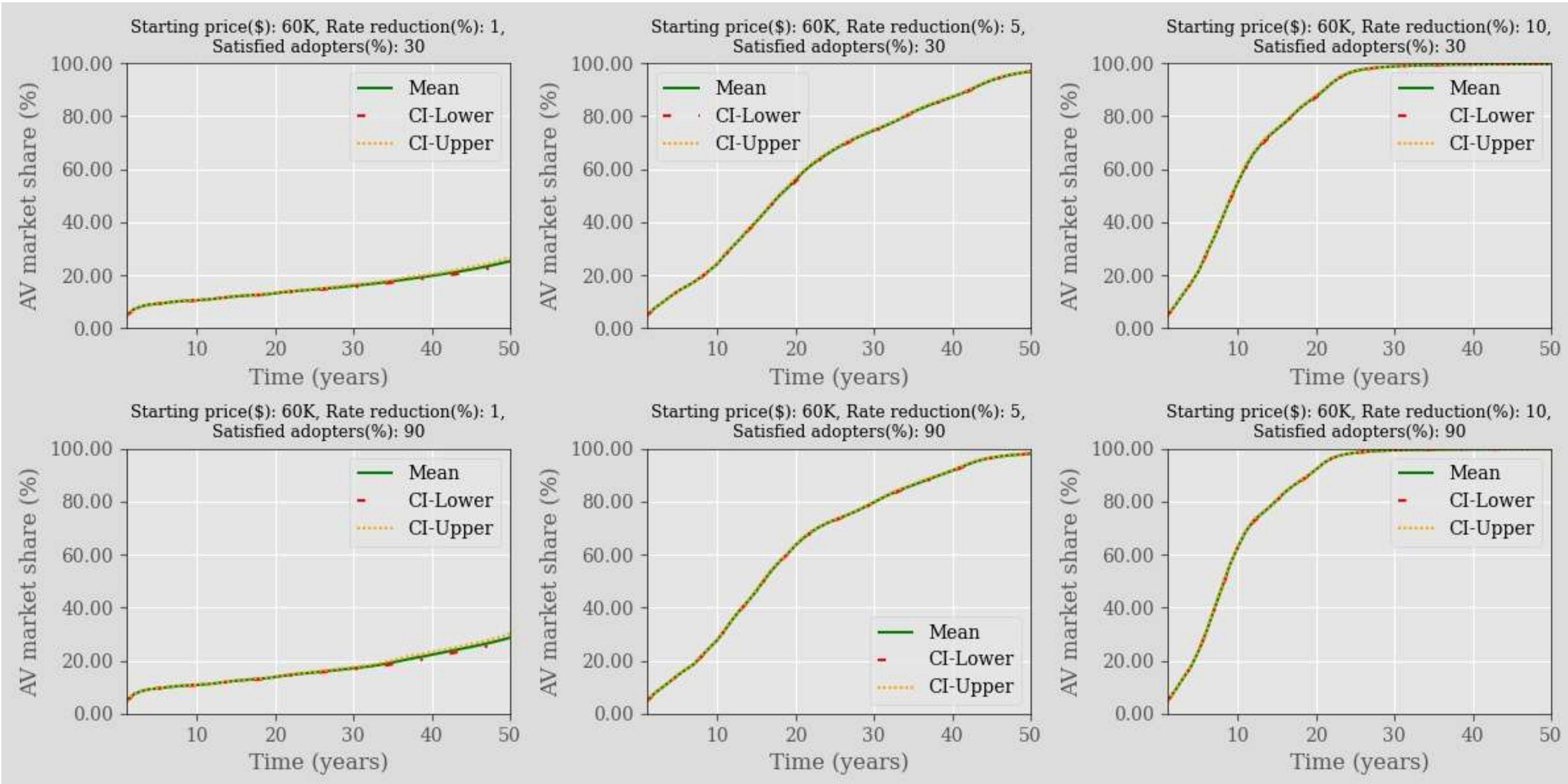


Figure S.4.4.2: Effect of AV price reduction and proportion of AV adopters with post-purchase satisfaction on AV adoption (Weight matrix based on spatial distance with five social ties)

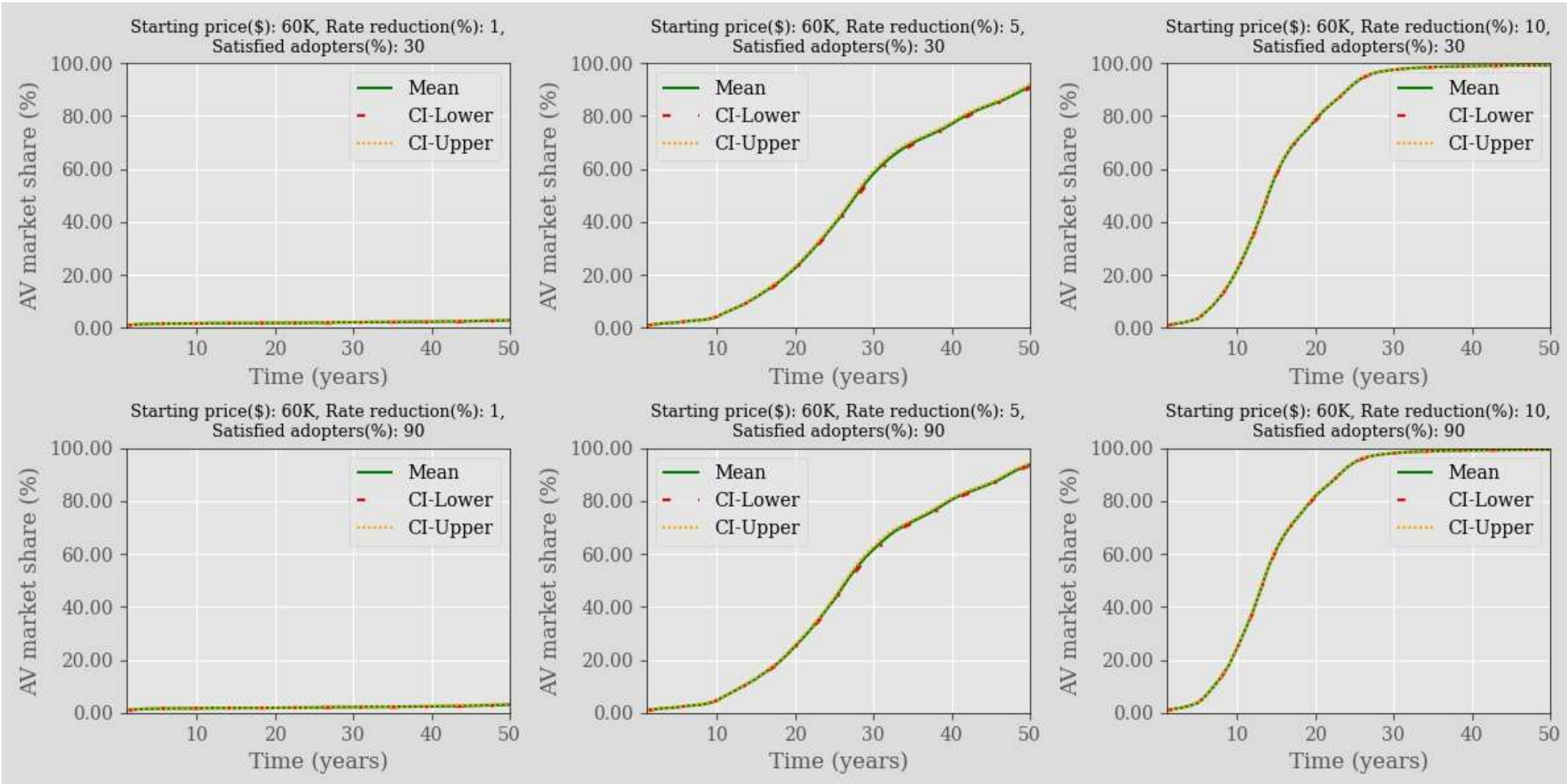


Figure S.4.4.3: Effect of AV price reduction and proportion of AV adopters with post-purchase satisfaction on AV adoption (Weight matrix based on Gower distance with ten social ties)

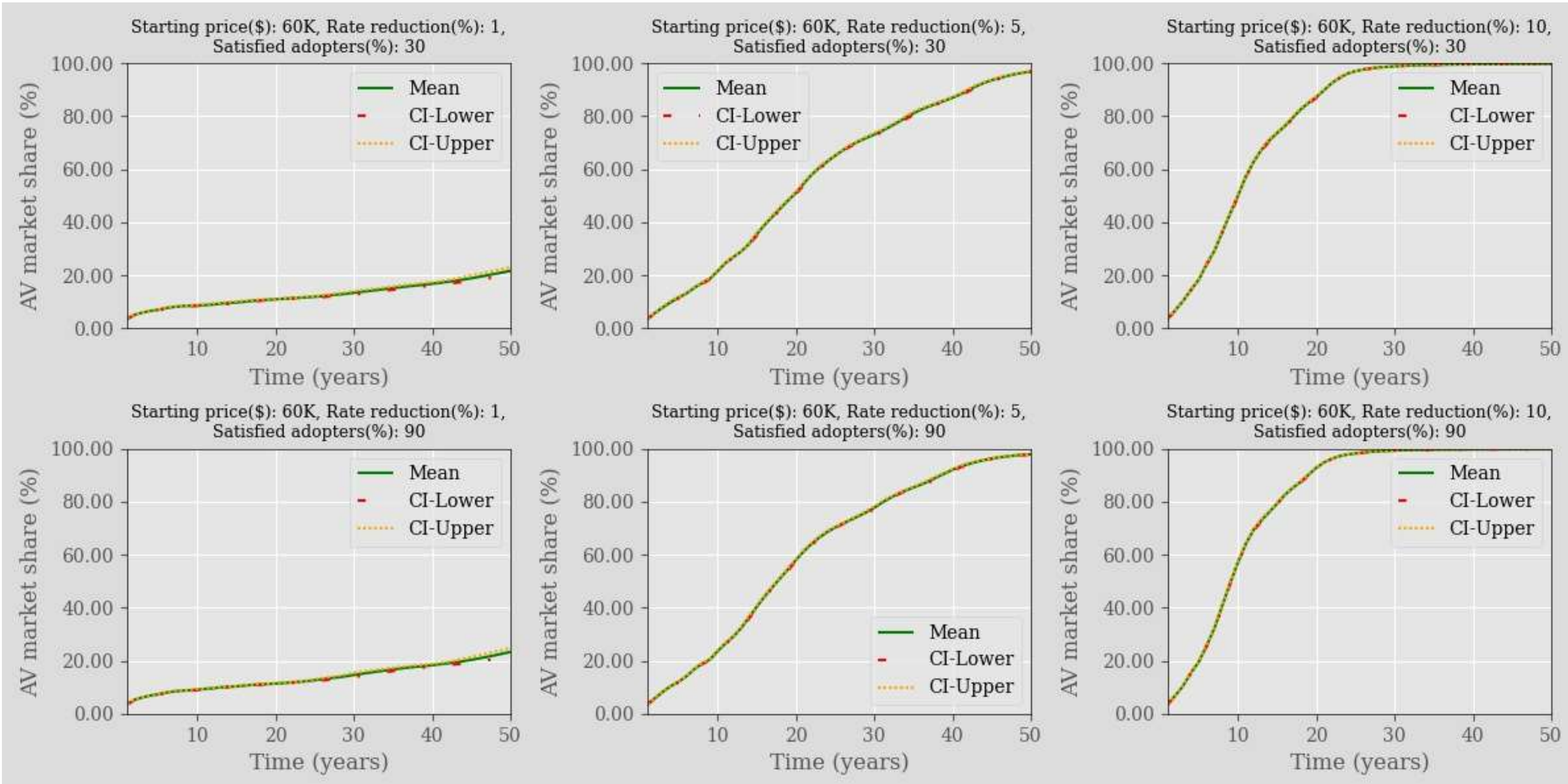


Figure S.4.4.4: Effect of AV price reduction and proportion of AV adopters with post-purchase satisfaction on AV adoption (Weight matrix based on spatial distance with ten social ties)

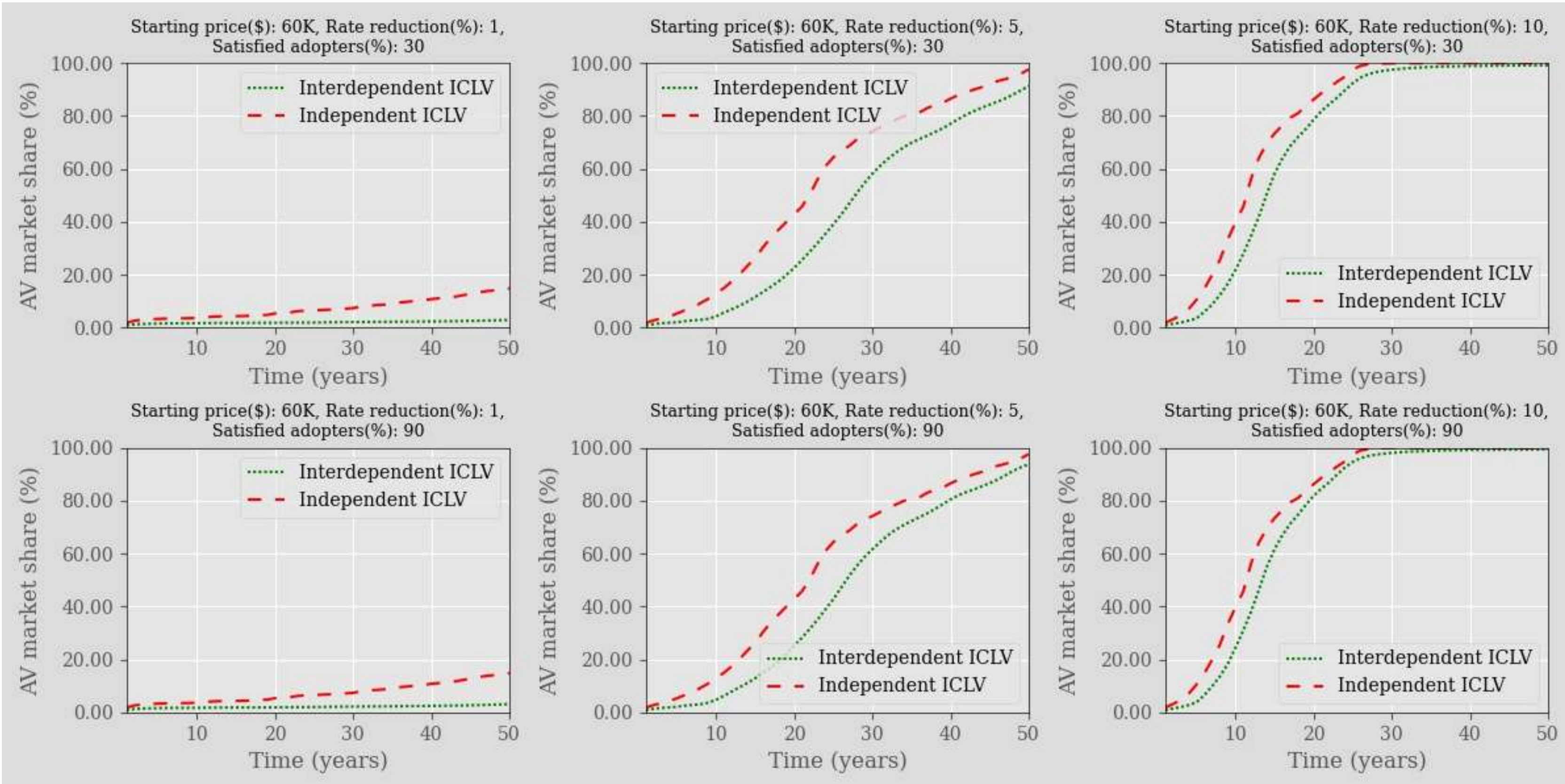


Figure S.4.4.5: Effect of interpersonal social network on AV adoption (Weight matrix based on Gower distance with ten social ties)

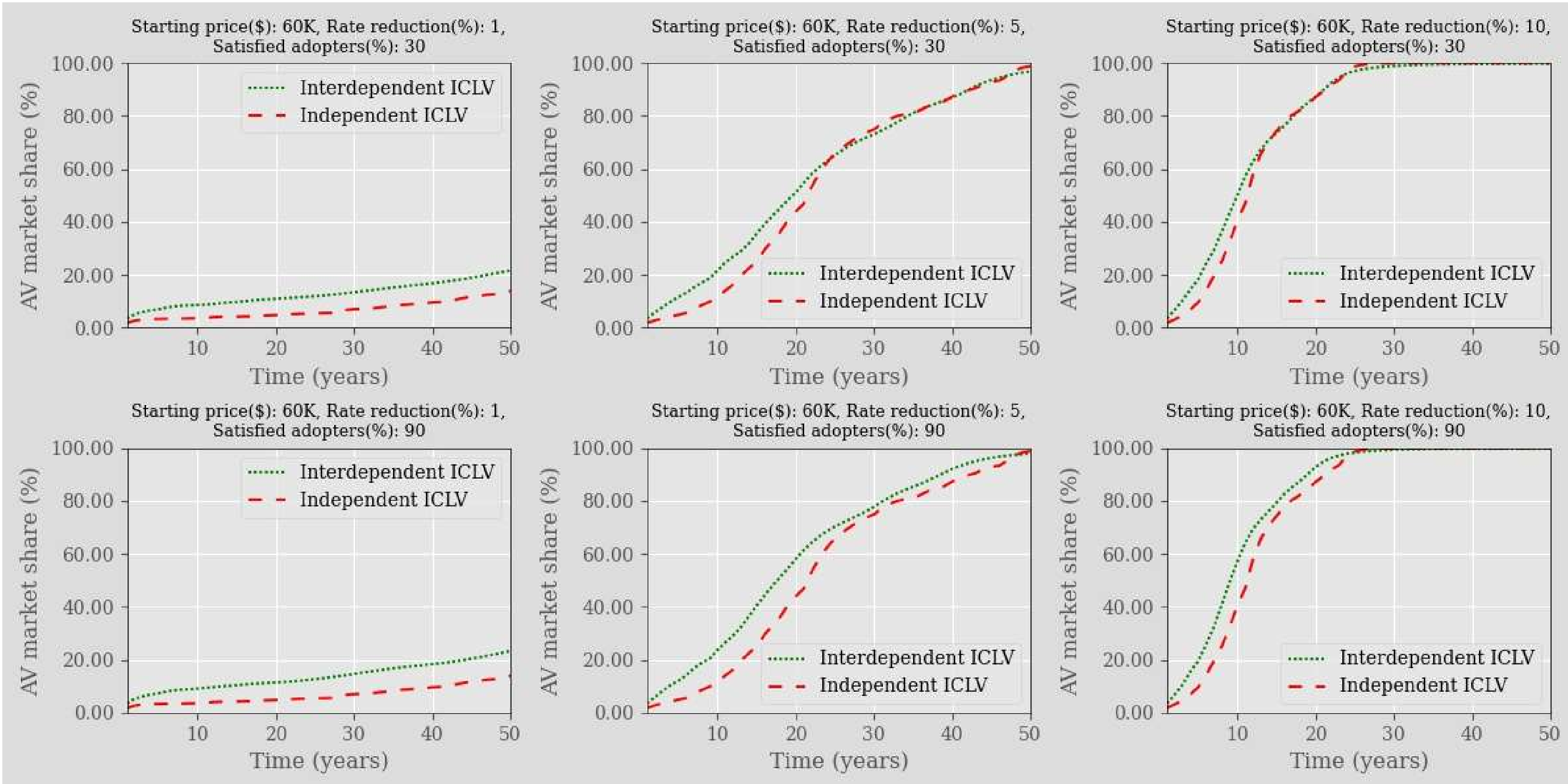


Figure S.4.4.6: Effect of interpersonal social network on AV adoption (Weight matrix based on spatial distance with ten social ties)

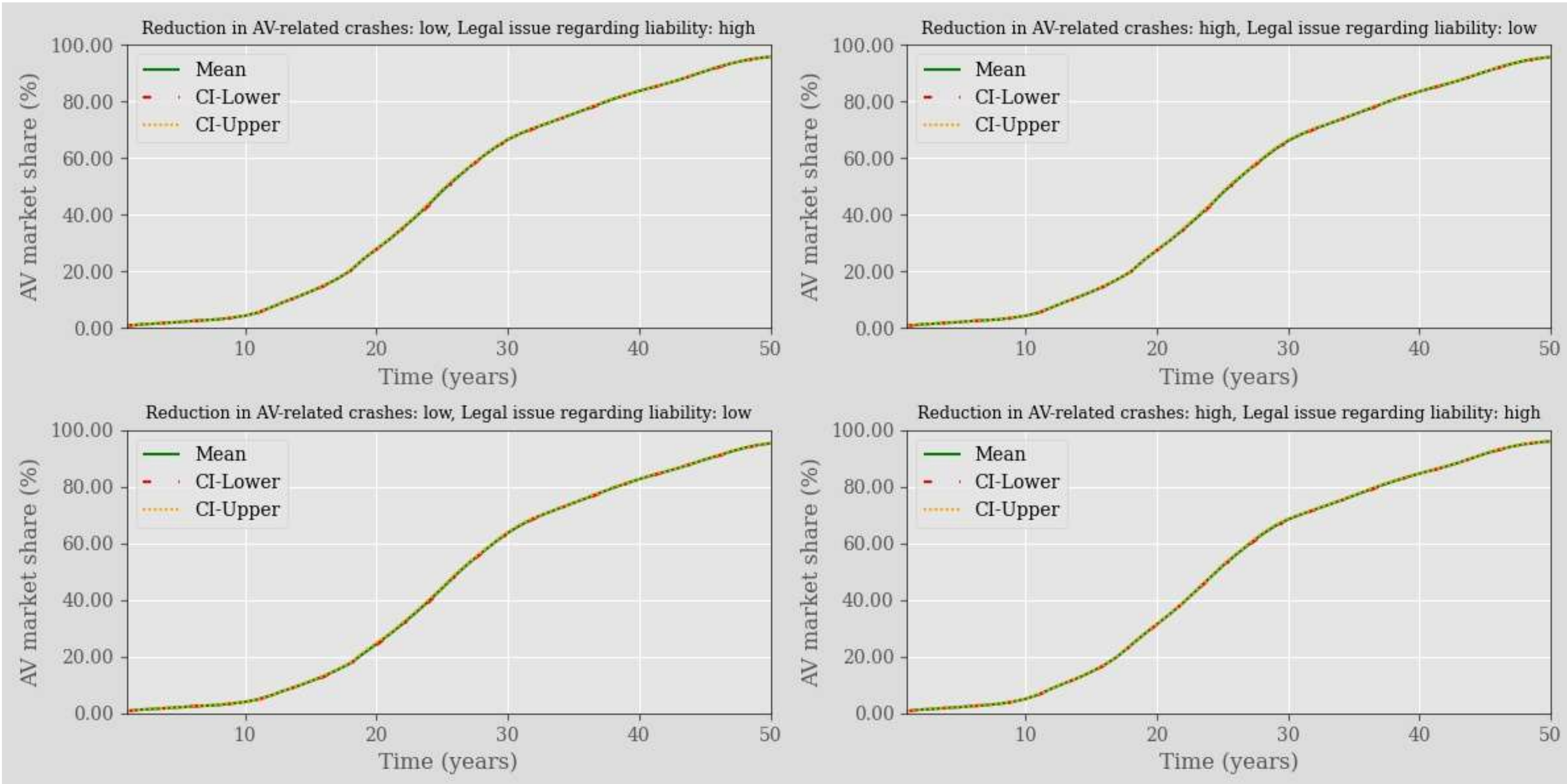


Figure S.4.4.7: Effect of reduction in AV-involved crashes and proportion of such crashes with legal issues on AV adoption (Weight matrix based on Gower distance with five social ties)

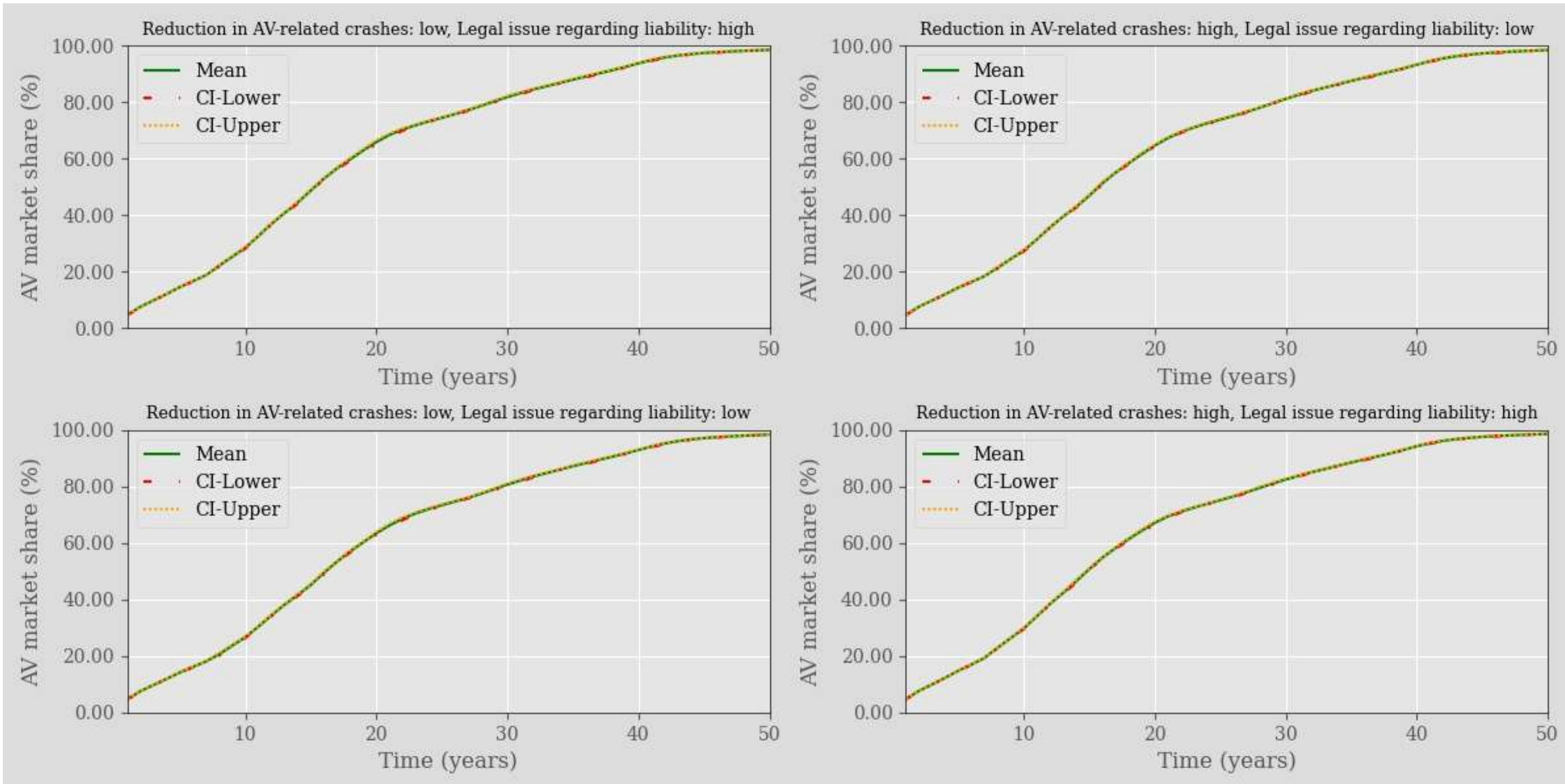


Figure S.4.4.8: Effect of reduction in AV-involved crashes and proportion of such crashes with legal issues on AV adoption (Weight matrix based on spatial distance with five social ties)

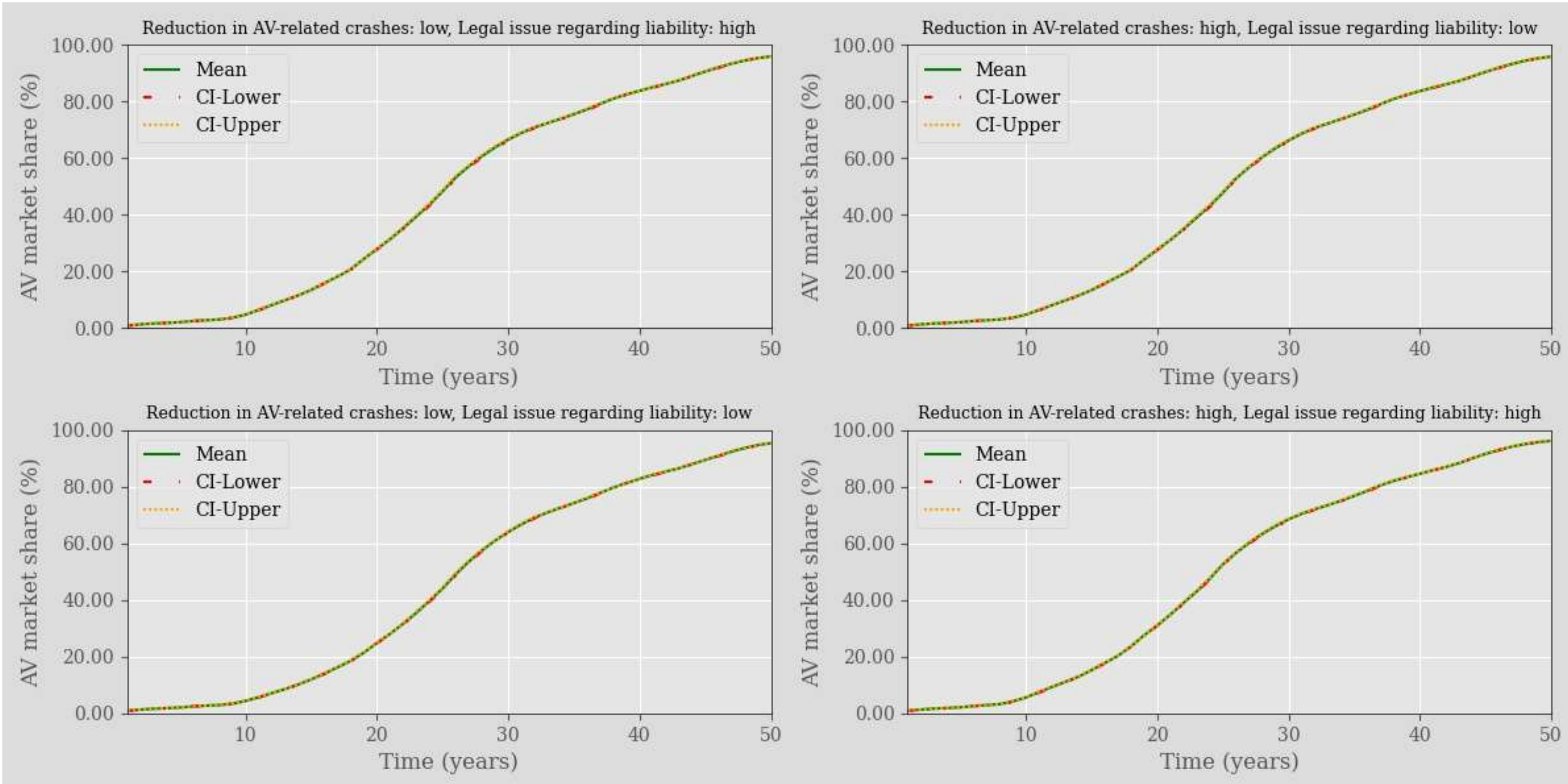


Figure S.4.4.9: Effect of reduction in AV-involved crashes and proportion of such crashes with legal issues on AV adoption (Weight matrix based on Gower distance with ten social ties)

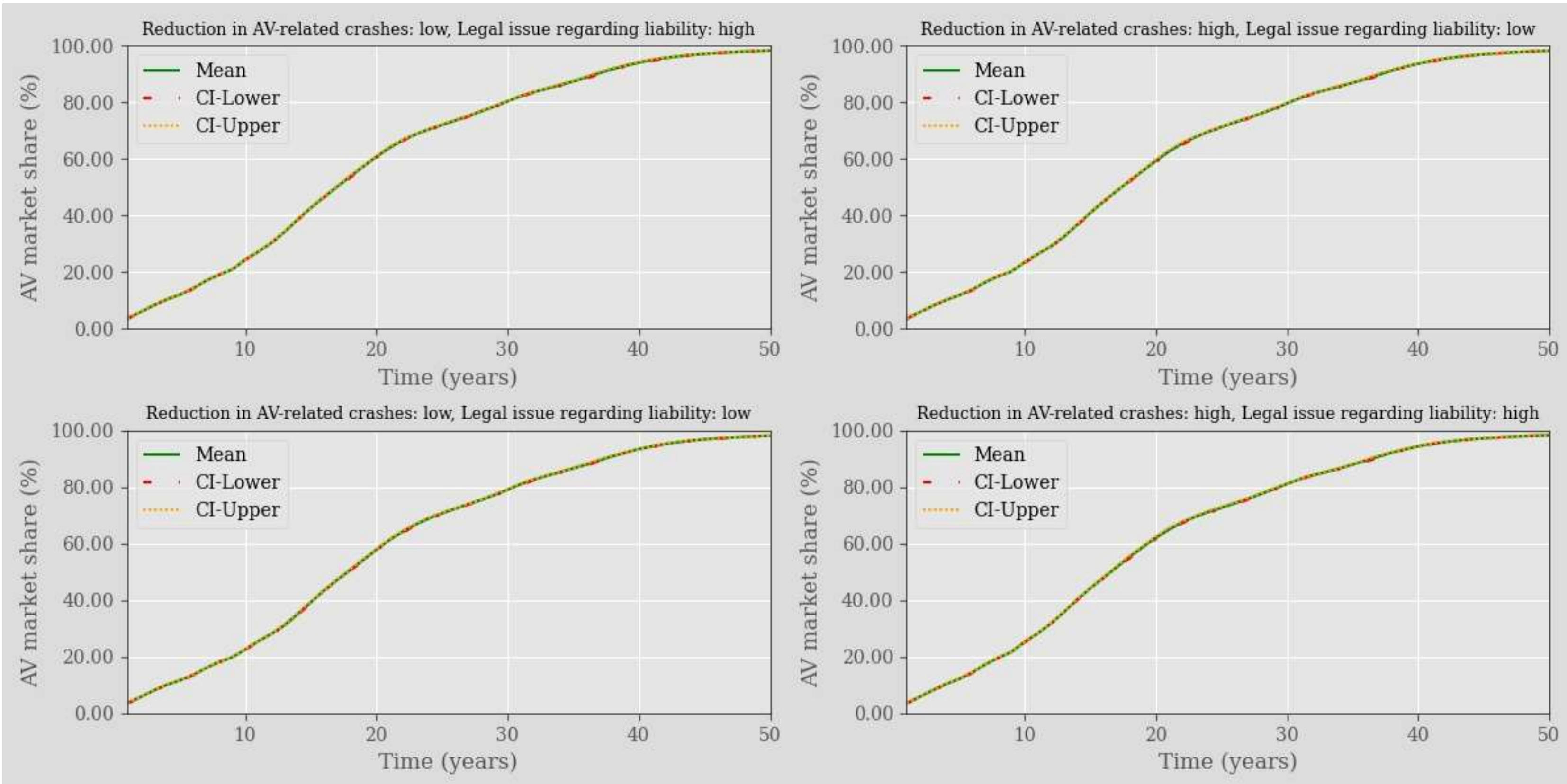


Figure S.4.4.10: Effect of reduction in AV-involved crashes and proportion of such crashes with legal issues on AV adoption (Weight matrix based on spatial distance with ten social ties)

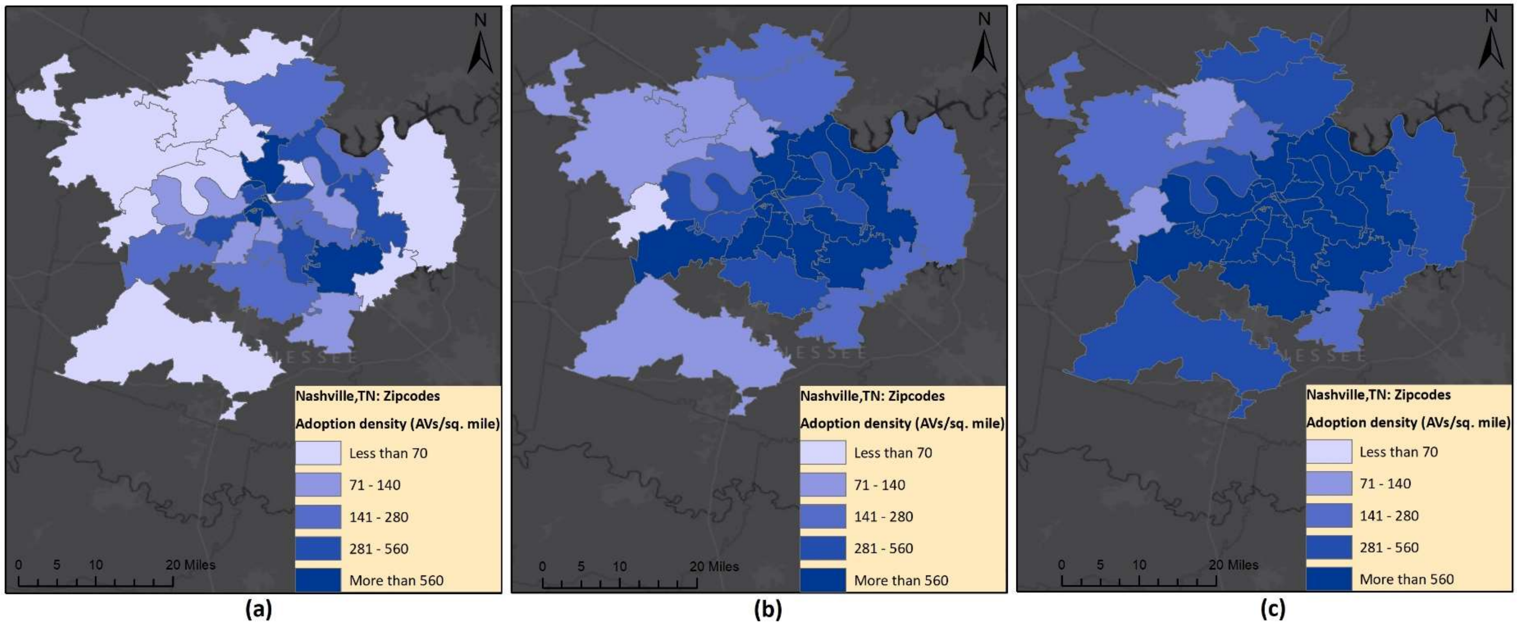


Figure S.4.4.11: AV adoption density in Nashville, TN (a) 2030 (b) 2040 (c) 2050 (weight matrix based on spatial distance with five social ties with information dissemination)

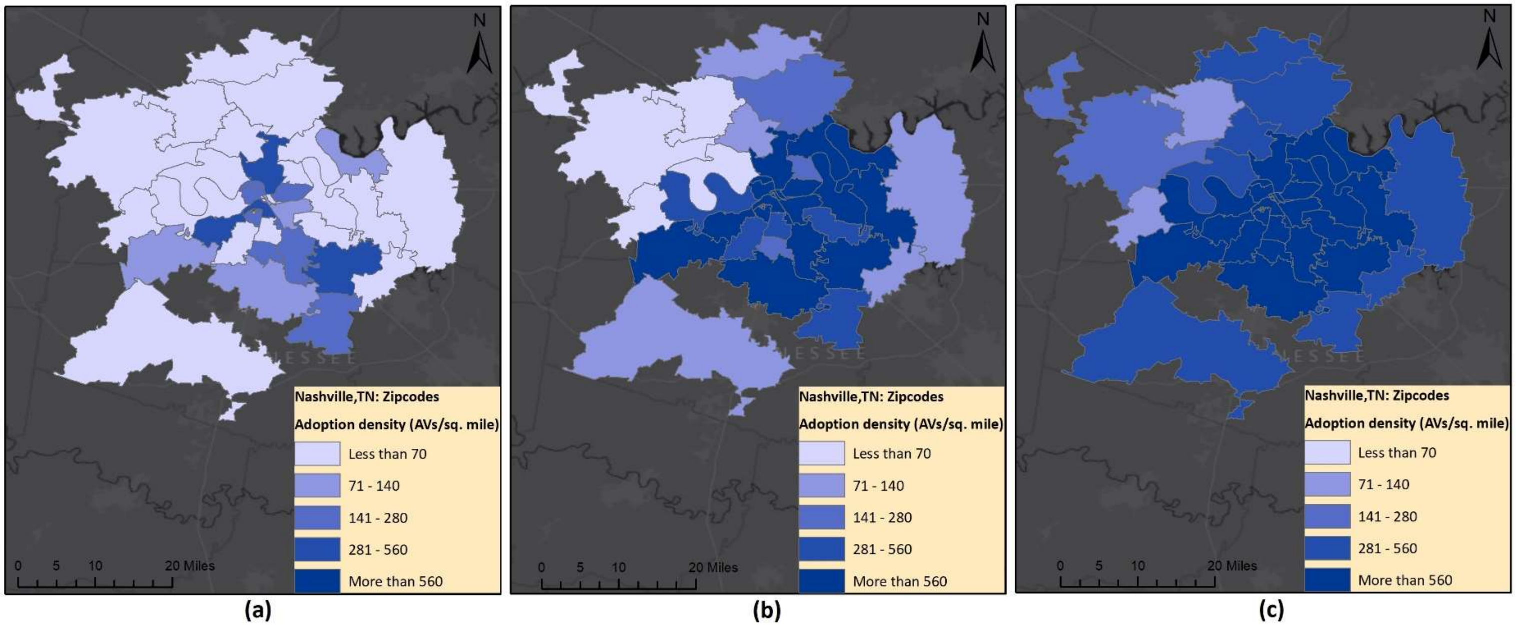


Figure S.4.4.12: AV adoption density in Nashville, TN (a) 2030 (b) 2040 (c) 2050 (weight matrix based on spatial distance with five social ties without information dissemination)

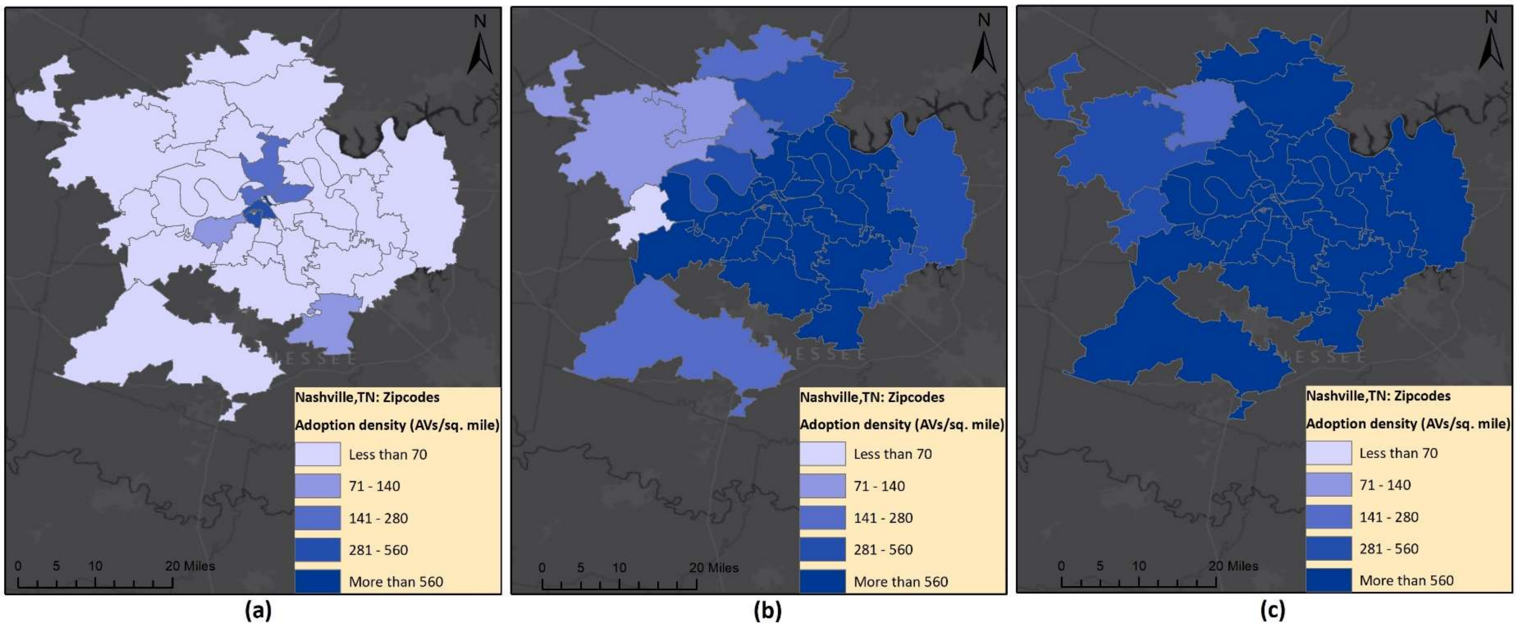


Figure S.4.4.13: AV adoption density in Nashville, TN (a) 2030 (b) 2040 (c) 2050 (weight matrix based on Gower distance with ten social ties with information dissemination)

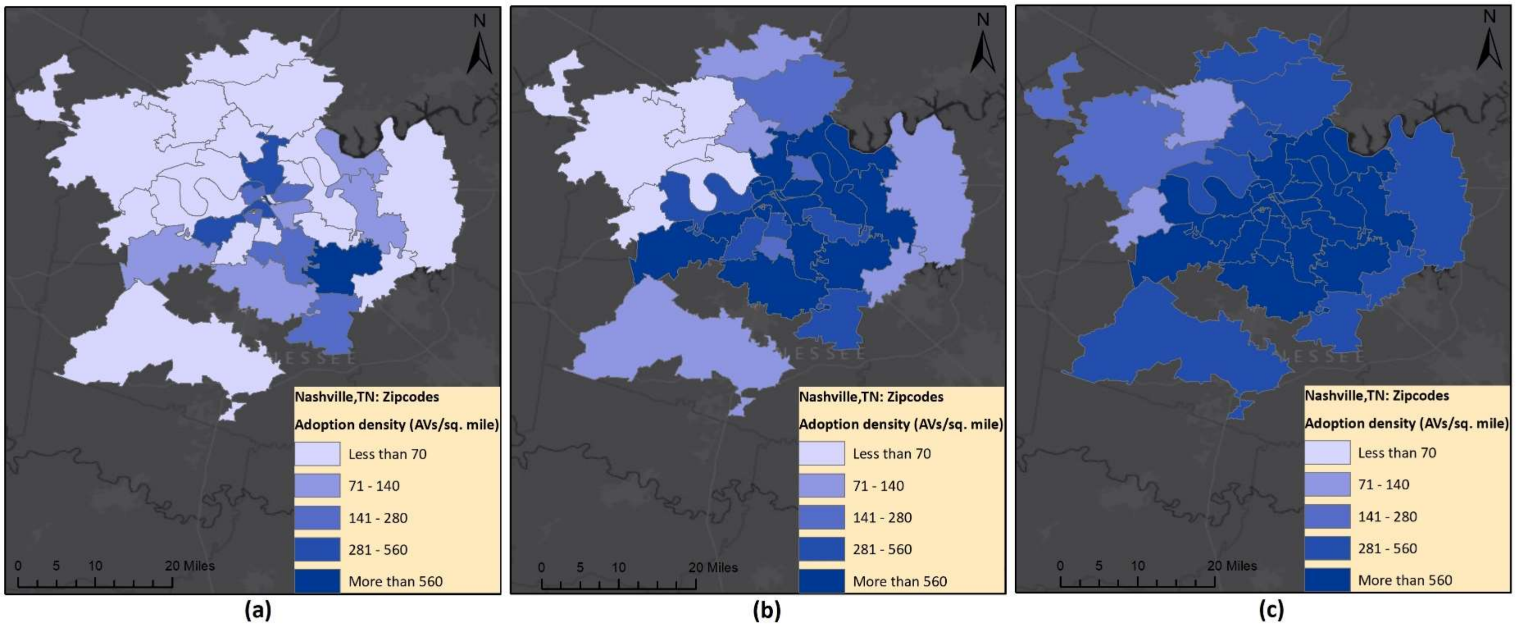


Figure S.4.4.14: AV adoption density in Nashville, TN (a) 2030 (b) 2040 (c) 2050 (weight matrix based on Gower distance with ten social ties without information dissemination)

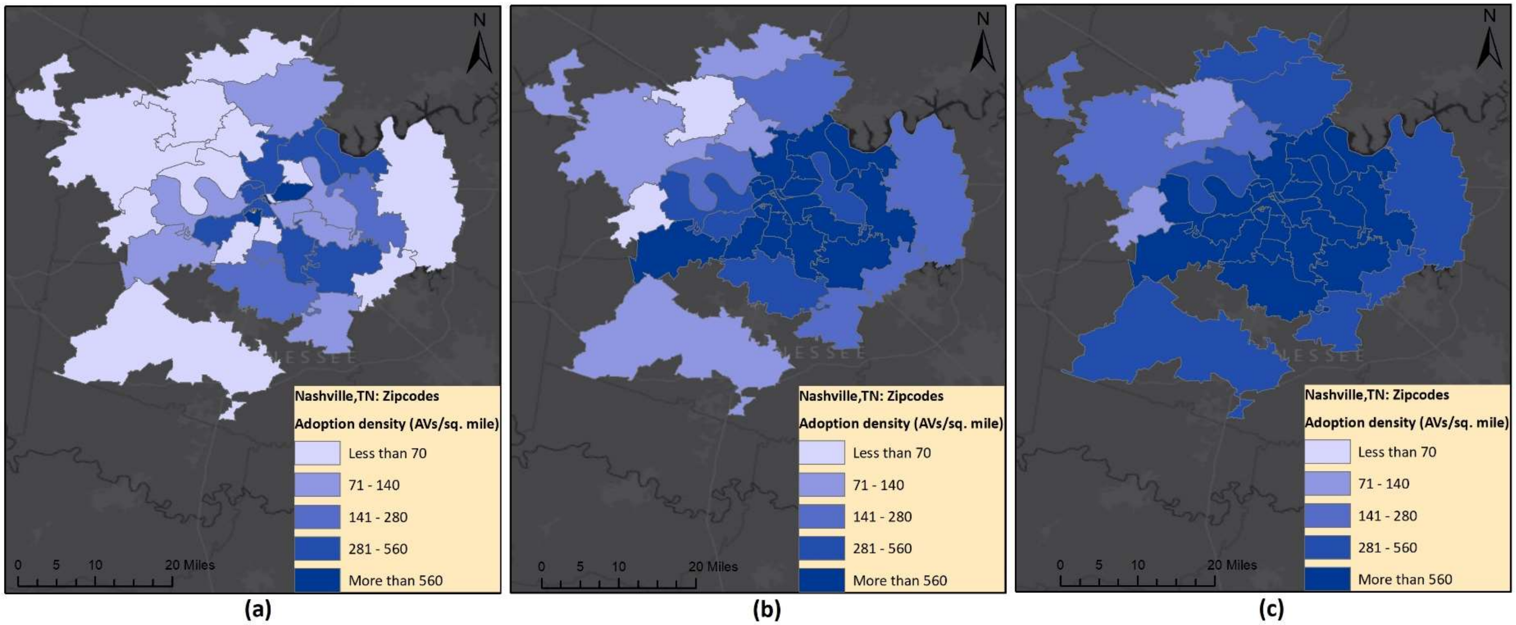


Figure S.4.4.15: AV adoption density in Nashville, TN (a) 2030 (b) 2040 (c) 2050 (weight matrix based on spatial distance with ten social ties with information dissemination)

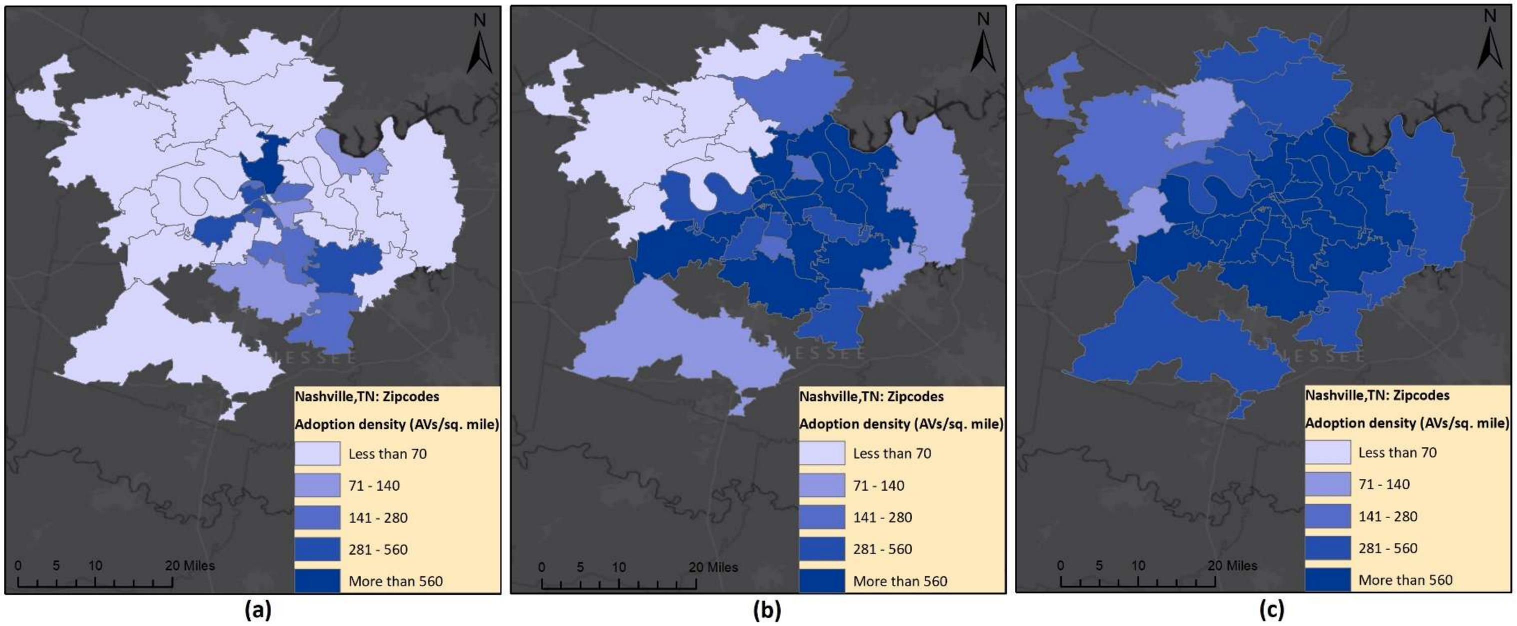


Figure S.4.4.16: AV adoption density in Nashville, TN (a) 2030 (b) 2040 (c) 2050 (weight matrix based on spatial distance with ten social ties without information dissemination)

Chapter 5 - Conclusion

With the overall objective of developing a comprehensive user preference module and subsequent validation in the context of mobility-on-demand (MOD) services, the current work contributes to the literature on flexible discrete choice models (DCM) and empirically demonstrates their capability to minimize the discrepancy between observed and modelled behaviour, i.e. improve model accuracy. Methods/approaches developed in this work can be used in other disciplines such as marketing, social sciences, etc., to improve our understanding of an individual's decision strategy. In this chapter, we synthesize the key findings, related policy implications and outline future research directions to address study limitations.

5.1 Main Findings

In this section, we discuss the key findings and insights corresponding to the three research questions posed in the Introduction.

Research question 1*: Formulate and validate a flexible discrete choice model within a random utility framework (RUM) to model various decision strategies with minimal to no a-priori assumptions (Chapter 2)*

To approximate various decision strategies in a single framework with minimal to no a-priori assumption, we utilized a flexible aggregation function called Choquet-Integral (CI). CI can approximate various widely used functions such as weighted sum, ordered weighted sum, and minimum or maximum from the set of attribute values. We further improved the model formulation through endogenous attribute cut-offs with the help of fuzzy membership functions. The proposed formulation is appealing to practitioners as it does not require deviation from the well-established random utility framework (RUM) and can easily be used in both logit and kernel-based discrete choice models. Despite being a highly non-linear model, the simulation exercises confirm excellent parameter recoverability and coverage probability (small deviation between finite sample standard error (FSSE) and asymptotic standard error (ASE)). The generality of the model is also established against a widely used multinomial probit (MNP) model with non-identical and independently distributed (IID) error configuration through simulation exercise. Finally, the model is empirically validated using mobility-on-demand (MOD) choice data. Results obtained for the CI model indicate the presence of non-compensatory choice behaviour with intuitive attribute importance ranking. However, the current DCM workhorse (MNP model) failed to obtain such behavioural insights and resulted in inferior data fit.

Research question 2*: Evaluate medium-to-long-term competition of MOD services through a context-aware survey and obtain pricing estimates necessary for achieving critical mass (Chapter 3)*

In evaluating medium-to-long-term competition of MOD services, we choose to focus our attention on regular trips. The travel mode decisions of regular trips are habit driven which implies the usage of simpler decision strategy and non-consideration of irrelevant options. Hence, we constructed individual-specific choice sets in a context-aware stated preference (SP) survey (individual-specific origin-destination pairs with non-hypothetical travel attributes obtained using Google Map API) consisting of only currently used primary mode and MOD options. This allows us to approximate a two-step choice process where irrelevant options are discarded in the first step followed by the evaluation of relevant options in the second stage.

Car and train users show potential for modal substitution with a potential shift towards using MOD services for their regular trips. As expected, travel cost is the most important determinant of the choice. However, the importance varies depending on the current primary mode with public transport users attributing high importance to the cost. We also found that MOD reliability (both travel and waiting time) is only relevant for car and train users. Based on the choice behaviour, a per km cost of 0.6€ or less may be required to attract a substantial share (68%) of car users towards the MOD service. Similarly, a per km cost of 0.3€ and 0.4€ for train/metro (70%) and bus/tram/light-rail (70%), respectively, will be needed to attract current public transport users. For reference, 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.

Research question 3*: Develop a framework to explicitly incorporate interpersonal network effects in the preference modelling framework to understand the effect of various policy levers (Chapter 4)*

The impact of social influence on behaviour is well recognized. Yet, mathematical modelling of the process has been elusive due to computational challenges. An explicit representation of information propagation in the modelling framework is paramount to simulate policy scenarios. We build upon the framework proposed by Bhat et. al., (2016) to represent word-of-mouth (WOM) propagation in an individual's interpersonal network. The framework is both behaviorally robust and computationally feasible. The framework is a combination of a well-known structural equation modelling (SEM) framework and a discrete choice model (DCM). Information propagation is captured by representing WOM as a weighted latent variable based on an interpersonal network.

The model is calibrated using automatic vehicle (AV) preference data collected through an SP survey for Davidson country (Tennessee, U.S.A) in the absence of MOD choice data with the required information. An agent-based simulation is used (representing more than 0.4 million households) to highlight the effect of various policies in the context of AV adoption such as the effects of price evaluation and post-purchase satisfaction on overall adoption. Model results suggest that ignoring WOM propagation may result in an over-estimation of the overall AV adoption trajectory. We found that an increase in the proportion of satisfied consumers (post-purchase) accelerates the overall adoption in the population due to the propagation of positive WOM. Results also suggest that an interpersonal network based on a distance matrix may lead to a faster adoption rate as compared to a socio-demographic similarity-based interpersonal network for the same proportion of satisfied consumers. Finally, a base price of 60,000$ with a 10% per annum reduction and 30% satisfied consumers (post-purchase) may result in a 100% adoption of AV over 28 years.

5.2 Policy Implications

In most cases, the use of flexible choice models results in an improvement in data fit. However, such an improvement may not necessarily translate into improved behavioural insights. For example, a mixed logit or probit model may provide a better data fit as compared to models with IID error structures. One of the main advantages of the models developed in this dissertation (CI-based choice model and choice model with the interpersonal network) is their ability to open the black box of heterogeneity. Below we discuss two key findings and their policy implications. First, in Chapter 2, we obtained a group-specific (defined based on a combination of demographic characteristics) non-linear preference curve for mode attributes (travel time, waiting time, and cost) in the context of MOD services choice in New York City. We also obtained varying attribute importance ranking and degree between MOD services and the current mode. These empirical findings align with the results (implicit) reported in the literature. An explicit confirmation enhances the validity of the model in terms of reducing the gap between the true underlying strategy and the modelled decision strategy. These empirical insights may allow operators to customize their offerings (differential pricing) and may increase their overall market share. Such a claim is further validated in Chapter 3 for the choice of MOD services in the Netherlands for regular trips. We observed that 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 MOD. These behavioural insights not only empower operators but may also help formulate policies to maintain a balance between equity and mobility. These findings related to public transport users are in particular interesting. The MOD pricing for public transport users suggests that only a limited proportion (around 35%) of such users can be brought into the pool of MOD prospective users. Hence, the notion of adverse impact on public transport due to the introduction of MOD services at least in the Netherlands is limited.

Second, in the social influence model (chapter 4), we observed a significant effect of word-of-mouth on risk aversion and purchase behaviour of automated vehicles (AV). It strengthens the importance of information (positive or negative) received from social circles in moulding one's behaviour. Specifically, we observed that the behaviour is more effectively explained through the utilization of an interpersonal network built upon the homophilic principle as compared to a geographical distance-based interpersonal network. This has several implications for the adoption of Avs.

1. **Personalized Services:** If individuals with similar interests and social connections tend to influence each other's behaviour more, automated vehicle services could be personalized based on the preferences and habits of specific social or interest groups. This might lead to an increase in the rate of adoption.

2. **Targeted Marketing:** Companies developing automated vehicles may use the knowledge of homophilic networks to target specific groups more effectively. They can design marketing strategies that resonate with the shared interests and values of these groups, potentially accelerating adoption.

3. **Policy Design:** Policymakers might consider the importance of social networks and shared interests when regulating and promoting automated vehicles. Policies could be designed to support initiatives that leverage these social connections for greater adoption.

5.3 Future Research Directions

In addition to the limitations and future directions identified at the end of each chapter (in the section- conclusion and future work), we identify a few key research directions to further improve the discrete choice model flexibility and, consequently, the empirical validity of the results in the context of MOD services. They are discussed below:

Individual-specific decision-strategy modeling

As demonstrated in Chapter 2, the Choquet-Integral (CI) based choice model is robust at approximating various decision strategies. However, the extracted decision strategy is an aggregate representation of the average behaviour in the sample. Eliciting decision strategy at an individual level requires estimation of as many CIs, a computationally infeasible strategy. To overcome this challenge, the fuzzy measures (parameter of CI) can be parametrized as a function of demographic features to extract feature importance (Shapley value) at the individual level. This creates an additional challenge due to the monotonicity requirements of CI. I.e., the coefficient of attributes (used for parametrization of fuzzy measures) should maintain monotonicity constraints at the individual level (defined as a combination of socio-demographic features). This effectively increases the number of inequality constraints from K (function of number of features) to NK (N : sample size). Solving a constrained problem with a large number of constraints (equality and inequality) through the sequential least square quadratic programming (SLSQP) approach needs to be evaluated for medium (10K or less) to large sample sizes to increase the practical relevance of the CI-based choice model.

Empirical validation of choice set construction in stated-preference (SP) survey

From a behavioural perspective, it is appealing to construct individual-specific choice sets based on the context and current usage in the SP survey. As discussed in Chapter 3, the SP survey employed in the study only included the currently used primary mode and MOD options. Removing irrelevant options (not reported by the individual in the revealed preference (RP) stage) in a deterministic way can be problematic due to self-reported bias. To minimize the bias, a few irrelevant options can be added randomly in the SP choice set for a few choice tasks. It can also help test the validity of the stated/assumed hypothesis on choice set construction based on elicited preference. Empirical validation of restricted choice set construction design across contexts can potentially minimize the discrepancy between true and observed decision strategy aided by application programming interface (API) based SP design and flexible choice models.

Dynamic pricing policy for MOD operators

In the current work, we restricted our focus to the demand side of the MOD service. It allowed us to attain point estimates of price attributes necessary for obtaining critical maas (mobility-as-a-service). The performance (pricing, ride availability, pick-up time) of the MoD service relies heavily on the interaction between demand (users) and supply (operator/operators). In a two-sided market, demand does not only depend on the supply but also on the number and type of consumers (known as network externality). Further, the number of individuals willing to use an MOD service is endogenously related to the quality (level of service) of the MOD service. The situation is further worsened in the presence of multiple MOD operators because the environment consists of other agents who are similarly adapting and thus the environment is no longer stationary, and the familiar theoretical guarantees no longer apply. Moreover, the non-stationarity of the environment is not generated only by a stochastic process (both known and unknown factors which impact the choice and, consequently determine the market share), but also by other agents, who might be presumed rational or at least regular in some important way (i.e., the decisions are not completely random). Further, in a multi-operator market, the consumers as well as drivers can choose to consume products from more than one supplier at any given time (also known as multihome). It may lead to a highly dynamic demand system (as observed by an operator on a day-to-day basis) depending upon the preferences of users.

To derive a dynamic pricing strategy (for both single and multi-operator cases), the demand is linked with supply where supply is represented through fleet size and requests for vehicle matching. While many matching algorithms exist as discussed in Chapter 1 (including Ma et. al., 2013; Alonso-Mora et. al., 2017, Kucharski and Cats, 2020), they cannot mimic a true real-time request to matching scenario. For example, the algorithm proposed by Alonso-Mora et. al., (2017) assumes perfect sharing among requests to minimize computation time. Similarly, the algorithm of Kucharski and Cats, (2020) requires a-priori knowledge of demand to construct a computationally feasible shareability graph. To mimic real-world matching, the algorithm needs to process requests over a small time window in a batch and be myopic to represent an imperfect knowledge of the demand pattern with an objective function of profit maximization or vehicle miles travelled (VMT) minimization. Constructing a myopic algorithm with a profit maximization objective function allows for differentiation between private and shared requests during the matching process and may increase the validity of the obtained pricing values. To the best of our knowledge, such a matching algorithm is yet to be developed. To obtain meaningful pricing strategies, one needs to model the two-sided nature of the MOD market jointly where demand can be represented using the choice model and parameters obtained in the current work and supply heterogeneity is represented using a realistic request to vehicle matching algorithm and driver preference and behaviour as reported by Ashkrof et. al., (2022; 2023). With such a framework, one can solve the dynamic pricing problem using a Markov decision process (MDP). In particular, one may use a deep deterministic policy gradient (DDPG) algorithm (Lillicrap et. al., 2015) to determine a dynamic pricing strategy for both single-operator and multi-operator scenarios based on the samples (pairs of MOD share corresponding to a price value) generated by the two-sided MOD framework.

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Summary

Due to rapid advancements in internet technology and computing capabilities in the last decade, Mobility-on-demand (MOD)/ride-hailing services (Uber, Lyft, Ola, DiDi, etc.) have emerged as an alternative to both private (de Souza Silva et al., 2018) and public-transport (Clewlow and Mishra, 2017) and traditional taxi services (Brown and LaValle, 2021). MOD services offer higher reliability and better accountability to customers and hence can be expected to draw share from public transport and taxis. Further, private vehicle owners may also shift to MOD services to avoid the hassle of finding parking and increase productivity during commutes.

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. New research on the usage of MOD services has found that individuals use ride-hailing to fill an occasional rather than regular travel need (Alemi et. al., 2018; Brown, 2018; Grahn et. al., 2019, Ilavarasan et. al., 2018; Tirachini and del Río 2019). There are also mixed results on the substitution and complementarity effect between public transport and MOD services. Hence, in this work, we evaluate the medium to long-term potential of MOD services for regular trips. Such an evaluation can shed more light on the changes in vehicle ownership levels and residential location, which may lead to long-term changes in land-use patterns. In this dissertation work, we attempt to develop and validate a comprehensive user preference module in the context of MOD services.

A significant proportion of the 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). Next, empirical evidence points to the usage of simple heuristics by decision makers (representing some variation of non-compensatory decision strategy) in familiar repeated choices such as grocery shopping, mode choice, etc., (Foerster, 1979; Hoyer, 1984; Hoyer and Brown, 1990; Aarts et al., 1997; Innocenti et al., 2013; Rashedi and Nurul Habib, 2020). These two observations suggest that the evaluation of MOD service for regular trips requires the construction of individual-specific choice sets and access to a flexible assumption-free (compensatory vs. non-compensatory) modelling framework. Next, the MOD services are not equally prevalent in all geographical areas. In areas where MOD services are relatively new or have low penetration, word-of-mouth (WOM) can also impact an individual's preference. I.e., positive or negative information about the service obtained from his/her interpersonal network may also regulate the preference known as social influence. Therefore, a comprehensive evaluation of MOD preference must include all three aspects: individual-specific choice set construction approach, assumption-free behavioural model, and social network effect.

In the first part of this dissertation, we focus on the development of a flexible discrete choice model. Presently, in the domain of flexible models, two approaches exist: attribute cut-off approach and utility regulation. The endogenous attribute cut-off model (Martinez et. al., 2009) is computationally challenging as it requires solving a complex fixed-point problem. The utility regulation model (Elord et. al., 2004) can be numerically challenging to optimize due to

trigonometric functions used to introduce spikes/drops in the utility function. Hence, to approximate various decision strategies in a single framework with minimal to no a-priori assumption. We utilize a flexible aggregation function called Choquet-Integral (CI). CI can approximate various widely used functions such as weighted sum, ordered weighted sum, and minimum or maximum from the set of attribute values. We further improve the model formulation through endogenous attribute cut-offs with the help of fuzzy membership functions. The proposed formulation is appealing to practitioners as it does not require deviation from the random utility framework (RUM) and can easily be used in both logit and probit kernel-based discrete choice models. Despite being a highly non-linear model, the model exhibits excellent parameter recoverability and coverage probability. Owing to the generality of the CI function, the CI-based discrete choice model can easily replace existing workhorse models such as mixed logit or probit.

Next, in the second part of the dissertation, we evaluate medium-to-long-term competition of MOD services. We design a stated preference (SP) survey using Google Map API to construct individual-specific choice sets. To ensure a non-spurious estimate of travel attributes. We include important travel aspects such as reliability and departure time preference. With the help of a CI-based discrete choice model, we empirically validate the evidence of a non-compensatory choice strategy in the choice of MOD services for regular trips. The policy implication of incorrect behaviour strategy is highlighted through price estimates necessary for obtaining critical maas (mobility-as-a-service).

In the third and last part of this dissertation, we develop a framework to accommodate social influence on behaviour through an information propagation mechanism. The framework is behaviorally appealing as it provides an explicit representation of information propagation in the modelling framework and is computationally feasible. The framework is a combination of a well-known structural equation modelling (SEM) framework and a discrete choice model (DCM). The information propagation is captured by representing information propagation (also known as word-of-mouth) as a weighted latent variable based on interpersonal network. The model is calibrated using automatic vehicle (AV) preference data collected through an SP survey in the absence of necessary MOD choice data. An agent-based simulation is used to highlight the importance of accommodating social influence in preference modelling through various policy scenarios in the context of AV adoption.

Overall, this dissertation develops a framework to evaluate the MOD preference for regular trips and assess its medium to long-term potential. The framework is general and can also be used in other disciplines such as marketing, social sciences, etc., to improve our understanding of an individual's decision strategy.

Samenvatting

Vanwege de snelle vooruitgang in internettechnologie en computercapaciteiten in het afgelopen decennium, zijn Mobility-on-demand (MOD)/ride-hailing-diensten (Uber, Lyft, Ola, DiDi, enz.) naar voren gekomen als een alternatief voor zowel particulier vervoer (de Souza Silva et al., 2018) als openbaar vervoer (Clewlow en Mishra, 2017) en traditionele taxidiensten (Brown en LaValle, 2021). MOD-diensten bieden een hogere betrouwbaarheid en betere verantwoordingsplicht aan klanten en zullen daarom naar verwachting een aandeel verwerven van het openbaar vervoer en taxi's. Verder kunnen eigenaren van particuliere voertuigen ook overstappen op MOD-diensten om de moeite van het vinden van parkeerplaatsen te vermijden en de productiviteit tijdens het woon-werkverkeer te verhogen.

Ondanks dergelijke aangekondigde voordelen is het marktaandeel van MOD-diensten relatief laag, vooral voor reguliere reizen. Volgens een rapport van DBS Asian Insights (2019) bedraagt de penetratie van ridesharing-diensten nog steeds minder dan 1% van alle reizen met personenauto's tot een afstand van 30 mijl in de Verenigde Staten. Uit nieuw onderzoek naar het gebruik van MOD-diensten is gebleken dat individuen ride-hailing gebruiken voor een incidentele reis in plaats van in regulier vervoer (Alemi et. al., 2018; Brown, 2018; Grahn et. al., 2019; Ilavarasan et. al. ., 2018; Tirachini en del Río 2019). Er zijn ook wisselende resultaten over het substitutie- en complementariteitseffect tussen openbaar vervoer en MOD-diensten. Daarom beoordelen we in deze studie het potentieel op de middellange tot lange termijn van MOD-diensten voor reguliere reizen. Een dergelijke beoordeling kan meer inzicht bieden op de veranderingen in het autobezit en de woonlocatie, wat kan leiden tot veranderingen op de lange termijn in de patronen voor het gebruik van land. In dit proefschrift proberen we een uitgebreide gebruikersvoorkeursmodule te ontwikkelen en te valideren in de context van MOD-diensten.

Een aanzienlijk deel van de ritten die op weekdagen worden gemaakt, betreft reguliere reizen zoals woon-werkverkeer, boodschappen doen en naar school/universiteit. Beslissingen over de manier van reizen voor reguliere/herhaalde taken zijn vaak gebaseerd op gewoontes en gedrag (Ramos et al., 2020). Daarom kan een individu de nieuwe MOD-dienst(en) alleen vergelijken met het momenteel gebruikte vervoermiddel (auto, openbaar vervoer, fiets en lopen) in de context van reguliere reizen. Een dergelijke veronderstelling is niet ongegrond en er bestaat empirisch bewijs voor dergelijk gedrag in de transportsector (Thøgersen, 2006; Gao et al., 2020) en andere contexten zoals landbouweconomie en marketing (Chang et al., 2009; Eliaz en Spiegler, 2011). Vervolgens wijst empirisch bewijsmateriaal op het gebruik van eenvoudige heuristieken door besluitvormers (die een variatie van een niet-compensatoir besluitvormingsstrategie vertegenwoordigen) bij bekende herhaalde keuzes zoals boodschappen doen, vervoerskeuze, enz. (Foerster, 1979; Hoyer, 1984; Hoyer, 1984; Hoyer en Brown, 1990; Aarts et al., 1997; Innocenti et al., 2013; Rashedi en Nurul Habib, 2020). Deze twee observaties suggereren dat de beoordeling van MOD-diensten voor reguliere ritten de constructie van individueel specifieke keuzesets vereist en toegang tot een flexibel aanname-vrij (compensatoir vs. niet-compensatoir) model. Overigens zijn MOD-diensten niet evenzeer aanwezig in alle geografische gebieden. In gebieden waar MOD-diensten relatief nieuw zijn of een lage penetratie hebben, kan mond-tot-mondreclame ook van invloed zijn op de voorkeur van een individu. Dat wil zeggen dat positieve of negatieve informatie over de dienst verkregen uit zijn/haar interpersoonlijke netwerk ook de voorkeur kan reguleren die bekend staat als sociale invloed. Daarom moet een alomvattende beoordeling van de MOD-voorkeur alle drie de aspecten omvatten: de individueel-specifieke aanpak van de keuzereeks, het aanname-vrije gedragsmodel en het sociale netwerkeffect.

In het eerste deel van dit proefschrift richten we ons op de ontwikkeling van een flexibel discreet keuzemodel. Momenteel bestaan er op het gebied van flexibele modellen twee benaderingen: attribute-cut-off en utility regulation. Het endogene attribute-cut-off-model (Martinez et. al., 2009) is computationeel uitdagend omdat het de oplossing van een complex probleem met een vast punt vereist. Het utility-regulation-model (Elord et. al., 2004) kan numeriek een uitdaging zijn om te optimaliseren vanwege trigonometrische functies die worden gebruikt om pieken/dalingen in de nutfunctie te introduceren. Vandaar dat we verschillende besluitvormingsstrategieën in één raamwerk kunnen benaderen, met minimale tot geen a-priori aannames. We gebruiken een flexibele aggregatiefunctie genaamd Choquet-Integral (CI). CI kan verschillende veelgebruikte functies benaderen, zoals gewogen som, geordende gewogen som en minimum of maximum uit de set eigenschapwaarden. We verbeteren de formulering van de modellen verder door middel van endogene attribute-cut-offs met behulp van vage lidmaatschapsfuncties. De voorgestelde formulering is aantrekkelijk voor praktijkmensen, omdat er geen afwijking van het Random Utility Framework (RUM) is vereist en gemakkelijk kan worden gebruikt in zowel logit- als probit-kernel-gebaseerde discrete keuzemodellen. Ondanks dat het een zeer niet-lineair model is, vertoont het model uitstekend herstel van parameters en dekkingswaarschijnlijkheid. Vanwege de algemeenheid van de CI-functie kan het CI-gebaseerde discreet keuzemodel gemakkelijk bestaande werkpaard-modellen vervangen, zoals gemengde logit of probit.

Vervolgens beoordelen we in het tweede deel van het proefschrift de concurrentie op de middellange tot lange termijn van MOD-diensten. We ontwerpen een 'stated preference' (SP) enquête met behulp van de Google Map API om individueel-specifieke keuzesets samen te stellen. Om een niet-onjuiste schatting van reiseigenschappen te waarborgen, nemen we belangrijke reisaspecten op zoals betrouwbaarheid en voorkeur voor vertrektijd. Met behulp van een op CI gebaseerd discreet keuzemodel valideren we empirisch het bewijs van een niet-compensatoir keuzestrategie bij de keuze van MOD-diensten voor reguliere reizen. De beleidsimplicaties van een onjuiste gedragsstrategie wordt belicht door prijsramingen die nodig zijn voor het verkrijgen van kritieke MaaS (mobiliteit-als-een-service).

In het derde en laatste deel van dit proefschrift ontwikkelen we een raamwerk om sociale invloed op gedrag te accommoderen via een mechanisme voor informatieverstrekking. Het raamwerk is gedragsmatig aantrekkelijk omdat het een expliciete representatie biedt van informatieoverdracht in de gebruikte modellen en computationeel haalbaar is. Het raamwerk is een combinatie van een bekend raamwerk voor structurele vergelijkingsmodellen (SEM) en een discreet keuzemodel (DCM). De informatieoverdracht wordt vastgelegd door informatieoverdracht (ook bekend als mond-tot-mondreclame) weer te geven als een gewogen latente variabele op basis van interpersoonlijk netwerk. Het model is gekalibreerd met behulp van gegevens over voorkeur voor automatische voertuigen (AV), verzameld via een SP-enquête bij gebrek aan noodzakelijke gegevens van MOD-keuzes. Een agent-based simulatie wordt gebruikt om het belang te benadrukken van het accommoderen van sociale invloed in voorkeursmodellering via verschillende beleidsscenario's in de context van AV-adoptie.

Al met al ontwikkelt dit proefschrift een raamwerk om de MOD-voorkeur voor reguliere reizen te evalueren en het potentieel ervan op de middellange tot lange termijn te beoordelen. Het raamwerk is algemeen en kan ook worden gebruikt in andere disciplines zoals marketing, sociale wetenschappen, enz., om ons begrip van de besluitvormingsstrategie van een individu te verbeteren.

About the author

Subodh Dubey was born in Ranchi, India in 1988. He completed his Bachelor's in Civil Engineering from Anna University, India in 2009. In 2011, he finished his Master of Engineering degree in Transport from Birla Institute of Technology and Science (BITS) Pilani, India. As part of his Master's thesis, he evaluated the feasibility of econometric methods (multinomial and mixed multinomial logit model), fuzzy logic (to accommodate non-crisp attributes) and adaptive neuro-fuzzy logic to model route choice behaviour of individuals.

He started his PhD at the Transport and Planning (T&P) department, Faculty of Civil Engineering and Geosciences, Delft University of Technology in 2019. Before joining Delft University, he has worked at the University of Texas at Austin, USA, Institute for Choice, Sydney, Australia and Tiger Analytics, Chennai as a researcher and Data analyst.

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List of Publications

Journal articles

1. **Dubey**, S., Cats, O., Hoogendoorn, S., & Bansal, P. (2022). A multinomial probit model with Choquet integral and attribute cut-offs. *Transportation Research Part B: Methodological*, *158*, 140-163.
2. **Dubey**, S., Sharma, I., Mishra, S., Cats, O., & Bansal, P. (2022). A general framework to forecast the adoption of novel products: A case of autonomous vehicles. *Transportation research part B: methodological*, *165*, 63-95.
3. **Dubey**, S. K., Cats, O., & Hoogendoorn, S. Understanding Preferences for Mobility-on-Demand Services through a Context-Aware Survey and Non-Compensatory Strategy. *Available at SSRN 4226856*. *(Under review).*

Peer-reviewed conference publications

1. **Dubey**, S., Cats, O., Hoogendoorn, S., & Bansal, P. (2022). A multinomial probit model with Choquet integral and attribute cut-offs. *International Choice Modelling Conference, Reykjavik, Iceland*.
2. **Dubey**, S., Cats, O., & Hoogendoorn, S. (2022). Understanding Preferences for Mobility-on-Demand Services through a Context-Aware Survey and Non-Compensatory Strategy. *32nd EURO Conference, Aalto University, Finland.*

TRAIL Thesis Series

Dubey, S., *A Flexible Behavioral Framework to Model Mobility-on-Demand Service Choice Preferences,* T2023/19, November 2023, TRAIL Thesis Series, the Netherlands

Sharma, S., *On-trip Behavior of Truck Drivers on Freeways: New mathematical models and control methods,* T2023/18, October 2023, TRAIL Thesis Series, the Netherlands

Ashkrof, P., *Supply-side Behavioural Dynamics and Operations of Ride-sourcing Platforms,* T2023/17, October 2023, TRAIL Thesis Series, the Netherlands

Sun, D., *Multi-level and Learning-based Model Predictive Control for Traffic Management,* T2023/16, October 2023, TRAIL Thesis Series, the Netherlands

Brederode, L.J.N., *Incorporating Congestion Phenomena into Large Scale Strategic Transport Model Systems*, T2023/15, October 2023, TRAIL Thesis Series, the Netherlands

Hernandez, J.I., *Data-driven Methods to study Individual Choice Behaviour: with applications to discrete choice experiments and Participatory Value Evaluation experiments*, T2023/14, October 2023, TRAIL Thesis Series, the Netherlands

Aoun, J., *Impact Assessment of Train-Centric Rail Signaling Technologies,* T2023/13, October 2023, TRAIL Thesis Series, the Netherlands

Pot, F.J., *The Extra Mile: Perceived accessibility in rural areas*, T2023/12, September 2023, TRAIL Thesis Series, the Netherlands

Nikghadam, S., *Cooperation between Vessel Service Providers for Port Call Performance Improvement,* T2023/11, July 2023, TRAIL Thesis Series, the Netherlands

Li, M., *Towards Closed-loop Maintenance Logistics for Offshore Wind Farms: Approaches for strategic and tactical decision-making*, T2023/10, July 2023, TRAIL Thesis Series, the Netherlands

Berg, T. van den, *Moral Values, Behaviour, and the Self: An empirical and conceptual analysis,* T2023/9, May 2023, TRAIL Thesis Series, the Netherlands

Shelat, S., *Route Choice Behaviour under Uncertainty in Public Transport Networks: Stated and revealed preference analyses,* T2023/8, June 2023, TRAIL Thesis Series, the Netherlands

Zhang, Y., Flexible, *Dynamic, and Collaborative Synchromodal Transport Planning Considering Preferences*, T2023/7, June 2023, TRAIL Thesis Series, the Netherlands

Kapetanović, M., *Improving Environmental Sustainability of Regional Railway Services,* T2023/6, June 2023, TRAIL Thesis Series, the Netherlands

Li, G., *Uncertainty Quantification and Predictability Analysis for Traffic Forecasting at Multiple Scales,* T2023/5, April 2023, TRAIL Thesis Series, the Netherlands

Harter, C., *Vulnerability through Vertical Collaboration in Transportation: A complex networks approach,* T2023/4, March 2023, TRAIL Thesis Series, the Netherlands

Razmi Rad, S., *Design and Evaluation of Dedicated Lanes for Connected and Automated Vehicles,* T2023/3, March 2023, TRAIL Thesis Series, the Netherlands

Eikenbroek, O., *Variations in Urban Traffic,* T2023/2, February 2023, TRAIL Thesis Series, the Netherlands

Wang, S., *Modeling Urban Automated Mobility on-Demand Systems: an Agent-Based Approach,* T2023/1, January 2023, TRAIL Thesis Series, the Netherlands

Szép, T., *Identifying Moral Antecedents of Decision-Making in Discrete Choice Models,* T2022/18, December 2022, TRAIL Thesis Series, the Netherlands

Zhou, Y., *Ship Behavior in Ports and Waterways: An empirical perspective,* T2022/17, December 2022, TRAIL Thesis Series, the Netherlands

Yan, Y., *Wear Behaviour of A Convex Pattern Surface for Bulk Handling Equipment,* T2022/16, December 2022, TRAIL Thesis Series, the Netherlands

Giudici, A., *Cooperation, Reliability, and Matching in Inland Freight Transport,* T2022/15, December 2022, TRAIL Thesis Series, the Netherlands

Nadi Najafabadi, A., *Data-Driven Modelling of Routing and Scheduling in Freight Transport,* T2022/14, October 2022, TRAIL Thesis Series, the Netherlands

Heuvel, J. van den, *Mind Your Passenger! The passenger capacity of platforms at railway stations in the Netherlands,* T2022/13, October 2022, TRAIL Thesis Series, the Netherlands

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