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Driver compliance with in-vehicle smart parking system advices

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Driver compliance with in-vehicle smart parking system advices

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Preface

This report presents a study on driver compliance with in-vehicle Smart Parking System (SPS) advice and serves as the graduation thesis for the Urban Systems and Real Estate track in the Architecture, Building, and Planning master's program at Eindhoven University of Technology. The objective of this study is to assess the effectiveness of in-vehicle SPS advice by examining hypothetical behavioral changes resulting from the treatment of such advice. Undertaking this research has provided me with the opportunity to apply the knowledge and skills acquired throughout my studies, allowing me to deepen my understanding of transportation planning and research methodologies.

I would like to express my sincere gratitude to my supervisors for their valuable feedback, engaging discussions, and the overall collaborative approach to supervision. I am particularly thankful to Aloys for his insights and guidance on the methodological aspects of the study, Peter for his extensive knowledge in the field of parking, and Sina for his assistance during the reporting process. Additionally, I extend my thanks to Zuid-Limburg bereikbaar for granting me permission to distribute the survey among their panel, which resulted in a large group of respondents and provided valuable data for the study.

Finally, I would like to express my heartfelt appreciation to my friends and family for their unwavering support throughout my graduation journey. I am especially grateful to my friends at Study Association SERVICE for the stimulating conversations over numerous cups of coffee.

I sincerely hope that you will find this thesis as enjoyable to read as I found it fulfilling to create.

Dennis Andreoli

Eindhoven, June 2023

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Listings

Terminology and abbreviations

BIC Bayesian Information Criterion. 32, 40, 66

CCTV Closed Circuit Television. 15

df dataframe. 102–104, 106, 107

DRIP Dynamic Route Information Panels. 24–26

LCM Latent Class Model. 9, 10, 14, 30, 31, 35, 47, 66, 69, 70, 77, 84, 86–88

LL Log Likelihood function. 32

LL0 Log Likelihood function of the null model. 32, 107

LRS Likelihood Ratio Statistic. 32, 45, 46, 54, 70, 77

MNL Multinominal Logit Model. 9, 10, 14, 30, 31, 35, 38, 40, 45–47, 53, 54, 65, 66, 70, 84–88

P+R Park and Ride. 13

PGIS Parking Guidance and Information System. 15, 24, 51, 59

SA Stated Adaptation. 9, 28–30, 89

SPS Smart Parking System. 2, 9, 10, 12, 13, 15–18, 24, 26, 27, 29, 33–35, 59, 65, 77, 84–90

SQ Status Quo. 28, 29, 33–35, 59, 65

TAM Technology Acceptance Model. 9, 18

VMS Variable Message Signage. 9, 24, 26, 51, 88

Summary

Intelligent parking, commonly known as smart parking, has gained significant attention from policy makers and academics over the past two decades. These systems have emerged as a potential solution to address the parking challenges associated with the increasing traffic demand resulting from urban revitalization efforts. A Smart Parking System (SPS) utilizes real-time information on parking spot occupancy in a specific area, providing drivers with informed parking advice and the convenience of reserving and paying for parking through a single online platform. While existing academic literature has predominantly focused on the technological aspects of SPSs, there has been a lack of emphasis on the human-centered approach to the technology and the desired compliant behavior towards the system's advice.

The primary objective of this study is to assess the effectiveness of in-vehicle SPS advice by investigating hypothetical behavior changes resulting from SPS advice treatment. To achieve this, the research question guiding this study is formulated as follows: "What factors influence driver compliance with advice provided by in-vehicle smart parking systems?"

The literature review highlights the key components of smart parking systems, which include sensors, software platforms, and networks. However, a crucial knowledge gap exists in understanding how to maximize driver compliance with the advice provided by these systems in order to enhance their implementation potential and reduce traffic congestion caused by parking. Examination of the Technology Acceptance Model (TAM) indicates that if a SPS offers advice that is well adjusted to the preferences of users, adoption of the technology could be enhanced. Using literature on driver behavior related to parking location choice and compliance with Variable Message Signage (VMS), socio-demographic characteristics such as gender, age, education level, and income, along with parking facility attributes such as parking fee, search times and egress time, and trip characteristics like purpose and delay, are identified as potential factors that influence compliance behavior.

The methodology chapter describes the experimental design and survey construction used in the study. A Stated Adaptation (SA) experiment employing stated preferences as a means to determine the status quo parking preferences of the driver is identified as the most suitable method for determining participants' adjusted choice behavior. After examining utility theory, which serves as the main theoretical framework for the study, and modeling approaches such as Multinominal Logit Model (MNL) and Latent Class Model (LCM), the attributes and the associated levels are further refined. Among the trip characteristics, purpose and delay are included in the experiment, and among the parking facility characteristics, type, fee, search time, egress time, and difference in travel time are included. These attributes are integrated into an orthogonal experiment with two consecutive choice tasks, consisting of 144 task profiles, using Ngene.

The data used in this study was collected through an online questionnaire administered in September and October 2022. Respondents were recruited through social media, house-to-house flyering, and the Zuid-Limburg Bereikbaar mobility panel. Besides the removal of incomplete and irrelevant responses, the effects of additional data filters on model performance were examined to reduce the number of less reliable observations. It was concluded that exclusion of respondents who showed excessive non-choice behavior most efficiently increased model performance. After the data filtering process, a total of 1,577 respondents remained in the sample for analysis. Additionally, several different approaches for how data should be structured for analysis were examined.

A descriptive analysis of socio-demographic characteristics of respondents in the sample indicates that the study sample is not representative of the entire Dutch traveling population based on gender, age, and level of education. The collected data was analyzed using a MNL model and two LCM

models in NLOGIT 6. The MNL model analysis shows that parking location choice is influenced by parking facility type, fee, search time, and egress time. During the adjusted parking choice after SPS advice treatment, respondents exhibit reluctance to switch from their initial parking choice to the smart parking system's advice, and all included parking facility characteristics seem to have an effect on this adjusted choice behavior. Of the trip characteristics included in the experiment, trip purpose only affect parking choice little both of the experimental stages, while delay has larger effects in both. The socio-demographic characteristics gender, age, and education also play a role in parking choice behavior.

The LCM analysis reveals distinct patterns among respondents. In the 2-class LCM model, class 2 exhibits stronger preferences and greater confidence in evaluating alternatives compared to class 1. This distinction is evident in the estimations for fees, search time, and egress time. Respondents in class 1, who have lower confidence in their decision-making, demonstrate a stronger tendency to disregard the provided SPS advice in the second stage. This pattern can be attributed to a stronger effect of cognitive dissonance. The results of the 3-class LCM model indicate extreme, but relatively comparable, valuation of preferences for classes 1 and 2 in the first stage of the experiment. For these classes, the constant for neither alternative and the hourly parking fee play significant roles in determining alternative utility. Unlike class 1, class 2 shows more significant context effects for trip purpose, while the effects of delay are comparable for the two classes. Overall, class 3 demonstrates weaker preferences in the first experimental stage. In the second stage, class 1 maintains extreme valuations, while class 2 aligns more closely with class 3, which also shows weaker preferences. Interestingly, class 2 exhibits a smaller negative value for the SPS advice constant compared to class 3.

Regarding compliance with SPS advice, the findings of this study suggest that recommended alternative parking facilities should surpass the initial option and address the inherent negative perception that drivers may have towards the suggested alternatives. In order to encourage compliance among a segment of system users, dynamic parking pricing strategies could be employed, as parking fees strongly influence parking location choices. However, for a larger portion of drivers, it is vital that the recommended SPS parking alternative significantly contributes to reducing their overall travel time. Therefore, the process of allocating drivers to available parking spots based on their routing, and especially their final destination, assumes great importance in ensuring effective implementation of SPSs.

For future research, it would be worthwhile to conduct a study that moves beyond the hypothetical context presented in this report and transitions into real-world implementation. By examining driver compliance in an actual smart parking pilot setting, the findings from this study could be validated, refuted, or expanded upon based on observed behavior. Additionally, conducting a similar study in different regions around the world could yield valuable insights for the implementation of SPS in non-Dutch or non-European contexts. Furthermore, investigating compliance with SPS advice in a time when the general public is more familiar with the smart parking concept could provide valuable insights into the impact of social environments on compliance behavior. This exploration of social dynamics would add depth to our understanding of the factors influencing compliance with SPSs.

1 Introduction

1.1 Problem definition

Due to urban revitalization, many metropolitan areas have experienced a significant surge in traffic demand, making parking a crucial aspect of traffic planning and management. Recognizing the limitations of cities in dealing with uncontrolled growth in car traffic, there is a growing consideration that parking policies contribute to the broader economic, environmental, and social objectives of towns and cities (Valleley et al., 1997). Well-designed parking policies play a vital role in promoting efficient utilization of the transportation network, reducing greenhouse gas and particulate matter emissions (Valleley et al., 1997), whilst poorly designed policies attribute to the opposite (Arnott & Inci, 2006; Shoup, 2006; Yang & Lam, 2019).

These parking policy measures aim to achieve the parking goals of the three main parking stakeholders: Local governments, parking facility owners and operators, and drivers (Van Der Waerden, 2021). Mcshane and Meyer (1982) identified a set of six general goal categories that align with the parking objectives proposed by local governments as reasons for implementing parking policies:

1. Healthy economic climate, and a business community able to support local employment needs;
2. most efficient use of existing transportation, land, and other public resources;
3. ease of mobility and accessibility of resources;
4. equity of resource distribution an preferential allocation of some resources;
5. environmental goals, especially reduced air pollution and the related goal of minimized energy consumption;
6. enhanced amenity and cultural attractiveness; preservation of a city's unique character.

The interests of parking facility owners and operators revolve around maximizing revenue, while drivers prioritize overall convenience, such as free or low parking fees and proximity to their destination. Beetham et al. (2014) highlights that some of these goals can conflict with each other, presenting challenges for policymakers.

Throughout history, various parking policy measures have been implemented to organize and regulate parking, many of which are still in use today. Examples of these policy measures include permits, pay-and-display, and time-limited parking, which are widely employed to regulate parking. Permit-based parking systems require individuals to obtain a parking permit to park in specific designated areas or zones. In the Netherlands, this approach is frequently utilized in residential neighborhoods where pay-and-display parking is implemented, to alleviate residents from having to pay at the parking meter (Rijksoverheid, 2022), while other European countries commonly employ permit holder only parking areas (Van Ommeren et al., 2014). Pay-and-display is a parking system where drivers are required to purchase a parking ticket from a parking meter and display it on their windshield while their vehicle is parked. In recent years, traditional physical parking tickets have been replaced by pay-by-phone systems, enabling drivers to make parking payments using their personal smart devices. With this method, the parking ticket is linked to the vehicle's license plate. This transition not only facilitates easier parking enforcement for authorities through the use of camera-equipped vehicles to scan license plates and verify parking payment (Gemeente Utrecht, 2023), but also enhances usage efficiency by allowing drivers to remotely extend their parking duration, among other features (Brighton & Hove City Council, 2023). Lastly, time-limited parking policies impose specific time restrictions on parking duration to ensure turnover of parking spaces.

In the past two decades, both policy makers and academics have shown interest in intelligent, or smart, parking systems as a new step in the ongoing process of parking policy development. A Smart Parking System (SPS) utilizes real-time information on parking spot occupancy in a specific area to provide drivers with informed parking advice and the convenience of reserving and paying for parking through a single online platform. While the existing academic literature has predominantly focused on the technological aspects of SPSs (e.g., Bagula et al. (2015), Khanna and Anand (2016), Kianpisheh et al. (2012), Lu et al. (2009), and Polycarpou et al. (2013)), a research gap can be identified regarding the impact of the advice generated by SPSs on driver parking behavior. Like any new technology, the efficacy of SPSs is contingent upon sufficient adoption. Therefore, this study aims to address this research gap and investigate driver compliance to in-vehicle SPS advices.

1.2 Research questions, objective and scope

The objective of this study is to examine the efficacy of in-vehicle SPS advice by investigating hypothetical behavior changes resulting from SPS advice treatment. To gain insights into compliance behavior towards the system, the following research question is formulated:

"What factors influence driver compliance with advice provided by in-vehicle smart parking systems?"

Having established the research question, as the central focus of this study, the subsequent part will delve into the various sub-questions formulated to gain a comprehensive understanding of the factors relevant in measuring driver compliance to SPS advice.

1. *"What is smart parking?"*
2. *"How can compliance be assessed?"*
3. *"What personal characteristics of drivers impact compliance with in-vehicle smart parking system advice?"*
4. *"What role do parking facility characteristics play in driver compliance with in-vehicle smart parking system advice?"*
5. *"What trip-related characteristics affect driver compliance with in-vehicle smart parking system advice?"*

The first sub-question aims to define and explore the concept of smart parking, elucidating its key features, benefits, and technological advancements. By addressing this question, a foundation of knowledge about SPSs and their potential can be established, which is crucial for further investigating driver compliance with in-vehicle SPS advice.

The second sub-question focuses on identifying and examining different methods that can be utilized to measure driver compliance with in-vehicle SPS advice. It aims to explore both quantitative and qualitative approaches to measure compliance.

The third to fifth sub-questions aim to investigate the influence of personal, parking facility, and trip-related characteristics on drivers' compliance with in-vehicle SPS advice. This study differentiates between various types of drivers, trips, and parking facilities because it is believed that these elements encompass the broader parking framework. By examining these characteristics, it can be understood how differences in drivers, facilities, and trips may affect driver compliance. Such understanding can inform the design and implementation of SPSs accordingly, promoting sustainable parking behavior, and improving overall parking management in urban areas.

To ensure the feasibility of the study, the focus was narrowed down to examining compliance with SPS advice specifically within the Dutch parking context. The Netherlands possesses a unique urban and transportation planning framework that distinguishes it from other regions worldwide. Consequently, the findings of this study may not be directly generalizable to parking contexts in other countries or regions.

Furthermore, it was decided that the study would exclude Park and Ride (P+R) facilities. These particular parking facilities serve as intermediate points in drivers' travel journeys rather than their ultimate destinations. Considering the presence of public transport connections associated with P+R facilities, it is highly likely that parking behavior around these areas is significantly influenced by such factors. Incorporating these complexities into the study would unnecessarily complicate the research focus and objectives.

Thus, the study's scope is limited to examining compliance with smart parking advice within the Dutch parking context, acknowledging the unique urban and transportation planning characteristics of the Netherlands. The exclusion of P+R facilities ensures a more focused investigation of compliance behavior without additional confounding variables associated with public transport connections.

1.3 Relevance

The abundance of academic literature focusing on various types of SPSs and their technical specifications has overlooked an important aspect: the examination of drivers' reactions and responses to the advice provided by these technologies. Within this context, studies like the one outlined in this report play a critical role in providing valuable insights into user compliance and behavioral adaptations within the realm of smart parking. Furthermore, this study holds the potential to contribute not only to the field of parking but also to the broader domain of human-technology interaction by investigating the impact of advice from information and communication technology systems on human behavior.

The findings of this study will also have societal relevance. Firstly, parking stakeholders will gain a fresh perspective on the potential of SPS technologies, enabling them to tailor the implementation and utilization of these technologies to effectively achieve their goals. Additionally, developers of SPSs will benefit from insights into the potential effects of these systems, enabling them to refine and customize the systems to better meet the needs of end users.

Moreover, the study's outcomes will directly influence the effectiveness of SPS technology, thereby contributing to positive outcomes such as reduced congestion, decreased air and noise pollution, and time savings commonly associated with SPSs. By shedding light on driver compliance, this research has the potential to enhance the overall performance and impact of SPSs, thereby delivering broader societal benefits.

In conclusion, this study's significance lies in its ability to provide valuable insights to parking stakeholders, developers of SPSs, and the broader field of human-technology interaction. By informing decision-making processes, it has the potential to optimize the implementation and utilization of SPS technologies, ultimately leading to positive outcomes such as reduced congestion, improved environmental conditions, and enhanced efficiency in urban transportation.

1.4 Reading guide

This first chapter provided a concise introduction to the study at hand. In Chapter 2, the relevant academic literature concerning smart parking and related topics is explored to identify attributes that may influence compliance with SPS advices. Chapter 3 outlines the methodology employed in the study. It examines the theoretical foundations of preference measurement and data analysis, describes the experimental setup, and explains how the experiment is presented to the research population. Chapter 4 elucidates the process of sample recruitment and the transformation and filtering of the resulting data to ensure its suitability for analysis. Subsequently, Chapter 5 presents a descriptive analysis of the data, followed by a discussion of the findings from the estimation of Multinominal Logit Model (MNL) and Latent Class Model (LCM) models. Finally, Chapter 6 presents the conclusions and discussions of the research, along with recommendations for policymakers and practitioners.

2 Related work

The related literature for this study has been divided into four parts. In the first section, the main topic of this study - being smart parking - will be discussed and will provide an overview of the academic understanding of this topic at the time of writing. Section 2.2, explores the concept of compliance in a psychological context, and examines its relation with technology acceptance. In Section 2.3, the extensive academic exploration of parking choice behavior will be elaborated upon. The fourth section explores literature on the related field of variable message signage, and its effects on route- and parking choices made by drivers. This chapter is ended with a conclusion.

2.1 Smart parking systems

There are various interpretations and definitions of smart parking, as demonstrated in recent literature (Barriga et al., 2019; Chandrahasan et al., 2016; El Khalidi et al., 2018; Lin et al., 2017; Paidi et al., 2018; Revathi & Dhulipala, 2012; Rosenkranz, 2021). According to this literature, smart parking refers to a parking solution that utilizes data generated by sensors and cameras, which use a networking protocol to connect to a software platform that informs consumers of available parking spaces and reservation possibilities near their destination via an in-vehicle smart device.

Figure 1 illustrates the architecture of a generic Smart Parking System (SPS), adapted from Kotb et al. (2017). The system involves two primary communication flows: one from the consumer to the allocation center (left), and one from the parking operator to the allocation center (right). On the consumer side, the individual interacts with a smart device in their vehicle, which transmits the request for parking information or reservation to the parking allocation center via a communication network. The allocation center then provides the consumer with parking advice using the network. On the parking operator side, Parking Guidance and Information System (PGIS) are also connected to the network. This often physical information system receives data on parking facility occupancy from the parking resource management center, which obtains information from the various parking facilities equipped with sensors and the parking allocation center. The three main communication components - sensors, software, and networking protocols - are discussed in greater detail below.

2.1.1 Sensors

As of today, it is challenging to determine the availability of parking spaces in parking facilities. Although facilities regularly count the number of vehicles entering and exiting the facility, they lack means to identify if individual parking spaces are vacant or not. The objective of sensors is to address this issue and communicate availability through a network gateway (Barriga et al., 2019). Since sensors usually do not cover large surface areas, a single parking facility requires multiple sensors. It should be noted that the integration of sensors also necessitates the installation of a (wireless) technological infrastructure for the transportation of data (Bagula et al., 2015; Lin et al., 2017).

Data gathering is one of the most crucial aspects of SPSs. Therefore, sensors must be reliable, with human interaction of any kind limited, and energy consumption minimized (Mair, 2015). The market offers various sensors for SPSs, with the most common ones being ultrasonic sensors, magnetometers, Closed Circuit Television (CCTV), and cellular sensors (Kotb et al., 2017).

2.1.2 Software platforms

Software solutions are a crucial component of SPSs as they determine how sensor data is handled. The platform architecture should be robust and able to handle large amounts of information while providing services on a large scale. When combined with a mobile app, these platforms become

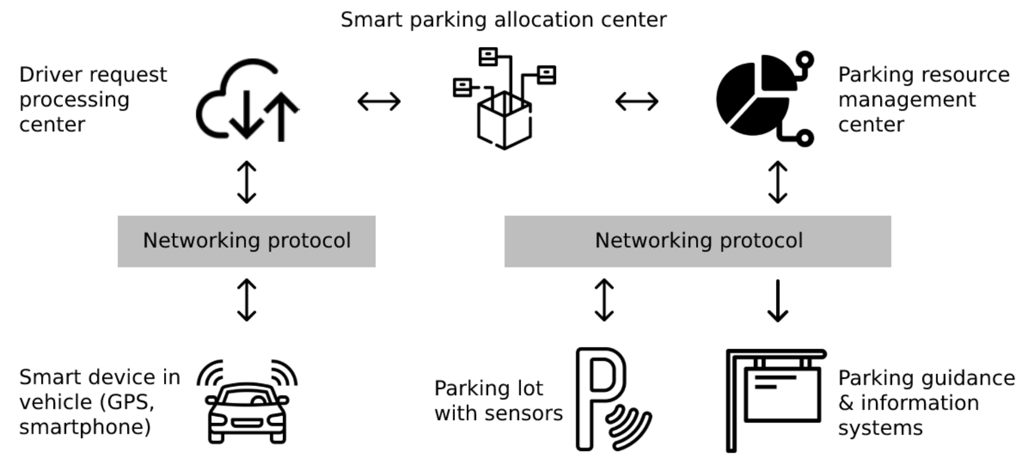


Figure 1: Schematic overview of a smart parking system (Adjusted from Kotb et al. (2017))

even more important because they allow users to locate and reserve parking spots based on real-time data. The data stored in these software solutions can be a valuable resource for local governments working on urban development and mobility improvements. For example, if there is enough related data available, SPS data could be used by these entities to identify congestion points and suggest alternatives to nearby users, or to predict parking availability in areas with limited sensor coverage. Commercial entities can also benefit from the data, as additional service access points or even parking facilities could be developed in areas with high demand (Barriga et al., 2019).

Although the specific purpose and functionalities of each software platform are defined by involved stakeholders (Mair, 2015), they are commonly used for three purposes: handling, integrating, and presenting information (Barriga et al., 2019; Lin et al., 2017). In SPSs, the most sought-after functionalities are those that improve existing data storage and processing operations or determine how and what information is presented to the system user. Secondly, once information has been gathered and structured, systems can be improved by integrating parking occupancy and access route traffic flow prediction. This way, the system can decrease search time and pollution emitted during the search process. The third purpose is that of E-Parking, in which information is presented to the user via an internet-based software solution, either through a mobile app or a web page. Users can interact with this system by reserving parking spaces, for example.

2.1.3 Networking

Networking protocols are crucial for transferring data from sensors to SPSs. The implementation of a SPS necessitates a communication infrastructure that can support a large number of devices, all of which are connected and transmitting data simultaneously. Short-range and long-range communications must both be taken into account when connecting sensors to gateways, which are then connected to software platforms (Lin et al., 2017). Two primary categories of networking solutions are defined in the extensive literature reviews on the technological perspective of SPSs by Barriga et al. (2019) and Lin et al. (2017). The first category, the sensor network category, describes the network architectures for sensor communications. The second category, the user network, describes the protocols used to provide the end user with useful information. Further discussion of the technological applications of this networking technology is beyond the scope of this study.

2.1.4 Benefits

As stated in the introduction of the report, a well-implemented and comprehensive SPS has significant potential, particularly in reducing traffic in urban areas. This reduction in traffic is due to two independent effects of SPSs: route-based parking allocation and a decrease in cruising behavior. Route-based parking allocation involves assigning parking facilities to drivers along the route to their destination to enhance parking efficiency. For example, if a driver enters a city from the north, it would be beneficial if they parked their car north of their destination to prevent unnecessary traffic. Cruising refers to the tendency of drivers to search for a suitable parking spot by driving around. According to Shoup (2006), cruising accounts for an average of 30% of all urban traffic and even rises to 74% in cities with significant parking problems. While the data used by Shoup (2006) is dated and somewhat unreliable because cruising has only been studied when a researcher expected to find it, he argues that cruising itself has not changed over time and that studies conducted throughout the last few decades demonstrate a prevailing inefficiency. Benefits associated with a reduction in traffic include reduced congestion, lower emission rates of greenhouse gases and particulate matter, and decreased time and fuel waste (Cookson & Pishue, 2017; Shoup, 2006; Yang & Lam, 2019). Thus far however, the focus in academics regrading the topic of SPSs has been on its technical challenges, and little to no studies have been conducted to the human factors related to the implementation of this technology.

2.2 Compliance and acceptance

After the collapse of the Third Reich in 1945, compliance has been extensively studied in academia to try to understand why such a large number of people supported or participated in the execution of the atrocities that occurred during its reign. Early studies have concluded that compliance, is a fundamental element in the structure of human social life that pertains to acquiescent responses of individuals or groups to rules, regulations, or requests (Milgram, 1963). According to Cialdini and Goldstein (2004) and Freedman and Fraser (1966) the request in this context may be explicit, like the solicitation of funds for a charity in a door-to-door campaign, or implicit like political campaigns that present the qualities of a candidate without asking for a vote directly. Regardless, individuals are aware that they are expected to respond in a certain way.

Freedman and Fraser (1966) described that historically, one of the most common ways to achieve compliance with a request is through external force or pressure. This is emphasized by the vast amount of academic literature on topics such as attitude change, conformity, imitation, obedience, and reward and punishment in learning. However, the use of force is not always desirable for ethical and practical reasons. As an alternative to force, Cialdini and Goldstein (2004) argue that individuals can be prompted to respond to situations in a particular way by appealing to their intrinsic goals, which are accuracy, affiliation, and maintaining a positive self-concept.

The goal of accuracy refers to people's motivation to reach a goal in the most effective and rewarding way possible. Applied to the context of smart parking, this means that offering a SPS advice alternative with more favorable characteristics than the current alternative could be a way to increase compliance. The second goal, affiliation, revolves around the intrinsic motivation of humans to create and maintain meaningful social relationships with others, and the idea that we engage in behaviors that others approve of. In itself, parking is often a very individualistic activity, in the sense that without any passengers, the driver conducts the activity with minimal interactions with others. Therefore, this goal seems to attribute little to SPS advice compliance. Lastly, the goal of maintaining a positive self-concept focuses on the role of self-perception, since people have a strong urge to behave consistently with their previous actions and expressions. In other words, when a person is accustomed to conducting a behavior, they are more likely to perform this behavior again in the future. In the case of SPSs, this would mean that getting drivers to use the system in the long run increases compliance to SPS advises.

Compliance with advice derived from technologies like SPSs is closely tied to the acceptance and adoption of the technology itself. One prominent theoretical framework for technology acceptance is the Technology Acceptance Model (TAM) proposed by Davis (1989). The TAM suggests that individuals' behavioral intentions to use a technology are determined by their perceived usefulness and perceived ease of use. Perceived usefulness refers to the extent to which individuals believe that a technology will enhance their performance or productivity, while perceived ease of use reflects the belief that using the technology will be effortless. In a met-analysis using 127 studies across a variety of academic fields, Venkatesh and Davis (2000) found consistent support for TAM. They also found that other external variables, such as system characteristics, individual differences, and social influences, affect technology acceptance. To capture the impact of social factors, they therefore suggest an extended TAM that includes subjective norm and image in the framework. Here subjective norm refers to the perceived social pressure to use or not use a technology, while image reflects the extent to which using the technology enhances an individual's self-image. Further extensions of the framework incorporate personal characteristics like trust in reliability and credibility as key determinants of technology acceptance (Venkatesh & Bala, 2008).

In the context of this study, the perceived usefulness aspect of TAM is particularly relevant. Understanding the conditions necessary for drivers to comply with SPS advice provides insights into the requirements for perceiving the technology as useful. There is an interesting interplay between the acceptance of SPS technology and compliance with its advice. By offering parking alternatives that improve travel performance and productivity, compliance potential can be increased, thereby enhancing technology adoption. To promote both technology adoption and compliance with SPS advice, it is important to understand driver preferences regarding parking and route alterations.

2.3 Parking choice behavior

Given the limited availability of literature specifically addressing driver compliance with SPS advice, this subsection delves into the literature on parking choice behavior to gain insights into the fundamental factors that influence parking choice behavior, with a focus on the three main groups of characteristics identified in the literature: socio-demographic, parking facility, and trip characteristics. Tables 1, 2, and 3 present a complete overview of which characteristics have been described in which resources. The tables are structured as follows: the first column provides the reviewed reference, and the identified characteristics found during the review are presented in all other columns. A check mark "✓" is used to indicate a resource that describes a relation between the characteristic and parking location choice, and a hyphen "-" is used otherwise.

2.3.1 Socio-demographic characteristics

Based on the literature review conducted on the impact of socio-demographic characteristics on parking choice behavior, as presented in Table 1, it is evident that income is the most frequently

Table 1: Parking choice behavior - Socio-demographic characteristics

	Socio-demographic characteristics			
Reference	Gender	Age	Education level	Income
(Anastasiadou et al., 2009)	-	✓	✓	✓
(Cools et al., 2013)	-	-	-	✓
(Gillen, 1978)	-	-	-	✓
(Harmatuck, 2007)	-	-	-	✓
(Kuppam et al., 1998)	-	-	-	✓
(Mo et al., 2008)	✓	-	-	-
(Salomon, 1986)	✓	-	✓	-
(Shiftan & Burd-Eden, 2001)	-	-	-	✓
(Teknomo & Hokao, 1997)	-	✓	-	-
(Tsamboulas, 2001)	✓	✓	-	✓
(Van Der Waerden et al., 2015)	✓	-	-	-
(Yun et al., 2008)	-	-	-	✓

reported characteristic, followed by gender, age, and education level. A brief explanation of how each of these characteristics influences parking choice behavior is provided below.

Gender

The effect of gender on parking choice behavior has been investigated in numerous studies. For instance, Salomon (1986) conducted a study on parking behavior in the central business district of Jerusalem and found that, on average, women spend about 20% less time searching for a parking spot than men, but they also reported higher rates of parking without a valid ticket. Van Der Waerden et al. (2015) found that men are more likely to park in the same facility when repeatedly visiting the same destination, indicating that men are more habitual than women. Moreover, Mo et al. (2008) found that females are more likely than males to consider parking fees as the main determinant in choosing a parking facility. This trend is supported by Tsamboulas (2001), who reported that women are more sensitive to increased parking fees.

Age

Age is a socio-demographic characteristic that has received some attention in the literature regarding parking choice behavior. While Anastasiadou et al. (2009) found that older drivers were less willing to pay higher parking prices and Teknomo and Hokao (1997) reported that younger people tend to prefer parking garages over other types of parking, other researchers such as Golias et al. (2002) found no significant relationship between age and parking choice behavior.

Education level

Similar to age, the impact of education level on parking choice has also been explored in the literature. According to Anastasiadou et al. (2009), individuals with a higher education are more willing to pay for parking as they are likely to have studied in larger cities and thus have more experience with paid parking policies. Conversely, Salomon (1986) observed a negative correlation between education level and search time, implying that individuals with higher education value their time more than those with lower education.

Income

The final socio-demographic characteristic addressed in this section is income. As mentioned previously, income is the most frequently studied characteristic in the academic community and appears to be a significant factor in parking location choice behavior through individuals' willingness to pay for parking. Several researchers, including Gillen (1978), Kuppam et al. (1998), and Shiftan and Burd-Eden (2001), have reported a positive correlation between income and the acceptance of higher parking prices. Furthermore, individuals with higher income tend to reduce egress time by parking closer to their destination (Gillen, 1978), while individuals with lower income have demonstrated less sensitivity to increasing walking distances (Harmatuck, 2007).

2.3.2 Parking facility characteristics

Table 2 displays the parking facility characteristics that have been identified as relevant in academic literature, including type, fee, egress time, size, occupation rates, operating hours, and security. Among these, fee and egress time are the most frequently described. As with the socio-demographic characteristics, a brief summary of the effects identified in the literature is presented below.

Type
In parking literature, parking facility types are often classified into three levels: on-street parking (angular, parallel, or perpendicular), surface-level parking, and (underground) multilevel parking. Another type of parking that is frequently studied is illegal parking. However, due to its vast variability, it falls outside the scope of this study. One of the primary studies conducted to investigate driver preferences regarding parking facility type is the study described in Ben Hassine et al. (2021). Using a revealed preference method, they examined the behavioral considerations that govern the choice of drivers for one of three parking facility types. Their results show significant effects from factors such as age, trip purpose, and trip duration, among others. Yanjie et al. (2008) observed choice effects related to security and convenience, aspects they argue are associated with parking facility type.

Fee
The cost of parking often varies depending on the type of parking and the duration of parking. It influences parking choice through its relationship with other factors, such as the willingness of drivers to pay or their household income (Brooke et al., 2014). Therefore, parking fee can be considered one of the more critical measures to create an effective parking policy (Hensher & King, 2001). For example, Kelly and Clinch (2009) found that drivers with different trip purposes were differently affected by varying parking prices, and that drivers who travel in periods with high traffic volume were most responsive to a change in parking price. Kobus et al. (2013) found that drivers showed increasing sensitivity to parking prices with an increasing duration.

Egress time
Egress time, referring to the time it takes to travel from a parking location to the final destination of the driver, is a characteristic that has been widely studied in parking literature. One of the most frequently discussed trade-offs is between parking fee and egress time (Yun et al., 2008); drivers must choose whether to walk a longer distance and pay less, or pay more for a shorter walking distance, an idea supported by Ergun (1971). Golias et al. (2002) found that an increasing egress time for on-street parking increased the attractiveness of off-street parking facilities, where the perceived likelihood of finding a parking space was higher. However, they also found that an increasing egress time for off-street parking also increased the attractiveness of on-street parking.

Size
Hunt and Teply (1993) observed a positive effect of the number of spaces in a parking facility on the choice for that facility. They argue that this effect may be due to a combination of the relatively greater noticeability of larger facilities and a size effect, meaning that the number of observations of facilities with more spaces is larger due to their greater proportion of publicly available spaces in the studied area. However, no relationships between size and parking location choice have been observed in the other papers considered in this review.

Table 2: Parking choice behavior - Parking facility characteristics

	Parking facility variables						
Reference	Type	Fee	Egress time	Size	Occupation	Operating hours	Security
(Anastasiadou et al., 2009)	-	✓	-	-	-	-	-
(Axhausen & Polak, 1991)	-	-	✓	-	-	-	-
(Ben Hassine et al., 2021)	✓	✓	✓	-	-	-	✓
(Bonsall & Palmer, 2004)	-	✓	✓	-	✓	-	-
(Ergun, 1971)	-	✓	✓	-	-	-	-
(Gillen, 1978)	-	✓	✓	-	-	-	-
(Golias et al., 2002)	-	✓	✓	-	-	-	-
(Harmatuck, 2007)	-	✓	✓	-	-	-	-
(Hess & Polak, 2004)	-	-	✓	-	-	-	-
(Hunt & Teply, 1993)	-	✓	✓	✓	-	-	-
(Kelly & Clinch, 2006)	-	✓	-	-	-	-	-
(Kelly & Clinch, 2009)	-	✓	-	-	-	-	-
(Kobus et al., 2013)	-	✓	-	-	-	-	-
(Kuppam et al., 1998)	-	✓	-	-	-	-	-
(Lam et al., 2006)	-	-	✓	-	-	-	-
(Lau et al., 2005)	-	-	✓	-	✓	-	-
(Li et al., 2007)	-	-	✓	-	-	-	-
(Mo et al., 2008)	-	✓	-	-	-	-	-
(Shiftan & Burd-Eden, 2001)	-	✓	-	-	-	-	-
(Simićević et al., 2013)	-	✓	-	-	-	✓	-
(Teknomo & Hokao, 1997)	-	✓	✓	-	✓	-	✓
(Thompson & Richardson, 1998)	-	-	-	-	✓	-	-
(Tsamboulas, 2001)	-	✓	✓	-	-	-	-
(Van Der Goot, 1982)	-	✓	✓	-	-	✓	-
(Van Der Waerden et al., 2006)	-	✓	-	-	-	-	-
(Yanjie et al., 2008)	✓	✓	✓	-	-	-	-
(Yun et al., 2008)	-	✓	✓	-	-	-	-

Occupation
Parking facility occupancy affects parking choice behavior through the availability of parking spaces. This concept was first observed by Van Der Goot (1982), who found that both search and travel time increased when drivers encountered a seemingly full parking facility. Teknomo and Hokao (1997) found that search time (the time it takes to find an empty parking space on a already entered facility) and queue time (the time it takes to get a valid parking ticket at that facility), both indicators of facility occupancy, had an effect on parking choice. In turn, Thompson and Richardson (1998) argue that during a waiting period on a parking facility due to the lack of available parking spaces, drivers periodically re-evaluate their parking option in light of observed departures of vehicles, with their perceptions of waiting times being updated regularly.

Parking time restrictions
The parking duration restrictions of a parking alternative may influence parking choice behavior since it determines whether and for how long drivers can park their vehicles there. According to Simićević et al. (2013), on-street parking becomes a more attractive option when the allowed parking duration is extended.

Security
The literature has also examined drivers' perceptions of personal and vehicle safety and security. For example, Teknomo and Hokao (1997) observed a difference in the importance of parking security for users of on-street and off-street spaces. Meanwhile, Ben Hassine et al. (2021) found that security was one of the main motivations for selecting a parking alternative when searching, especially for women in their sample.

2.3.3 Trip characteristics

In addition to socio-demographic and parking facility characteristics, trip-related factors also influence parking location decisions. Trip characteristics refer to all activities that occur with departure until arrival at the destination or are related to these activities. Table 3 shows a more even distribution of the discussion of these different characteristics compared to the distributions in Tables 1 and 2. Among the identified relations with parking choice behavior, the effects of trip purpose and familiarity with the road network are the most commonly discussed in the literature. The following sections will discuss the effects of each of these characteristics.

Search time
In the context of a trip, search time refers to the time a driver spends searching for a suitable parking facility among multiple options. Two studies on parking choice behavior were conducted by Axhausen and Polak (1991) in Karlsruhe, Germany, and Birmingham, United Kingdom, both of which included search time for an available parking space, which always had a negative effect on parking alternative choice. They found that the relative estimated values in a work situation were comparable for all locations. However, in a shopping context, the valuation of search time varied among different locations. Golias et al. (2002) confirmed the negative effect of search time on parking choice and further observed that both the parking cost and egress time parameters were evaluated not only absolutely, but also in relation to reduced search time, underscoring the importance of search time in parking choice.

Travel time
Travel time is a time-related variable that has received little attention in academic literature. Axhausen and Polak (1991) discovered a significant negative valuation of travel time when selecting a parking alternative, an to be expected trend that is confirmed by Hess and Polak (2004).

Table 3: Parking choice behavior - Trip characteristics

	Trip characteristics				
Reference	Search time	Travel time	Purpose	Duration	Familiarity
(Aarts et al., 1997)	-	-	-	-	✓
(Axhausen & Polak, 1991)	✓	✓	✓	-	-
(Bonsall & Palmer, 2004)	-	-	-	-	✓
(Cools et al., 2013)	-	-	-	-	✓
(Golias et al., 2002)	✓	-	-	✓	-
(Hess & Polak, 2004)	✓	✓	-	-	-
(Kelly & Clinch, 2006)	-	-	✓	-	-
(Kelly & Clinch, 2009)	-	-	✓	-	-
(Khattak & Polak, 1993)	-	-	-	-	✓
(Kobus et al., 2013)	-	-	-	✓	-
(Lau et al., 2005)	✓	-	-	-	-
(Mo et al., 2008)	-	-	✓	✓	-
(Simićević et al., 2013)	-	-	✓	-	-
(Teknomo & Hokao, 1997)	✓	-	✓	✓	-
(Thompson et al., 1998)	-	-	-	-	✓
(Thompson & Richardson, 1998)	-	-	-	-	✓
(Tsamboulas, 2001)	-	-	-	✓	✓
(Van Der Goot, 1982)	-	-	✓	-	-
(Van Der Waerden et al., 2006)	-	-	-	-	✓
(Verplanken et al., 1998)	-	-	-	-	✓
(Yun et al., 2008)	-	-	✓	-	-

Purpose

Although some researchers, including Teknomo and Hokao (1997), found direct relationships between trip purpose and parking choice behavior, the effect of trip purpose on parking choice behavior is often visible through time-related attributes in experiments. For example, drivers traveling to a city for shopping or a work appointment have different constraints in terms of the time spent searching for an available space, parking duration, or walking to the final destination. In addition to interactions with time-related attributes, Van Der Goot (1982) and Axhausen et al. (1993) identified that the valuation of other attributes, such as fee, also change for different trip purposes in their experiments.

Duration

Golias et al. (2002) discovered that parking duration has a lesser impact on off-street parking selection compared to other attributes in their experiment. However, the discovered effect was positive because of which off-street parking alternatives become more appealing with a longer parking duration. The researchers attribute this to the fact that in their study area, the pricing on off-street parking facilities becomes more beneficial with increasing parking duration. In a comparable study, Kobus et al. (2013) found that parking duration has a negative effect on the selection of on-street parking, which supports the observation of Golias et al. (2002). Additionally, Tsamboulas (2001) observed that drivers who parked for a longer duration were more sensitive to an increase in the hourly parking price. Interestingly, Teknomo and Hokao (1997) found a strong correlation between trip purpose and parking duration, suggesting that each type of trip has an associated trip duration.

Familiarity

Familiarity with the network is a commonly reported characteristic that generally describes a habitual effect formed after repeated visits to areas on the selection of parking facilities. According to Aarts et al. (1997), many of the initially important factors required for knowledge-based decision-making are often disregarded, and a form of intuitive decision-making based on previous behaviors is applied. For cases in which drivers make rational parking decisions in familiar areas, Khattak and Polak (1993) argue that drivers use their stronger knowledge base to evaluate alternative utilities. Meanwhile, in a study of the awareness of regular visitors to the variety of parking alternatives in the area, Cools et al. (2013) concluded that parking place familiarity differs greatly among user groups in their sample. On the other hand, Bonsall and Palmer (2004) found that having no familiarity with the network and available parking options resulted in seemingly random parking choices.

2.4 Variable message signage

An extensively studied and implemented traffic intervention is the deployment of Variable Message Signage (VMS). VMS are dynamic electronic panels positioned alongside or above lanes that remotely communicate travel information to drivers, such as queue warnings, variable speed limits, route information, and dynamic lane assignments (Washington State Department of Transportation, 2022). While the communication from a SPS to the driver occurs inside the vehicle via a smart device, VMS relay information outside of the vehicle. Despite this difference, the nature of these two systems is comparable. Therefore, in this section, we explore driver compliance to this technology, by distinguishing two types of VMS: PGIS and Dynamic Route Information Panels (DRIP).

2.4.1 Parking guidance and information systems (PGIS)

PGIS use VMS to decrease the time spent by drivers searching for available parking spaces and to discourage drivers from entering an area when no spaces are available by providing them with information about the parking situation in an area (Ji et al., 2012). Since their introduction in the 1970s in Aachen, Germany, PGIS has been extensively studied in transportation engineering. However, there is little agreement among scholars regarding the factors that influence compliance with PGIS. One characteristic that has shown effects in various sources is trip purpose. For example, Thompson et al. (1998) observed varying levels of PGIS utilization among different groups of visitors to the city center. Shoppers frequently reported using PGIS, whereas commuters did not. Similarly, Thompson and Bonsall (1997) noted that tourists visiting the city center were more likely to use PGIS in their parking journey. The effects of trip purpose or type of visit appear to be closely related to those of frequency of visit in this context. Thompson and Richardson (1998) confirmed this and found that high-frequency travelers relied less on information on waiting times and parking facility locations than infrequent travelers. Similarly, Waterson et al. (2001) found that travelers unfamiliar with the area attached greater importance to PGIS in their parking choice.

2.4.2 Dynamic route information panels (DRIP)

DRIP are a type of VMS frequently installed on highways and in cities to display real-time traffic information to road users in the form of delay times, road safety warnings, or alternative travel routes (Q-LITE, 2023). Driver compliance to DRIP is regularly studied by examining the effect of DRIP on the travel route choice decisions of drivers. In these studies, one of the most commonly observed category of characteristics is socio-demographics. To provide a more concise discussion of the included factors, a literature overview table, Table 4, has been created. As with the literature tables discussed in Section 2.3, a check mark "✓" indicates whether a relationship between compliance to DRIP and the respective socio-demographic characteristic is observed in a resource, otherwise, a hyphen "-" is used.

Table 4: Dynamic Route Information Panels - Socio-demographic characteristics

	Socio-demographic characteristics				
Reference	Gender	Age	Education level	Income	Driving experience
(Dia, 2002)	✓	✓	-	-	-
(Emmerink et al., 1996)	✓	-	-	-	-
(Kattan et al., 2010)	-	✓	-	-	-
(Khattak, Koppelman, et al., 1993)	✓	-	-	-	-
(Lai & Yen, 2004)	✓	✓	✓	-	-
(Ma et al., 2014)	✓	-	-	-	✓
(Peeta et al., 2000)	✓	✓	✓	-	-
(Wardman et al., 1997)	✓	✓	-	-	-
(Zhong et al., 2012)	-	✓	-	✓	✓

Gender is a socio-demographic characteristic that is regularly studied in relation to compliance with DRIP. Emmerink et al. (1996) found that male drivers were more likely to be influenced by roadside information than female drivers in a study on the effects of radio transmitted traffic information and roadside traffic information on route choice of drivers. This finding was confirmed by Khattak, Schofer, et al. (1993) and Wardman et al. (1997). However, Van Der Waerden et al. (2019) and Zhong et al. (2012) found no significant relationship between gender and compliance to DRIP communicated traffic information, while Ma et al. (2014) observed an effect opposite to that described by Emmerink et al. (1996).

Age is also an important factor in compliance with DRIP. According to Kattan et al. (2010), older drivers were more likely to diverge to an alternative route suggested by DRIP than younger drivers. Similar observations were made by Zhong et al. (2012), while Peeta et al. (2000) concluded that younger drivers were more likely to comply in a study on driver response to DRIP in Northwestern Indiana, USA.

Regarding education level, Peeta et al. (2000) found that well-educated drivers exhibited greater compliance to DRIP. Driver compliance also increased with a rise in monthly income, as reported by Zhong et al. (2012). Interestingly, the number of years of driving experience and annual mileage had an opposing effect in the study of Zhong et al. (2012). Participants with driving experience of less than a year were more likely to comply than drivers with 5 or more years of experience, while participants with an average annual mileage of less than 10,000 kilometers were less likely to comply than participants with an annual mileage of over 30,000 kilometers. Meanwhile, Ma et al. (2014) also found that participants with less experience were less likely to diverge routes based on information presented on DRIP.

With regards to trip characteristics, the level of driver familiarity with the network is widely considered to be influential in compliance with DRIP. Several studies, including those by Polydoropoulou et al. (1996), Wardman et al. (1997), and Zhong et al. (2012), have found a negative relationship between network familiarity and compliance, indicating that drivers who are more familiar with a network are less likely to comply with DRIP. However, Ma et al. (2014) found a relationship opposite to the previously stated finding. In attempts to model driver route choice behavior, Ben-Akiva and Lerman (1991), Bonsall (1992), and Dia (2002) note that drivers have optimization goals during travel between a given origin and destination. Therefore, although empirical evidence in the literature is lacking, expected travel distance, expected travel time, delay, and the flexibility in arrival time could be important predictors of trip-related effects of DRIP on route choice behavior. In addition to these factors, the point in the travel at which the DRIP information is communicated to the driver is often included in the modeling of route choice behavior.

In addition to socio-demographic and trip characteristics, several message-related factors appear to influence driver compliance with DRIP. Although these factors are less applicable to SPS advice, they are briefly discussed here to provide a complete overview of the factors affecting compliance with DRIP. Khattak, Schofer, et al. (1993) identified that message content-related factors such as relevance and level of detail have an impact on compliance. As expected, they found that compliance increases with the increasing relevance or detail of the message. Lai and Yen (2004) added that aspects related to the presentation of information, such as phrasing, font, and color, affect the readability of DRIP and, therefore, compliance with the information displayed on the panels. The presentation of information on DRIP is often standardized in guidelines such as those provided by CROW (2017) and Dudek (1991).

2.5 Conclusion

In summary, it can be stated that SPSs comprise three main technological components, namely sensors, software platforms, and networks, and that these components have received the majority of academic attention. To increase the implementation potential of the technology, and thus achieve its ultimate goal of reducing the amount of traffic generated by parking, a better understanding needs to be developed on how to maximize driver compliance to the advices provided by such a SPS. Literature on the related topics of parking choice behavior and VMS has been studied to formulate a broad set of characteristics that might influence compliance to SPS advices.

Among the socio-demographic characteristics, gender, age, education level, and income have been found to hold the most potential in influencing compliance. Regarding parking facility characteristics, factors such as type, fee, egress time, and occupancy are deemed relevant. Additionally, various trip characteristics including search time, travel time, purpose, duration, and familiarity should be taken into account. Although literature on related topics such as parking choice behavior and VMS can provide some insight into the factors that determine SPS advice compliance, further research in an smart parking choice context is necessary to gain a deeper understanding of these determinants. This study, described in this report, aims to address this research gap.

Because smart parking is still a relatively unknown concept to the general population at the time of writing this report, and the extent of its future use throughout society is uncertain, this research focuses on the individual-level effects on SPS advice compliance and the environmental factors that arise from individual characteristics, rather than the social structures that influence decision-making.

3 Methodology

As evidenced by the literature review in Chapter 2, various studies have investigated the effect of characteristics on parking location choice. However, due to novelty of the technology, little has been reported on the impact of in-vehicle Smart Parking System (SPS) advice on this decision. As Section 2.1 reveals, SPSs have the potential to reduce the number of vehicles on streets in and around our inner cities, resulting in less congestion and a reduction of greenhouse gas and particulate matter emissions. However, there are few examples of comprehensive implementation of this technology, which highlights the importance of understanding how socio-demographic, trip, and parking facility attributes influence driver compliance with SPS advice.

This chapter provides an overview of the methods used to collect individual preferences in this study. Section 3.1 presents a general overview of preference measurement techniques. Subsequently, the stated adaptation experiment technique is examined in detail, including the rationale behind choosing a specific experiment type. A description of utility theory follows, along with a section on models for discrete choice analysis. Section 3.6 outlines the attributes and attribute levels included in the experiment. Finally, the last section explains how the experiment is designed and implemented as an online survey.

3.1 Measuring preferences

Individuals rely on their personal preferences to make various decisions in their daily lives. While it is relatively straightforward to observe decision outcomes, understanding the underlying preferences that drive these choices is more challenging. In behavioral research, two commonly employed approaches to measure individual preferences are self-report measures and choice-based methods.

Self-report methods typically involve participants rating options based on their personal preferences, and allow individuals to directly express their preferences and provide insights into their subjective evaluations. When using a rating approach, individuals are asked to evaluate a made choice or several alternative choice profiles based on predefined scales. This technique has the significant drawback that it does not require respondents to compare and evaluate different attribute levels when making their decisions. Consequently, it does not closely mirror real-life choice scenarios where individuals assess and compare alternatives based on their respective attribute levels. Approaches using ranking, on the other hand, involve asking respondents to rank a set of alternatives from most to least preferred. It provides ordinal measurement, allowing determination of the relative preference order among alternatives. Alternatively, the ordinal measurements can be reformatted into multiple indicated stated preference sets. A disadvantage of using the ranking method is that it evaluating a multitude of alternatives simultaneously to come to a ranking is rather demanding.

Choice-based methods involve presenting individuals with alternative options and requiring them to make choices, either in the real world, on in an experimental context using hypothetical choice scenarios. By analyzing individuals' choices, researchers can derive relative preferences for different attributes or levels within the options (see Section 3.3). This information can then be used to predict future choices.

Overall, choice-based methods offer a more comprehensive and realistic approach to understanding and quantifying individual preferences in decision-making scenarios. Within this context, a further refinement in the way preference data is collected can be made. Researchers have the option to utilize data observed in real world non-experimental contexts, known as revealed preferences, or to collect data on choices in a hypothetical context, the stated preferences. Revealed preferences, while providing a closer alignment with real-life choices, have limitations in capturing choices beyond the existing environment. In contrast, stated preferences provide researchers greater experimental control, enabling the inclusion of attributes, attribute levels and attribute level combinations that may not be observable in the real world during the study period. This control empowers researchers to explore hypothetical scenarios and investigate preferences under specific conditions that may not be readily available in the real world (Louviere et al., 2000).

3.2 Stated adaptation techniques

A commonly employed research methodology within the choice experiment family for testing the behavioral effects of an implementation or adjustment that have not yet reached a stage where ethnographic studies are possible is the Stated Adaptation (SA) experiment (Faivre D'arcier et al., 1998). The SA experiment is a variant of the conventional stated preference experiment, with a particular focus on examining the likelihood and nature of behavioral change in hypothetical environments. However, using this technique comes with the drawback that respondents are required to construct a mental model of the altered decision context, resulting in a higher cognitive load for the participants (Faivre D'arcier et al., 1998; van Bladel et al., 2008). Thus, a trade-off must be made between task realism and respondent burden, as simplifying the choice scenario allows for more realistic responses from the respondents, but increased task realism enhances the study's validity unless participants do not fully grasp the meaning of the decision context due to the information processing challenge. Various research approaches can be identified, with the most relevant ones discussed below.

3.2.1 Stated adaptation based on face-to-face interviews

One of the earliest SA experiments used in traffic engineering is the face-to-face game-simulation interview SA (Faivre D'arcier et al., 1998). These experiments are structured around participants maintaining a travel diary, which serves as the basis for discussing their travel behavior in semi-structured interviews. During the interviews, the interviewer presents hypothetical scenarios, incorporating the specific innovation or adjustment tailored to each participant's travel behavior, thus maximizing their familiarity with the choice context. Subsequently, participants are given the opportunity to freely elaborate on their behavior within these hypothetical scenarios. According to Faivre D'arcier et al. (1998), it is recommended to involve 20 to 30 unique respondents in such an experiment to ensure a sufficient range of distinct behavioral responses. However, consolidating this data would result in significant data loss, rendering quantitative analysis of the data impractical.

3.2.2 Stated adaptation based on revealed preferences in (online) survey

An alternative approach to the face-to-face interviews is a stated adaptation based on revealed behavior in a survey. The general procedure of this type of experiment is as follows: The researcher gathers information on the behavior of a large group of participants and subsequently sends them a personalized follow-up survey. In this survey, participants are presented with a hypothetical choice scenario and asked to select between their current travel behavior (Status Quo (SQ)) and one or more alternative options. The execution of these experiments may vary across studies, particularly in how the SQ of the participants is determined.

One common approach is similar to that employed by Abdel-Aty et al. (1997) in their study on the effects of advanced traffic information on drivers' route choice. In their study, they collected route choices from a large group of participants through computer-aided telephone interviews. Subsequently, participants receive a customized mail-back follow-up questionnaire containing hypothetical choice scenarios. Alternatively, researchers can target specific groups of individuals whose SQ is known or ask respondents to self-report their SQ and provide them with a follow-up questionnaire, tailored to their specific situation. This approach requires less time per participant, allowing for a larger sample size compared to the face-to-face interview method. Furthermore, the gathered data can be subjected to statistical analysis using discrete choice modeling techniques.

3.2.3 Stated adaptation based on stated preferences in (online) survey

The SA based on stated preferences in a survey follows a similar setup to the method utilizing revealed behavior. The distinction between the two approaches lies in the determination of the concept of SQ. In this method, the SQ of the participant is determined through a stated choice task. In this task, participants are presented with a hypothetical choice scenario and asked to select one alternative among two or more options based on their respective characteristics. The chosen alternative is then used as the SQ in a subsequent task involving a modified hypothetical choice scenario.

Using stated preferences instead of revealed preferences comes with certain drawbacks, including increased respondent burden and potential reduction in task realism if participants are unable to fully engage with the presented scenarios. However, the advantage of utilizing stated preferences is that it enables the collection of data on the initial choice behavior of the participant group in the survey, rather than solely focusing on data pertaining to behavioral change.

3.2.4 Experiment decision

When considering the various SA approaches for the current study, it becomes evident that the face-to-face interviews approach is not feasible. Identifying different types of behaviors is irrelevant since participants either follow or do not follow the SPS advice. Furthermore, it would be challenging to argue that the small research population represents the entire population. On the other hand, the revealed preferences approach appears to be a viable alternative. It allows for statistical analysis, the research population could be sufficiently large to represent society, and the SQ behavior of respondents could be easily identified by recruiting participants at urban parking facilities.

However, there are some challenges associated with the revealed preferences approach. Past experiences have shown that both private and public parking facility operators in the Netherlands have been reluctant to engage in academic research initiatives. While not impossible, this would significantly complicate the process of determining the SQ for each participant. Alternatively, an initial contact moment followed by a survey or an extensive online survey that tailors the choice task to each respondent based on a SQ submitted earlier in the survey could be used. However, both options fall outside the scope of this graduation project due to time constraints and the need for a custom survey environment.

Considering these factors, the SA using stated preferences in an online survey appears to address these issues. Since parking in an urban area is a familiar practice for the majority of the Dutch population, respondents should be able to easily imagine themselves in the stated preference choice task. To avoid further complicating the experiment's description, the stated choice and SA components of the experiment will be referred to as Stage 1 and Stage 2, respectively, going forward.

3.3 Utility theory

When discussing choice scenarios, individuals may exhibit different behavior based on their personal preferences. According to the utility theory, when presented with a choice scenario, individuals will choose the alternative that provides the greatest utility or preference. This concept of utility maximization is frequently assumed in preference experiments (Train, 2009). Utility is based on the extend to which individuals value attributes of the alternative. By alternately fixing these attributes, their importance can be determined. Hensher et al. (2015) argue that the utility U_{iaq} of an alternative i in choice context a for individual q can be partitioned into an observed component V_{iaq} and an unobserved component ε_{iaq} (equation 1). The observed component includes the partial utilities of all attributes included in the experiment, while the unobserved component covers the utility of attributes that are relevant to the individual making the choice but have not been included in the experiment. Because the latter remains unknown, it is treated as a random component.

$$U_{iaq} = V_{iaq} + \varepsilon_{iaq} \tag{1}$$

The observed component of utility V_{iaq} is defined as a function of K variables with their associated preference weights β (equation 2) (Hensher et al., 2015).

$$V_{iaq} = f(\boldsymbol{X_{iaq}}, \boldsymbol{\beta})\,. \tag{2}$$

Here, $\boldsymbol{X_{iaq}}$ is a vector of K attributes describing alternative i in context a, describing individual characteristics of the decision maker and/or aspects related to the decision context. Although the specific functional form of the observed utility function is defined by the researcher, Hensher et al. (2015) state that the most often reported utility function concerns a simple linear combination of the attributes and their respective parameter estimates, as shown in equation 3.

$$V_{iaq} = \sum_{k=1}^{K} \beta_k x_{iaqk}\,. \tag{3}$$

3.4 Models for analysis

The data collected using the SA technique provides insight into an individual's preferences among a discrete set of alternatives. These preferences are expressed through utilities that reflect the strength of those preferences. However, as only relative preferences rather than true preferences are revealed by the data, relatively simple regression analysis methods are not appropriate. Instead, different methods must be utilized (Hensher et al., 2015). The family of discrete choice models is well-suited for analyzing this type of data. Within this model family, the Multinominal Logit Model (MNL) and the Latent Class Model (LCM) are commonly applied and will therefore be described in more detail below.

3.4.1 Multinominal logit models

The MNL is the most commonly used but also the most restrictive of the logit modeling approaches. The utility function for a generic logit model estimation is given by Equation 4 (Hensher et al., 2015).

$$U_{iaq} = \lambda_i V_{iaq} + \varepsilon_{iaq}\,. \tag{4}$$

This equation is similar to Equation 1, however, in this case ε_{iaq} has variance σ_i^2, which is equal to $\pi^2/6\lambda_i^2$ for an unstandardized Gumbel or Extreme Value Type 1 distribution, and λ_i is a scale parameter. Normalization of the observed utilities is necessary since only rankings of alternatives and not actual utilities are available in the data. Thus, λ_i is included. Although λ_i can be assigned any value, it is typically set to 1. Logit models are frequently specified under the assumption that unobserved effects are equal for all i in the set of alternatives I, which necessitates further normalization of σ_i^2 (Hensher et al., 2015). The MNL restricts all covariances to be 0 (Hensher et al., 2015). The probabilities according to an MNL model can be calculated easily by filling out the relevant quantities in the probability function in equation 5:

$$P_{iaq} = \frac{\exp(V_{iaq})}{\sum_{i'} \exp(V_{i'aq})}, \qquad i, i' \in I_{aq}\,, \tag{5}$$

in which P_{iaq} is the probability that individual q selects alternative i out of alternative set I_{aq}.

3.4.2 Latent class models

One notable drawback of utilizing a MNL estimation is its incapability to handle panel data. Given that the collected data comprises repeated choice entries by individuals observed over time, the observations of the same respondent are interdependent. To address this effect, one of the models that can be employed is the LCM. According to the theory behind LCM, choice behavior is not solely based on observable attributes but also on latent heterogeneity that varies based on unobserved components. The model assumes that respondents can be grouped into a finite set of latent classes based on their preferences. Therefore, the choice probabilities calculated by LCM differ from those given by a MNL. In fact, LCM estimates three types of probabilities (Hensher et al., 2015). Equation 6 calculates the probability that an individual q is part of a particular latent class c.

$$P_{qc} = \frac{\exp(V_{qc})}{\sum_{c' \in C} \exp(V_{qc'})}\,. \tag{6}$$

Here, $V_{qc} = \delta_c h_q$ represents the observed utility component from the class assignment model, and h_q are respondent-specific covariates that condition class membership.

In addition to class probability, a LCM also estimates the probability of respondent q choosing alternative i in choice context a given their membership of latent class c. However, because the data set is composed of panel data, the model should not estimate the within-choice task choice probability but rather the probability of observing sequential choices being made. This is represented as the product of the probabilities of a respondent choosing a set of alternatives in equation 7:

$$P_{iaq|c} = \prod_s \frac{\exp\big(V_{iaqs|c}\big)}{\sum_{i'} \exp\big(V_{i'aqs|c}\big)}\,, \tag{7}$$

in which s is a choice situation in a.

The final set of probabilities calculated by the LCM are the alternative conditioned class probabilities. These probabilities are calculated based on both the class assignment (equation 6) and the within choice situation choice probabilities, all conditioned on observed choices. These probabilities are represented by equation 8:

$$P_{aqs|c} = \frac{\prod_s y_{iaqs} P_{iaqs|c} . P_{qc}}{\sum_{c' \in C} \prod_s y_{iaqs} P_{iaqs|c'} . P_{qc'}}, \qquad \forall c \in C\,, \tag{8}$$

where $P_{iaqs|c} = \frac{\exp(V_iaqs|c)}{\sum_{i'} \exp\big(V_{i'aqs}\big)}$ and y_{iaqs} equals 1 if respondent q chose alternative i in the s-th observation under context a and 0 otherwise.

3.4.3 Model performance

In this report, model performances are evaluated and compared using the McFadden pseudo R^2 (ρ^2) statistic, the Likelihood Ratio Statistic (LRS) and the Bayesian Information Criterion (BIC). All of these widely accepted evaluation techniques are based on the logarithmic function of the maximum likelihood estimation of a model (Log Likelihood function (LL)). The LL is the sum of the product of the recorded choice y_{iaq} and the logarithm of probability P_{iaq} for all contexts a, all alternatives i and all individuals q:

$$LL(\beta) = \sum_q \sum_a \sum_i y_{iaq} \cdot \ln(P_{iaq})\,. \tag{9}$$

The LL of the unrestricted model can be compared to that of a restricted, often generalized base model to determine which one provides the best predictions. The null model, which assumes an equal probability for each alternative $i \in I_{aq}$, is often used as the restricted model for comparison. The Log Likelihood function of the null model (LL0) can be computed as

$$LL(0) = \sum_q \sum_a \sum_i y_{iaq} \cdot \ln\left(\frac{1}{I_{aq}}\right)\,, \tag{10}$$

in which I_{aq} is the number of alternatives in choice set A_{aq}.

One way to determine if a model outperforms another is to use the LRS (Hensher et al., 2015). The LRS is calculated as twice the difference between the LL of the restricted and unrestricted models (equation 11). This value is then compared to the critical Chi-square statistic for n degrees of freedom at a desired confidence interval (95% in this report), where n equals the difference in the number of parameters δK between the restricted and unrestricted models. If the LRS is larger than the critical Chi-square value, the unrestricted model is considered to outperform the restricted model.

$$LRS = 2(LL \,|\, Unrestricted\ model - \ LL \,|\, Restricted\ model)\,. \tag{11}$$

The McFadden pseudo R^2 (ρ^2) statistic (Hensher et al., 2015) is used to determine the goodness-of-fit of a model, and is computed as follows:

$$\rho^2 = 1 - \frac{LL \,|\, Unrestricted\ model}{LL \,|\, Restricted\ model}\,. \tag{12}$$

Lastly, the BIC is used for model selection amongst a finite set of models. This criterion aims to prevent the over-fitting of models by introducing a penalty term for the number of parameters included in the model and is computed as:

$$BIC = K \ln(N) - 2LL\,, \tag{13}$$

in which K is the number of parameters estimated by the model, and N is the number of observations in the data set. When fitting models, models with a lower BIC are preferred (Schwarz, 1978).

3.5 Refining attributes

Now that the type of experiment, the underlying theories and the methods of analysis have been explored, the attributes included in the experiment can be identified. According to Hensher et al. (2015), the first step is to identify the alternatives presented to the respondent. In the experiment, respondents will chose from a universal but finite list of parking alternatives that are unlabeled (only a generic label will be provided, e.g., *"Alternative 1"*). Because the alternatives are labeled neutrally, problems following from the assigning of alternative-specific unobserved characteristics by the participant are minimized.

Next, the attributes included in the experiment for both the choice context as well as the parking alternatives can be defined based on the literature review in Chapter 2. For the choice context, the following attributes seem of interest: trip purpose, visit duration, delay, flexibility of arrival time, and familiarity with network. Because ambiguity and correlation between attributes should be prevented as much as possible (Hensher et al., 2015), it has been decided to include trip purpose and drop visit duration and flexibility of arrival time, albeit that there is some flexibility of these factors included in trip purpose. Furthermore, delay has been included in the choice context. Because the familiarity of a respondent with the network is difficult to determine in a hypothetical choice context, this attribute will be approached as a constant factor in the choice context by requesting respondents to make a choice as if they were travelling to a city they visit frequently. Next, the attributes in the choice alternatives can be defined. Because the offered alternatives are non-specific, the included set of attributes are equal for all alternatives in the task. As for parking facility characteristics, type, hourly fee, and egress-time are included in the experiment. Furthermore, parking facility occupation rates and waiting times for an available spot have been included in the form of search time for an available parking spot. In the second stage of the experiment, an additional time-related attribute is also included for the smart parking alternative, which is the difference in travel time, to cover the increased or decreased travel time required to drive to the alternative offered by the SPS.

Once the attributes have been determined, levels can be assigned. Although the number of levels per attribute can be considered independently for each attribute, it has been decided to use three levels for all attributes. Three levels are preferred over two, as they allow for the observation of non-linear utility relationships between the levels rather than assuming linear relations (Hensher et al., 2015). Although an increasing number of levels would enable better observation of potential non-linear relationships, this would also increase the number of profiles required in the choice experiment, as well as the number of effect- or dummy-coded variables in the analysis of nominal-level attributes. The objective of the level range distribution is to maximize end-points while maintaining task realism. Therefore, the trip purpose variable ranges from a formal activity like a dentist appointment (with no flexibility in arrival time) to an informal activity such as shopping (with large flexibility in arrival time). The delay variable ranges from 0 to 10 minutes. The types of parking facilities included in the experiment, as well as all other attribute levels are based on parking availability in medium to large sized cities in the Netherlands including Eindhoven, Maastricht, Utrecht, and 's-Hertogenbosch. The levels of the search time for parking spot attribute are relatively high for the Netherlands. However, reducing the levels of this attribute further is expected to make their differences negligible in contrast to the other time-related variables. To prevent overlap between the offered SPS advice alternative in the second stage and the alternatives in the first, the levels of the parking alternative in the second stage are an alteration of the SQ advice alternative chosen in the first stage. The lower bound of the hourly price, search time and egress-time attributes is half of the respective SQ value, whilst the upper bound is one and a half times this value. The difference in travel time is computed based on the respondent's travel time to the city center and is therefore respondent-specific. Table 5 presents all attributes and their related levels.

Table 5: Attributes and attribute levels

Attribute	Levels		
Context			
Trip purpose	Dentist appointment	Meeting with a friend	Doing some shopping
Delay	0 minutes	5 minutes	10 minutes
Stage 1 - Parking location choice			
Type of parking facility	On-street parking	Surface level parking	Parking garage
Price per hour	€1.00	€3.00	€5.00
Search time for parking spot	2 minutes	5 minutes	8 minutes
Walking time to final destination	2 minutes	7 minutes	12 minutes
Stage 2 - Adapted parking choice			
Type of parking facility	On-street parking	Surface level parking	Parking garage
Price per hour	SQ - 50%	Equal to SQ	SQ + 50%
Search time for parking spot	SQ - 50%	Equal to SQ	SQ + 50%
Walking time to final destination	SQ - 50%	Equal to SQ	SQ + 50%
Difference in travel time[a]	-20% minutes	0 minutes	20% minutes

a. Of the participant's indicated travel time; capped at +/- 5 minutes.

3.6 Questionnaire and experiment design

The aim of the study is to evaluate the probability of an individual changing their parking behavior due to an offered SPS advice. To achieve this, an online questionnaire consisting of four parts has been set up in the LimeSurvey environment. The questionnaire was available in both Dutch and English. After a brief introduction to the study, the questionnaire begins with questions related to current travel behavior, such as possession of a driver's license, driving frequency, and frequency of visits to a city center. The first part ends with questions about parking behavior, such as repeated parking behavior and parking choice diversion. These questions are used to introduce the participants to the topic and the questionnaire are not included in the reported models discussed later in this report since no evidence of correlation with parking location choice has been found in the literature review.

The second part of the questionnaire forms the core and starts with an introductory choice scenario explaining the workings of the experiment, the main principle of SPSs, and the attributes included in the experiment. After this, six randomly selected sequential choice scenarios are administered to respondents. In the first stage, respondents have the opportunity to choose between one of two parking alternatives and a neither option. Upon selecting one of the parking alternatives, the respondent is presented with the second stage choice task in which they are asked to choose between the SQ alternative selected in stage 1 and a new SPS advice alternative.

Regarding the composition of the offered choice tasks, it was decided to generate the 2 consecutive choice tasks as one experiment to prevent interdependence between the attributes in the context, the two parking alternatives in stage 1, and the SPS advice in stage 2. If the two context attributes, the four alternative specific attributes for each alternative in stage 1 and the five attributes of the SPS advice alternative in stage 2 were to be estimated in a full factorial design, this would result into 14,348,907 profiles (Hensher et al., 2015). To reduce the number of possible profiles while satisfying the attribute balance condition and allowing interaction between the context and all other variables, an orthogonal fractional factorial design with 144 profiles has been generated with 40,676 evaluations in Ngene (Rose et al., 2021). This experiment design is presented in Table A1 in appendix A. Each attribute contains three levels (0,1,2) representing the true attribute levels. The code required generate this design, is also available in Listing A1 in Appendix A.

The experiment design profiles were transformed into textual descriptions of the alternatives by associating a label with each attribute and by substituting each attribute level code with a value or description. According to Hensher et al. (2015), researchers have the flexibility to assign attributes to columns and attribute levels to the corresponding coding without impacting the orthogonal nature of the experiment. However, in Table A1, columns A and B are reserved for the context variables due to their integrated interaction effects with all other columns. This allocation of attributes is intended to decrease the number of choice situations in which two alternatives are equal or where choice alternatives are ordered lexicographically (i.e., one alternative is dominant and therefore always outperforms the other) (Scott, 2002). Although it is not possible to determine dominant alternatives with complete certainty before analysis, the attribute effects outlined in the literature review in Chapter 2 were used as a reference. Here, all monetary and time-related attributes were assumed to have a negative effect on alternative selection, and the different types of parking facilities were considered equally distinct. Thus, a task containing two alternatives of the same type, where one performs better than the other on all other attributes, is considered lexicographically ordered, while a similar task with two alternatives of different types is not. This process was conducted manually, and the resulting attribute and attribute level distribution is presented in Table 6. Based on this distribution, there are nine dominant alternatives in the first stage, with three favoring alternative A and six favoring alternative B. In the second stage, six dominant alternatives can be identified, with two favoring the SQ alternative and four favoring the alternative recommended by the SPS. Since the attribute values in the second stage of the experiment depend on those in the first stage, the number of dominant alternatives in this stage can reach up to 20, depending on the chosen SQ alternatives. The experiment does not include any choice situations in which the respondent has to choose between two equal alternatives. If the respondent could not make a choice between the two alternatives, they could select a 'neither' option. An example of the consecutive choice experiment is presented in Figure 2.

In the final stage of the questionnaire, participants are required to provide their socio-demographic profile, including characteristics such as gender, age, household income, level of education, country of residence and postal code. If respondents preferred not to answer one of these questions, they could select a 'prefer not to say' option. Given that a large number of respondents would be needed if each respondent preformed in just 6 of the sequential choice scenarios and assuming 30 observations per choice task as a rule of thumb, respondents were given the option to perform in up to 12 additional choice scenarios. At this stage, respondents were already familiar with the choice contexts and could choose the number of additional choice scenarios that suited their personal situation. This approach helps to limit the factors that may cause a shift from analytical knowledge-based decision making to intuitive rule-based decision making (Wickens et al., 2004). In turn, this helps to minimize the associated unreliability of the results.

3.7 Conclusion

This chapter has provided an exploration of the methodological approach employed in the study, including the experimental design and survey construction. After considering various preference measuring techniques, it was determined that the stated adaptation experiment, utilizing stated preferences within an online survey, was the most suitable method for determining participants' choice behavior.

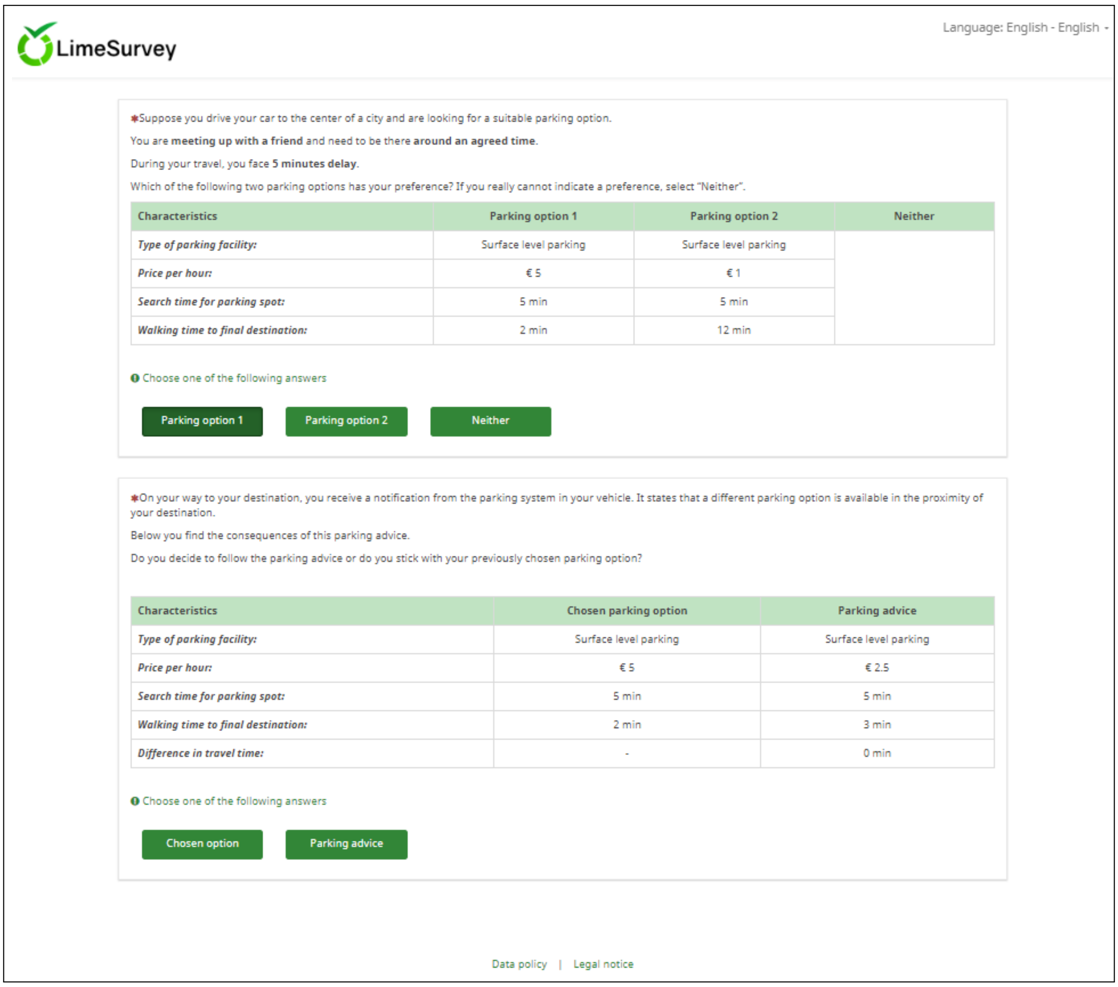
The chapter commenced with an examination of utility theory, followed by an overview of the MNL and LCM models, accompanied by relevant model evaluation theories. Section 3.5 presented a comprehensive set of eight attributes, derived from the literature review outlined in Chapter 2. These attributes encompassed trip purpose, delay, type of parking facility, hourly parking fee, search time for a parking spot, walking time to the final destination, and the difference in travel time.

Table 6: Attributes and attribute level allocation

Col.	Attribute label	Coding 0	1	2
Context				
A	Trip purpose	Dentist appointment	Meeting with a friend	Doing some shopping
B	Delay	0 minutes	5 minutes	10 minutes
Stage 1 - Parking location choice; alternative A				
C	Type of parking facility	On-street parking	Surface level parking	Parking garage
D	Price per hour	€1.00	€3.00	€5.00
E	Search time for parking spot	8 minutes	2 minutes	5 minutes
F	Walking time to final destination	2 minutes	7 minutes	12 minutes
Stage 1 - Parking location choice; alternative B				
G	Type of parking facility	On-street parking	Surface level parking	Parking garage
H	Price per hour	€5.00	€1.00	€3.00
I	Search time for parking spot	2 minutes	5 minutes	8 minutes
J	Walking time to final destination	2 minutes	7 minutes	12 minutes
Stage 2 - Adapted parking choice				
K	Type of parking facility	On-street parking	Surface level parking	Parking garage
L	Price per hour	SQ + 50%	SQ - 50%	Equal to SQ
M	Search time for parking spot	SQ - 50%	Equal to SQ	SQ + 50%
N	Walking time to final destination	SQ + 50%	Equal to SQ	SQ - 50%
O	Difference in travel time[a]	20% minutes	0 minutes	-20% minutes

a. Of the participant's indicated travel time; capped at +/- 5 minutes.

Based on this attribute set, an orthogonal experiment with 144 profiles was generated with the use of Ngene. This experimental design enabled interactions between the two context attributes and all other attributes. The generated experiment was subsequently integrated into the third part of a four-part online questionnaire administered via Limesurvey.



LimeSurvey

Language: English - English

*Suppose you drive your car to the center of a city and are looking for a suitable parking option.

You are **meeting up with a friend** and need to be there **around an agreed time**.

During your travel, you face **5 minutes delay**.

Which of the following two parking options has your preference? If you really cannot indicate a preference, select "Neither".

Characteristics	Parking option 1	Parking option 2	Neither
Type of parking facility:	Surface level parking	Surface level parking	
Price per hour:	€ 5	€ 1	
Search time for parking spot:	5 min	5 min	
Walking time to final destination:	2 min	12 min	

Choose one of the following answers

Parking option 1 | Parking option 2 | Neither

*On your way to your destination, you receive a notification from the parking system in your vehicle. It states that a different parking option is available in the proximity of your destination.

Below you find the consequences of this parking advice.

Do you decide to follow the parking advice or do you stick with your previously chosen parking option?

Characteristics	Chosen parking option	Parking advice
Type of parking facility:	Surface level parking	Surface level parking
Price per hour:	€ 5	€ 2.5
Search time for parking spot:	5 min	5 min
Walking time to final destination:	2 min	3 min
Difference in travel time:	-	0 min

Choose one of the following answers

Chosen option | Parking advice

Data policy | Legal notice

Figure 2: Example consecutive choice tasks

4 Data collection and refinement

This chapter commences with a comprehensive account of the participant recruitment process employed in the study. Section 4.2 provides a detailed exposition of the data transformation procedures employed to convert the collected data into a format amenable to analysis. Section 4.3 of this chapter examines the data filtering techniques utilized in order to refine the dataset for subsequent analysis. The chapter is ended with a conclusion.

4.1 Sample recruitment

The data used in this study was collected through an online questionnaire administered in September and October 2022. Respondents were recruited through social media, house-to-house flyering, and the Zuid-Limburg Bereikbaar mobility panel. The Zuid-Limburg Bereikbaar program office focuses on improving accessibility, promoting efficient car use, and encouraging sustainable transportation in Zuid-Limburg, a region in the southern most part of the Netherlands ("Zuid-Limburg Bereikbaar", 2023). The online questionnaire was developed using LimeSurvey, an open-source commercial surveying tool that enables stated choice experiments.

During the data cleaning process, 669 responses out of the 2288 recorded responses were removed, leaving a total of 1619 respondents that can be included in the analysis. The 669 deleted responses consisted of incomplete responses, responses from participants without a driver's license, responses with an indicated travel time to the city center of more than 120 minutes, respondents who indicated that they misinterpreted the difference in travel time variable, and repeated and test entries. It should also be noted that some study participants found it difficult to position themselves in the provided choice contexts and responded neutral (i.e., selecting a single answer option for every task). Because the effect of these entries on the predictive power of the model is unknown at this stage of the study, a new indicator indicating the non-choice behavior of the respondent is added to the dataset. This indicator is valued at 0 if the respondent always selected option 1 or option 2 in all presented choice tasks, or if the respondent has selected the neither option in every 3-level choice task. The latter is only based on the initial six choice tasks presented to the respondent since the amount of choice tasks completed by the respondent in the second set of tasks differs per respondent, and it is common for the respondent to never select the neither option. The effects of these responses on model performance are described in Section 4.3.

4.2 Transforming data-structure

The survey data obtained from the online Limesurvey platform is organized in a wide-format, where each respondent entry occupies a single row in the dataset. While this data structure is suitable for Multinominal Logit Model (MNL) model-based analysis using the NLOGIT 6 package (Econometric Software Inc., 2016), it is not compatible with more sophisticated analysis types. Therefore, the Python script presented in Appendix B was executed to convert the data from wide to long-format. In this new format, each choice alternative for all choice tasks and each respondent is represented in a single row. Besides this, the type of visit attribute included in the choice context has been effect-coded into two new variables for analysis. These variables hold values $\begin{bmatrix}-1 & -1\end{bmatrix}$ for a dentist appointment, $\begin{bmatrix}1 & 0\end{bmatrix}$ for visiting a friend, and $\begin{bmatrix}0 & 1\end{bmatrix}$ for doing some shopping. Similarly, the parking facility type variable has been effect-coded into two new variables with values $\begin{bmatrix}-1 & -1\end{bmatrix}$ for on-street parking, $\begin{bmatrix}1 & 0\end{bmatrix}$ for surface level parking, and $\begin{bmatrix}0 & 1\end{bmatrix}$ for parking garage.

As the data generated by the two stages may be positioned differently relative to each other, four distinct data structures were established to investigate the optimal performance. These structures are formulated in accordance with the formats in Tables 7 to 10. In data format A, the parameter values of the same parameters in stages 1 and 2 are presented under the same variable. This means that the part worth utilities of equal variables are estimated in a single beta. Format B only includes data from the first experimental stage, and format C only includes data from the second stage. The setups of B and C are combined into a single structure in D, in which the second stage is coded in such a way that it has no effect on the estimation of the first, and vice versa. This way, the effects of a variable in the first stage are estimated independently of the effect of the same variable in the second stage. Although the parameter estimations for the same parameters in formats B and C should theoretically be equal to those in format D, the inclusion of a larger set of parameters in a model might have a small effect on the estimated part worth utilities.

Table 7: Data format A

Q	A	$i \in a$	Con. 1	Con. 2	k_1	k_2	$\dots$	k_i
$q_i \in Q$	$a_i \in A$	$i_1 \in a_i$	0	0	.	.	$\dots$	.
$q_i \in Q$	$a_i \in A$	$i_2 \in a_i$	0	0	.	.	$\dots$	.
$q_i \in Q$	$a_i \in A$	$i_3 \in a_i$	1	0	.	.	$\dots$	.
$q_i \in Q$	$a_i' \in A$	$i_1 \in a_i'$	0	0	.	.	$\dots$	.
$q_i \in Q$	$a_i' \in A$	$i_2 \in a_i'$	0	1	.	.	$\dots$	.
			β_0	γ_0	β_1	β_2	$\dots$	β_i

Table 8: Data format B

Q	A	$i \in a$	Con. 1	k_1	k_2	$\dots$	k_i
$q_i \in Q$	$a_i \in A$	$i_1 \in a_i$	0	.	.	$\dots$	.
$q_i \in Q$	$a_i \in A$	$i_2 \in a_i$	0	.	.	$\dots$	.
$q_i \in Q$	$a_i \in A$	$i_3 \in a_i$	1	.	.	$\dots$	.
			β_0	β_1	β_2	$\dots$	β_i

Table 9: Data format C

Q	A	$i \in a$	Con. 2	k_1	k_2	$\dots$	k_i
$q_i \in Q$	$a_i' \in A$	$i_1 \in a_i'$	0	.	.	$\dots$	.
$q_i \in Q$	$a_i' \in A$	$i_2 \in a_i'$	1	.	.	$\dots$	.
			γ_0	γ_1	γ_2	$\dots$	γ_i

Table 10: Data format D

Q	A	$i \in a$	Con. 1	k_{1a}	k_{2a}	$\dots$	k_{ia}	Con. 2	k_{1b}	k_{2b}	$\dots$	k_{ib}
$q_i \in Q$	$a_i \in A$	$i_1 \in a_i$	0	.	.	$\dots$	.	0	0	0	$\dots$	0
$q_i \in Q$	$a_i \in A$	$i_2 \in a_i$	0	.	.	$\dots$	.	0	0	0	$\dots$	0
$q_i \in Q$	$a_i \in A$	$i_3 \in a_i$	1	.	.	$\dots$	.	0	0	0	$\dots$	0
$q_i \in Q$	$a_i' \in A$	$i_1 \in a_i'$	0	0	0	$\dots$	0	0	.	.	$\dots$	.
$q_i \in Q$	$a_i' \in A$	$i_2 \in a_i'$	0	0	0	$\dots$	0	1	.	.	$\dots$	.
			β_0	β_1	β_2	$\dots$	β_i	γ_0	γ_1	γ_2	$\dots$	γ_i

Table 11: Model fit MNL models

	LL	*LL0*	*K*	*N*	ρ^2	*BIC*	$\delta BIC/\delta N$
Data structure A							
All respondents	-18,464.86	-27,555.41	32	30,459	0.330	37,260.09	-
Filter out non-choice respondents	-17,019.61	-27,064.28	32	30,009	0.371	34,369.12	6.42
Filter out non-visiting respondents	-14,799.89	-22,805.28	32	25,248	0.351	29,924.15	1.41
Filter out non-visiting and non-choice	-13,910.40	-22,519.18	32	24,985	0.382	28,144.83	1.67
Data structure B							
All respondents	-10,925.45	-17,456.95	24	15,890	0.374	22,083.05	-
Filter out non-choice	-95,51.71	-16,971.36	24	15,448	0.437	19,334.91	6.22
Filter out non-visiting respondents	-8,546.00	-14,373.14	24	13,083	0.405	17,319.50	1.70
Filter out non-visiting and non-choice	-7,703.22	-14,091.90	24	12,827	0.453	15,633.47	2.11
Data structure C							
All respondents	-7,309.70	-10,098.46	28	14,569	0.276	14,887.83	-
Filter out non-choice respondents	-7,301.23	-10,092.92	28	14,561	0.277	14,870.87	2.12
Filter out non-visiting respondents	-6,075.85	-8,432.14	28	12,165	0.279	12,415.08	1.03
Filter out non-visiting and non-choice	-6,067.46	-8,427.28	28	12,158	0.280	12,398.28	1.03
Data structure D							
All respondents	-18,234.92	-27,555.41	52	30,459	0.338	37,006.70	-
Filter out non-choice respondents	-16,852.72	-27,064.28	52	30,009	0.377	34,241.52	6.14
Filter out non-visiting respondents	-14,621.65	-22,805.28	52	25,248	0.359	29,770.39	1.39
Filter out non-visiting and non-choice	-13,770.47	-22,519.18	52	24,985	0.389	28,067.50	1.63

4.3 Data filtering

To further refine the choice data collected in the experiment described in Chapter 3.6, four different MNL models with varying data filters were estimated for four different data structures. The input and output used to estimate these models can be found in Appendix C. For each of the data structures, the first set of MNL models was estimated for the complete unfiltered set. The second set of models excluded the 42 respondents who only answered either choice option 1 or 2 in all presented choice tasks, or responded by selecting the neither option in the first six 3-level choice tasks. In the third set of MNL models, the 225 respondents who indicated that they never visit a city center by car were removed from the set because they likely have greater difficulty building a mental model of the choice scenario (van Bladel et al., 2008). In the fourth model, both the filters were applied. Table 11 provides an overview of the model performances.

Table 11 shows that all filters improve the goodness-of-fit and model performance of all models, although the improvements for data structure C are limited. Filtering out the respondents with a value of 0 for the non-choice indicator offers the largest improvement of the Bayesian Information Criterion (BIC) per removed observation. This filter will therefore be used for the remainder of model estimation. The effecs estimated in the MNLs of data structures A to D can be found in Tables 12 to 15, respectively.

Table 12: Estimation MNL model data structure A

		Pw Util.	*Pw Util. distribution*	*Std. Error*	$\|z\|>Z*$
Parameters in utility function					
Main effects					
Constant 1 (neither)		-7.878***		0.142	0.00
Constant 2 (parking advise)		-0.692***		0.032	0.00
Type of parking facility	On-street	-0.265[a]		-	-
	Surface level	0.045*		0.024	0.06
	Garage	0.220***		0.023	0.00
Fee (/€)		-1.013***[b]		0.025	0.00
Search time (/min)		-0.166***[b]		0.012	0.00
Egress time (/min)		-0.214***[b]		0.008	0.00
Diff in travelt (/min)		-0.098***[b]		0.013	0.00
Context effects trip purpose					
Dentist (fixed)	Constant 1	-0.078[a]		-	-
	Constant 2	0.027[a]		-	-
	On-street parking	0.093[a]		-	-
	Surface level parking	-0.061[a]		-	-
	Parking garage	-0.032[a]		-	-
	Fee (/€)	-0.294[a,b]		-	-
	Search time (/min)	0.120[a,b]		-	-
	Egress time (/min)	0.061[a,b]		-	-
	Diff in travelt (/min)	0.006[a,b]		-	-
Friend (flexible)	Constant 1	-0.040		0.111	0.72
	Constant 2	-0.032		0.028	0.24
	On-street parking	-0.038[a]		-	-
	Surface level parking	0.054**		0.021	0.01
	Parking garage	-0.017		0.021	0.43
	Fee (/€)	0.061**[b]		0.027	0.02
	Search time (/min)	-0.029**[b]		0.013	0.02
	Egress time (/min)	0.002[b]		0.009	0.81
	Diff in travelt (/min)	-0.003[b]		0.011	0.80
Shopping (free)	Constant 1	0.119		0.108	0.27
	Constant 2	0.006		0.028	0.84
	On-street parking	-0.056[a]		-	-
	Surface level parking	0.008		0.020	0.71
	Parking garage	0.049**		0.021	0.02
	Fee (/€)	0.233***[b]		0.046	0.00
	Search time (/min)	-0.091***[b]		0.023	0.00
	Egress time (/min)	-0.063***[b]		0.017	0.00
	Diff in travelt (/min)	0.008[b]		0.011	0.44
Context effects delay					
Delay (/min)	Constant 1	0.144***[c]		0.020	0.00
	Constant 2	0.035***[c]		0.005	0.00
	On-street parking	0.020[a,c]		-	-
	Surface level parking	0.002[c]		0.004	0.58
	Parking garage	-0.022***[c]		0.004	0.00
	Fee (/€)	0.025***[c,b]		0.003	0.00
	Search time (/min)	0.001[c,b]		0.001	0.72
	Egress time (/min)	0.006***[c,b]		0.001	0.00
	Diff in travelt (/min)	-0.005***[c,b]		0.002	0.01

***,**,* →Parameter is significant at the 1%, 5%, 10% level.

a. Part worth utility has been computed manually.

b. Parameter is continuous; part worth utility per unit.

c. Context effect is continuous; part worth utility per unit.

Table 13: Estimation MNL model data structure B

		Pw Util.	*Pw Util. distribution*	*Std. Error*	*|z|>Z∗*
Parameters in utility function					
Main effects					
Constant 1 (neither)		-6.918***		0.157	0.00
Type of parking facility	On-street	-0.233		-	-
	Surface level	-0.116***		0.036	0.00
	Garage	0.349***		0.035	0.00
Fee (/€)		-0.910***,[b]		0.028	0.00
Search time (/min)		-0.119***,[b]		0.014	0.00
Egress time (/min)		-0.184***,[b]		0.010	0.00
Context effects trip purpose					
Dentist (fixed)	Constant 1	-0.143[a]		-	-
	On-street parking	0.063[a]		-	-
	Surface level parking	-0.020[a]		-	-
	Parking garage	-0.043[a]		-	-
	Fee (/€)	-0.336[a,b]		-	-
	Search time (/min)	0.044[a,b]		-	-
	Egress time (/min)	0.053[a,b]		-	-
Friend (flexible)	Constant 1	0.136		0.122	0.26
	On-street parking	0.004[a]		-	-
	Surface level parking	-0.003		0.034	0.94
	Parking garage	-0.002		0.031	0.95
	Fee (/€)	0.082***,[b]		0.029	0.00
	Search time (/min)	0.002[b]		0.015	0.88
	Egress time (/min)	0.005[b]		0.010	0.64
Shopping (free)	Constant 1	0.007		0.117	0.95
	On-street parking	-0.067[a]		-	-
	Surface level parking	0.023		0.032	0.48
	Parking garage	0.044		0.031	0.16
	Fee (/€)	0.254***,[b]		0.050	0.00
	Search time (/min)	-0.047*,[b]		0.027	0.09
	Egress time (/min)	-0.058***,[b]		0.018	0.00
Context effects delay					
Delay (/min)	Constant 1	0.097***,[c]		0.022	0.00
	On-street parking	0.015[a,c]		-	-
	Surface level parking	0.029***,[c]		0.005	0.00
	Parking garage	-0.044***,[c]		0.006	0.00
	Fee (/€)	0.023***,[c,b]		0.003	0.00
	Search time (/min)	-0.004**,[c,b]		0.002	0.02
	Egress time (/min)	0.004***,[c,b]		0.001	0.00

***,**,* →Parameter is significant at the 1%, 5%, 10% level.
a. Part worth utility has been computed manually.
b. Parameter is continuous; part worth utility per unit.
c. Context effect is continuous; part worth utility per unit.

Table 14: Estimation MNL model data structure C

		Pw Util.	*Pw Util. distribution*	*Std. Error*	$\|z\|>Z*$
Parameters in utility function					
Main effects					
Constant 2 (parking advise)		-0.786***		0.036	0.00
Type of parking facility	On-street	-0.250[a]		-	-
	Surface level	0.125***		0.037	0.00
	Garage	0.125***		0.032	0.00
Fee (/€)		-1.340***,[b]		0.056	0.00
Search time (/min)		-0.257***,[b]		0.023	0.00
Egress time (/min)		-0.282***,[b]		0.017	0.00
Diff in travelt (/min)		-0.080***,[b]		0.014	0.00
Context effects trip purpose					
Dentist (fixed)	Constant 2	0.061[a]		-	-
	On-street parking	0.037[a]		-	-
	Surface level parking	-0.022[a]		-	-
	Parking garage	-0.015[a]		-	-
	Fee (/€)	-0.459[a,b]		-	-
	Search time (/min)	0.140[a,b]		-	-
	Egress time (/min)	-0.049[a,b]		-	-
	Diff in travelt (/min)	-0.005[a,b]		-	-
Friend (flexible)	Constant 2	-0.047		0.030	0.13
	On-street parking	-0.018[a]		-	-
	Surface level parking	0.045		0.028	0.11
	Parking garage	-0.027		0.030	0.37
	Fee (/€)	0.087[b]		0.062	0.16
	Search time (/min)	-0.052**,[b]		0.024	0.03
	Egress time (/min)	0.039**,[b]		0.018	0.04
	Diff in travelt (/min)	-0.008[b]		0.012	0.49
Shopping (free)	Constant 2	-0.015		0.030	0.62
	On-street parking	-0.019[a]		-	-
	Surface level parking	-0.023		0.028	0.40
	Parking garage	0.043		0.030	0.15
	Fee (/€)	0.372***,[b]		0.106	0.00
	Search time (/min)	-0.088**,[b]		0.042	0.04
	Egress time (/min)	0.010[b]		0.032	0.75
	Diff in travelt (/min)	0.013[b]		0.012	0.26
Context effects delay					
Delay (/min)	Constant 2	0.041***,[c]		0.005	0.00
	On-street parking	0.019[a,c]		-	-
	Surface level parking	-0.013**,[c]		0.005	0.01
	Parking garage	-0.006[c]		0.005	0.26
	Fee (/€)	0.021***,[c,b]		0.006	0.00
	Search time (/min)	0.006**,[c,b]		0.003	0.02
	Egress time (/min)	0.008***,[c,b]		0.002	0.00
	Diff in travelt (/min)	-0.011***,[c,b]		0.002	0.00

***,**,* →Parameter is significant at the 1%, 5%, 10% level.

a. Part worth utility has been computed manually.

b. Parameter is continuous; part worth utility per unit.

c. Context effect is continuous; part worth utility per unit.

Table 15: Estimation MNL model data structure D

		Pw Util.	*Pw Util. Dist.*	*Std. Error*	*|z|>Z∗*
Parameters in utility function					
1st stage - Parking location choice					
Main effects					
Constant 1 (neither)		-6.918***		0.157	0.00
Type of parking facility	On-street	-0.233[a]		-	-
	Surface level	-0.116***		0.036	0.00
	Garage	0.349***		0.035	0.00
Fee (/€)		-0.910***[b]		0.028	0.00
Search time (/min)		-0.119***[b]		0.014	0.00
Egress time (/min)		-0.184***[b]		0.010	0.00
Context effects trip purpose					
Dentist (fixed)	Constant 1	-0.143[a]		-	-
	On-street parking	0.063[a]		-	-
	Surface level parking	-0.020[a]		-	-
	Parking garage	-0.043[a]		-	-
	Fee (/€)	-0.336[a,b]		-	-
	Search time (/min)	0.044[a,b]		-	-
	Egress time (/min)	0.053[a,b]		-	-
Friend (flexible)	Constant 1	0.136		0.122	0.26
	On-street parking	0.004[a]		-	-
	Surface level parking	-0.003		0.034	0.94
	Parking garage	-0.002		0.031	0.95
	Fee (/€)	0.082***[b]		0.029	0.00
	Search time (/min)	0.002[b]		0.015	0.88
	Egress time (/min)	0.005[b]		0.010	0.64
Shopping (free)	Constant 1	0.007		0.117	0.95
	On-street parking	-0.067[a]		-	-
	Surface level parking	0.023		0.032	0.48
	Parking garage	0.044		0.031	0.16
	Fee (/€)	0.254***[b]		0.050	0.00
	Search time (/min)	-0.047*[b]		0.027	0.09
	Egress time (/min)	-0.058***[b]		0.018	0.00
Context effects delay					
Delay (/min)	Constant 1	0.097***[c]		0.022	0.00
	On-street parking	0.015[a,c]		-	-
	Surface level parking	0.029***[c]		0.005	0.00
	Parking garage	-0.044***[c]		0.006	0.00
	Fee (/€)	0.023***[c,b]		0.003	0.00
	Search time (/min)	-0.004**[c,b]		0.002	0.02
	Egress time (/min)	0.004***[c,b]		0.001	0.00
2nd stage - Adapted parking choice					
Main effects					
Constant 2 (parking advise)		-0.786***		0.036	0.00
Type of parking facility	On-street	-0.250[a]		-	-
	Surface level	0.125***		0.037	0.00
	Garage	0.125***		0.032	0.00
Fee (/€)		-1.340***[b]		0.056	0.00
Search time (/min)		-0.257***[b]		0.023	0.00
Egress time (/min)		-0.282***[b]		0.017	0.00
Diff in travelt (/min)		-0.080***[b]		0.014	0.00

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Table 15 – continued from previous page

		Pw Util.	*Pw Util. Dist.*	*Std. Error*	*|z|>Z**
Context effects trip purpose					
Dentist (fixed)	Constant 2	0.061[a]		-	-
	On-street parking	0.037[a]		-	-
	Surface level parking	-0.022[a]		-	-
	Parking garage	-0.015[a]		-	-
	Fee (/€)	-0.459[a,b]		-	-
	Search time (/min)	0.140[a,b]		-	-
	Egress time (/min)	-0.049[a,b]		-	-
	Diff in travelt (/min)	-0.005[a,b]		-	-
Friend (flexible)	Constant 2	-0.047		0.030	0.12
	On-street parking	-0.018[a]		-	-
	Surface level parking	0.045		0.028	0.11
	Parking garage	-0.027		0.030	0.37
	Fee (/€)	0.087[b]		0.062	0.16
	Search time (/min)	-0.052**[b]		0.024	0.03
	Egress time (/min)	0.039**[b]		0.018	0.04
	Diff in travelt (/min)	-0.008[b]		0.012	0.50
Shopping (free)	Constant 2	-0.015		0.030	0.62
	On-street parking	-0.019[a]		-	-
	Surface level parking	-0.023		0.028	0.40
	Parking garage	0.043		0.030	0.15
	Fee (/€)	0.372***[b]		0.106	0.00
	Search time (/min)	-0.088**[b]		0.042	0.04
	Egress time (/min)	0.010[b]		0.032	0.75
	Diff in travelt (/min)	0.013[b]		0.012	0.26
Context effects delay					
Delay (/min)	Constant 2	0.041***[c]		0.005	0.00
	On-street parking	0.019[a,c]		-	-
	Surface level parking	-0.013**[c]		0.005	0.01
	Parking garage	-0.006[c]		0.005	0.26
	Fee (/€)	0.021***[c,b]		0.006	0.00
	Search time (/min)	0.006**[c,b]		0.003	0.02
	Egress time (/min)	0.008***[c,b]		0.002	0.00
	Diff in travelt (/min)	-0.011***[c,b]		0.002	0.00

***,**,* →Parameter is significant at the 1%, 5%, 10% level.
a. Part worth utility has been computed manually.
b. Parameter is continuous; part worth utility per unit.
c. Context effect is continuous; part worth utility per unit.

As expected, the parameter estimates of the MNL models of data structures B (Table 13) and C (Table 14) are equal or almost equal to their related estimates in structure D (Table 15). Although the dependent variable in the two experiment stages explains a different tendency, there is no reason to use separate models. The comparison of the models of Structures A and D is more complex because the parameter estimates in the two models explain the same behavior differently. The estimates in Table 12 comprise the effects of both the stated preference (Stage 1) and the stated adaptation (Stage 2) experiment, allowing for a less accurate prediction of parking location choice behavior. Table 15, on the other hand, includes a larger set of parameters, allowing for a more detailed prediction of behavior in the first and second stage contexts. Since the goodness-of-fit for both models is considered excellent, as indicated by the respective McFadden Pseudo R-Squared statistics of 0.371 and 0.377 (McFadden, 1979), the Likelihood Ratio Statistic (LRS) is used to determine which of the two structures explains the observed choice behavior more efficiently. Model D is considered the unrestricted and A the restricted model due to the increased number of variables K in Model D. With an LRS of 333.78 and a critical Chi-square of 31.41, the model of Structure D performs significantly better than the model of Structure A.

4.4 Conclusion

In this chapter, we provide a description of the data collection and refinement process conducted for the study. The recruitment of participants involved employing various methods, including social media, house-to-house flyering, and the Zuid-Limburg Bereikbaar mobility panel. Initial data cleaning procedures resulted in the exclusion of 669 incomplete or irrelevant responses, leaving a total of 1619 respondents available for analysis. The collected data initially adopted a wide-format, which was appropriate for conducting MNL analysis. However, in order to facilitate more advanced analysis techniques, a Python script was employed to transform the data into a long-format. This revised format allowed for the representation of each choice alternative, pertaining to all tasks and respondents, in a single row.

Furthermore, the dataset underwent additional refinement by filtering out respondents who exhibited excessive non-choice behavior. Subsequently, from a set of four different data structures, the most optimal one was selected. By utilizing this selected data structure, it became possible to estimate the effects of attributes in stages 1 and 2 of the experiment as distinct parameters in the subsequent analysis.

5 Results

This chapter presents the results of the data analysis conducted in the study. In Section 5.1, a descriptive analysis is performed to assess the representativeness of the sample for the Dutch traveling population and examine the characteristics of the sample's travel and parking behavior. Section 5.2 provides an overview of the results obtained from a basic Multinominal Logit Model (MNL) model, including a statistical comparison of the estimated parameters between the two stages of the experiment. Lastly, Section 5.3 presents the results of a two- and three-class Latent Class Model (LCM).

5.1 Descriptive analysis

As mentioned in Section 3.6, the data has been collected in September and October 2022. Of the 2288 individuals that started the survey, 633 did not complete it to a point where analysis would be possible. The completion rate of the survey therefore is 72.3%. Alongside the consecutive stated choice experiment, the questionnaire collected socio-demographic and behavioral data of the respondents. Besides its uses in model estimations, this allows the creation of a better understanding of the composition of the sample.

5.1.1 Socio-demographic characteristics

This section aims to compare the socio-demographic characteristics of the sample to the 'Onderweg in Nederland (ODiN) 2021' sample created by Statistics Netherlands (2022b) when possible. The ODiN 2021 sample provides information about the daily mobility of Dutch citizens, and is widely considered representative for the travelling Dutch population. To match the ODiN sample to the target group of this study, the ODiN sample has been filtered to only include the 48,474 respondents in possession of a car drivers license. For comparisons sake, questionnaire respondents that indicated they would rather not answer a personal question have been removed from the sample, further reducing the overall sample size from 1577 to 1546.

Gender
Figure 3 shows the distribution of both the study and ODiN 2021 samples on the bases of gender. The gender distribution of the sample is comparable to that in the ODiN set, albeit there is a slight over-representation of woman in the sample. A chi-square goodness of fit test is used to statistically determine if the study sample represents the population included in the ODiN 2021 set. The test has a chi-square (χ^2) statistic of 5.82 with 1 degree of freedom and therefore has a p-value of 0.02. This means the study sample is different than the ODiN 2021 sample and therefore does not represent the Dutch travelling population on the basis of gender.

Age
From Figure 4 it becomes clear the study sample contains a relative over-representation of people in the 41-65 years age class, resulting in an under-representation of the 20-40 and 66-80 classes. This distribution can be explained by the composition of the 'Zuid-Limburg Bereikbaar' panel which forms the largest group of respondents. This age distribution is similar to that observed by Burger (2021) and Sanders (2022), who also made use of the 'Zuid-Limburg Bereikbaar' panel in their studies. The goodness of fit test also has a result significant at 1% and thus confirms that the sample is not representative for the Dutch traveling population.

Highest finished level of education
As for the highest finished level of education, Figure 5 shows a large over-representation in the sample for the higher educated respondent class. As expected, the chi-square test confirms that the sample

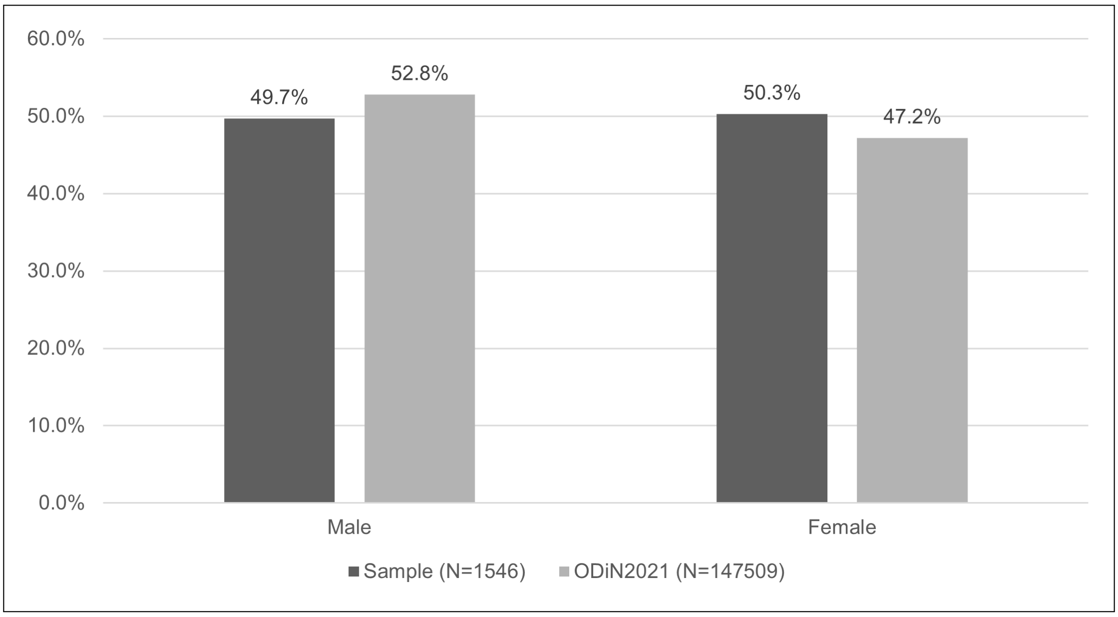

Figure 3: Gender distribution

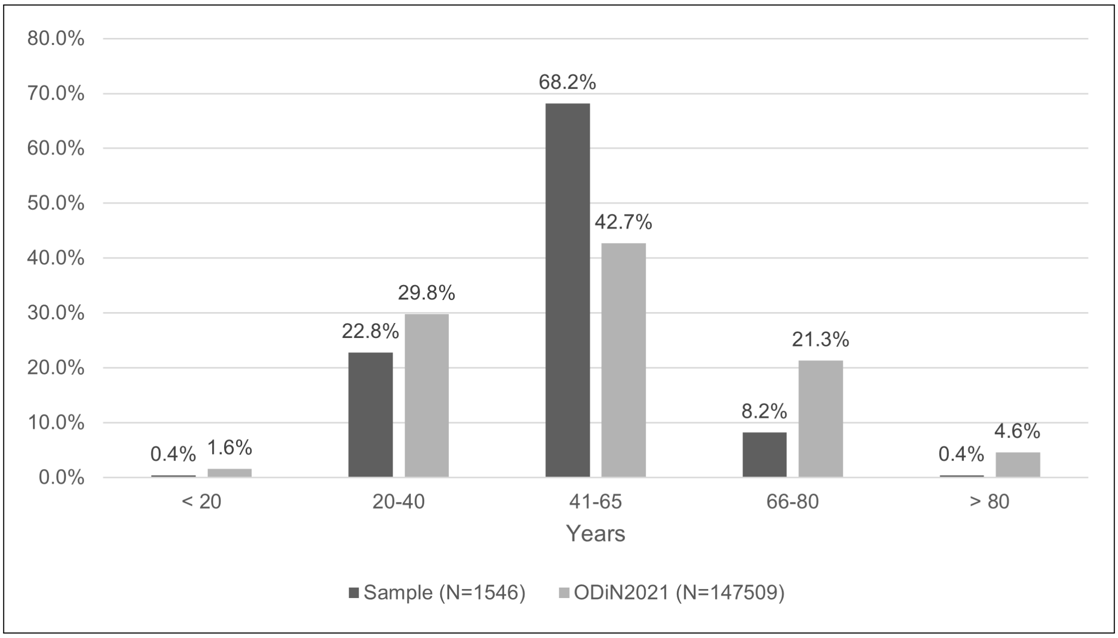

Figure 4: Age distribution

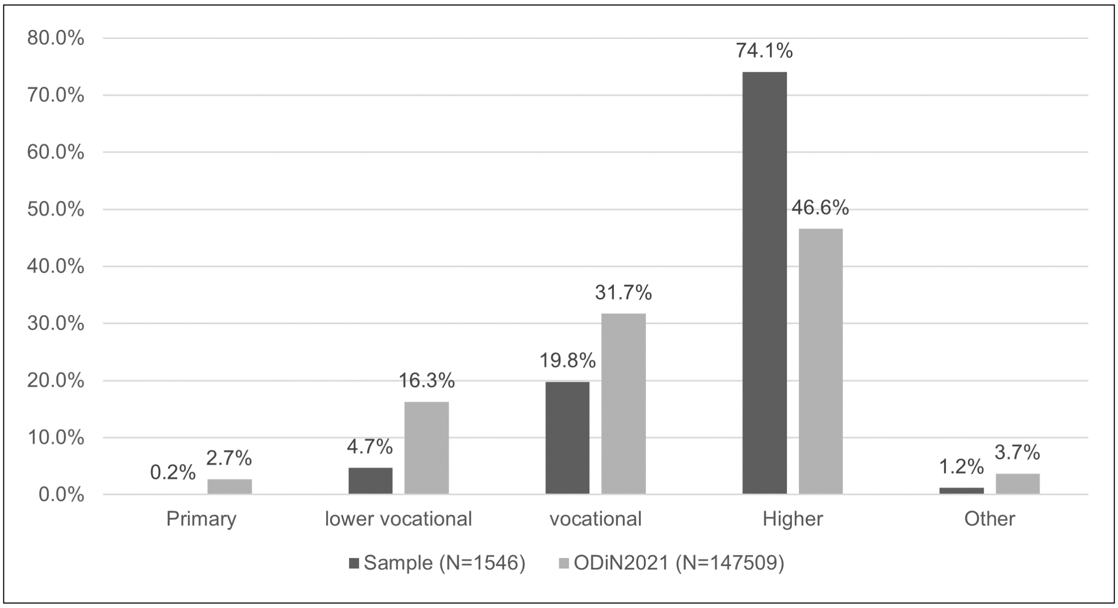

Figure 5: Education distribution

does not represent the traveling Dutch population. In the study sample, the higher educated group is separated into individuals that finished a Bachelors degree and those that finished a Master/PhD to allow for a more in-dept analysis of this group. These groups form 37.8% and 36.3% of the sample respectively. The lower vocational, and vocational classes are under-represented in the sample.

Annual net household income

Unfortunately, a large portion of the respondents in the sample indicated they rather not disclose information about the annual net income of their household. Besides this, the ODiN 2021 set only provides respondent household income data on the basis of 10% groups; because of which comparison of the sample with ODiN 2021 is not possible. Therefore, the study sample is compared to the average annual net income of a Dutch household (Statistics Netherlands, 2022a) of €48.800 in 2020. The mean of the respondents in the sample that did provide information about income however lays slightly higher than the border between the 40,000-50,000 and 50,000-100,000 income groups. This means respondents in the sample, on average, have a higher annual net income than the average Dutch household. This is not surprising considering that drivers license possession was a participation requirement, and that license possession rates are lower for lower income groups in the Netherlands (Statistics Netherlands, 2018).

Living country

The vast majority of respondents live in the Netherlands. Small groups 4.9%, 0.7% and 0.1% live in Belgium, Germany, and Luxembourg, respectively.

Conclusion

From the descriptive analysis on the basis of socio-demographic characteristics, it can be concluded with certainty that the study sample does not properly represent the Dutch travelling population on the basis of gender, age, and level of education. Although the sample is not limited to Dutch citizens, this group is by far the largest in the sample. A good representation would have therefore allowed generalization of the results for the entire population. Since this is not the case, generalization to

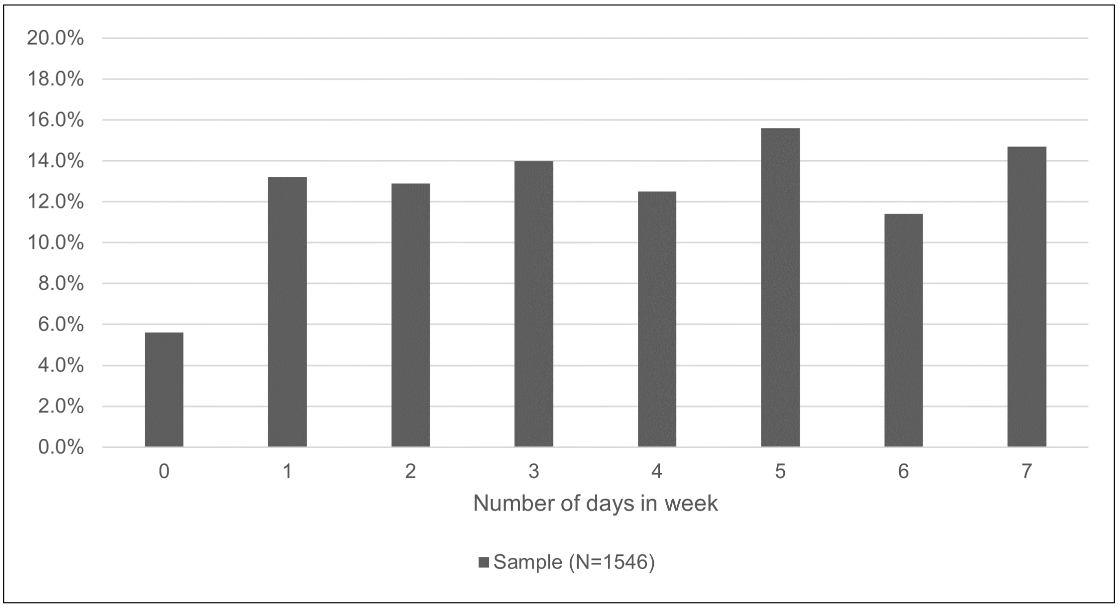

Figure 6: Driving frequency

the level of the traveling Dutch population is only possible via respondent weighting, or by including socio-demographic characteristics in the latent class analysis, of which the former falls outside of the scope of the study.

5.1.2 Behavioral characteristics

Like the socio-demographic characteristics of the sample, the behavioral characteristics of the respondents in the sample provide information on how members of the sample behave. Unfortunately, no apparent data suitable for comparison is available at the time of writing. Therefore, this section has an increased focus on the description of how the sample behaves in some travel and parking related contexts, rather than the respresentability of the sample.

Driving frequency

Figure 6 shows the distribution of the number of weekdays on which a respondent in the sample drives a car. 5.6% of the sample does not use a car on a weekly basis. The remaining 94.4% is spread out relatively equally over the weekdays in the set, varying between 11.4% (six days a week) and 15.6% (five days a week); indicating the presence of a good variety in car use frequency in the sample.

Visits to city center

Regarding the frequency distributions of visits to the city center by car (Figure 7), it was found that 9.4% of the respondents in the sample reported never visiting a city center by car. Over 80% of the respondents in the sample visit a city center by car at least once per quartile, with the largest proportion of respondents (29.9%) visiting the city center once per month. This suggests that the respondents are acquainted with parking situations in city centers.

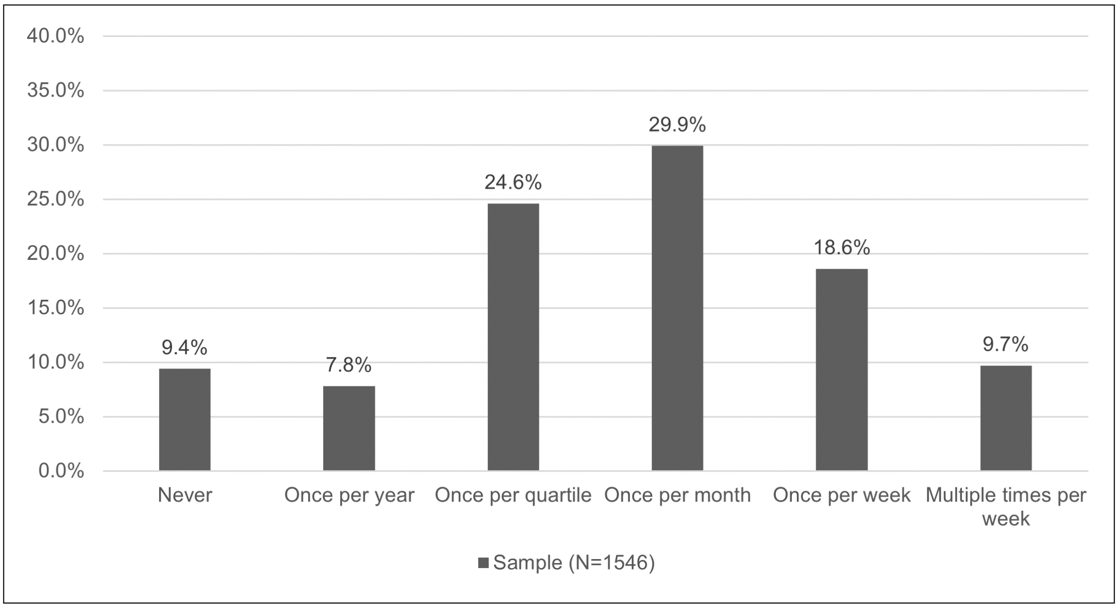

Figure 7: Visits to city center by car

Travel time to city center
The travel time of respondents in the sample (Figure 8) varies between 1 and 120 minutes. The largest group of respondents have travel times of 6 to 10 minutes, followed by 11 to 15 and 16 to 20 minutes.

Repeated parking behavior
Figure 9 shows the distribution of answers to the question *'How regularly do you park in the same parking facility when you visit the city center?'*. To examine this particular characteristic, the 146 respondents that indicated they never visit a city center by car have been temporarily excluded from the analysis. From the responses it becomes clear that over half of the respondents often park their car in the same parking facility when visiting a city center whilst 15.9% always parks their car in the same facility, meaning that just over one third of the respondents does not regularly park in the same facility; an unsurprising result considering that humans are often described as creatures of habit that find comfort in routines (Grohol, 2016).

Reasons to diverge to other parking facility
In the first part of the questionnaire, the respondents were asked to select whether they would diverge to another parking facility for the following four reasons: The parking facility seems to be full; a Parking Guidance and Information System (PGIS) indicates the parking facility is full; upon arrival, the parking lot is too expensive and; you have to diverge routes to reach the facility. The distributions the 'yes' responses to this question are presented in Figure 10. From the results it becomes clear that respondents in the sample are most likely to diverge when they observe the parking lot is full. Interestingly, 18.2% less respondents indicated to diverge when a PGIS provides them with the same information. This observation might indicate a lack of trust in types of Variable Message Signage (VMS) or technology in general. With a 34.2% diversion rate, a too high parking fee is also an important reason for drivers to diverge, whilst a road blockage seems to be the least likely of the four reasons to diverge.

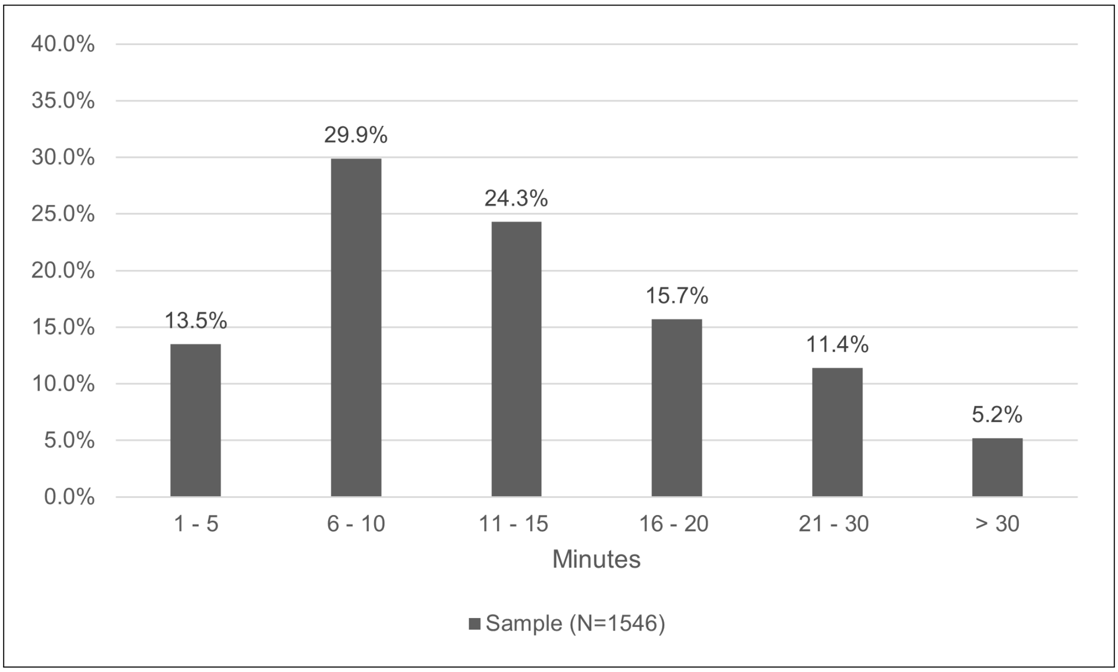

Figure 8: Travel time by car

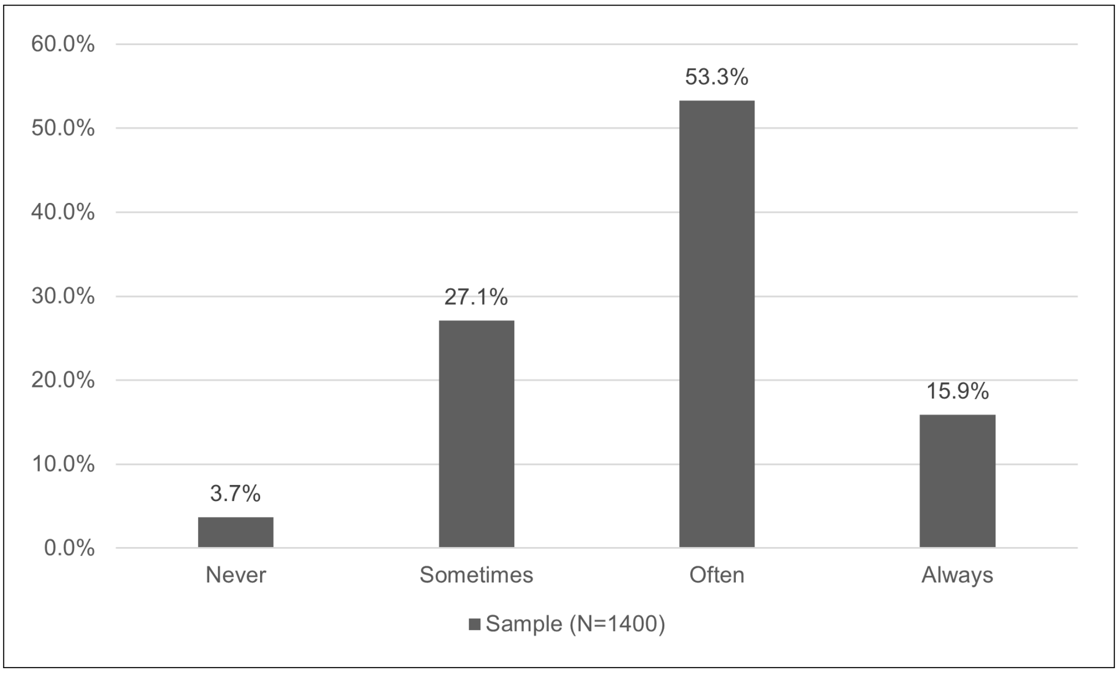

Figure 9: Repeated parking behavior

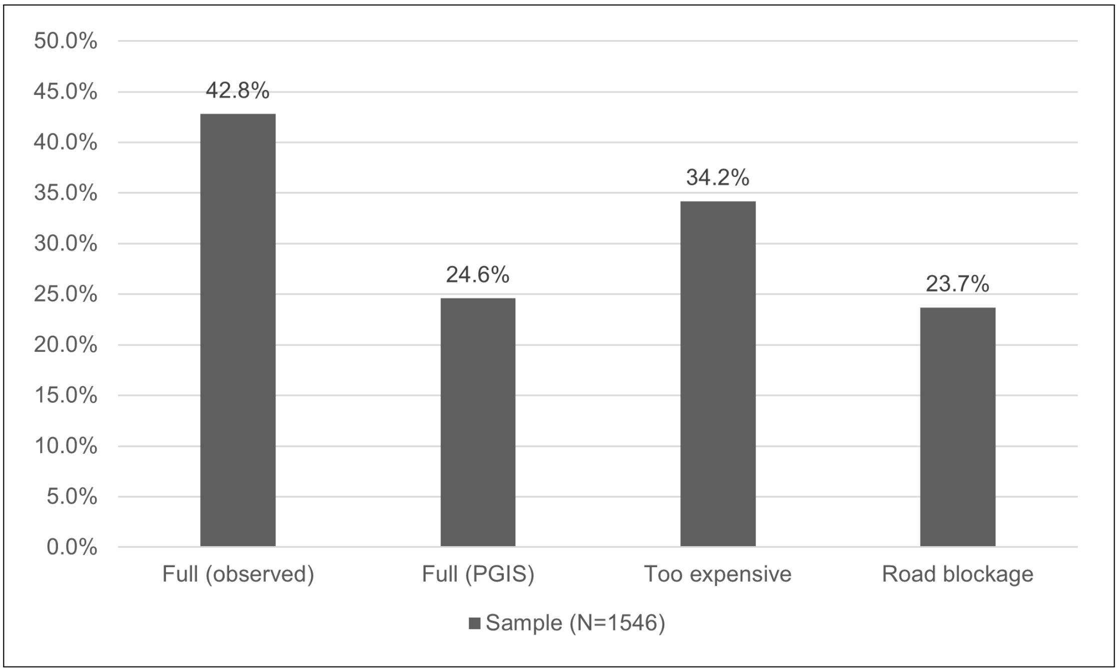

Figure 10: Reasons to diverge to another parking facility

5.1.3 Creating 3-level respondent data

To limit the number of effect coded variables required for the analysis of the socio-demographic data on the nominal level, as well as to limit variable levels with a low frequency distribution, these variables have been re-coded to a format with a maximum of 3 levels using the Python programming language. The full coding used for the transformation of these variables can be found in listing B3 in appendix B. For age this results in the following grouping: younger than 40, 40 to 65, and older than 65. Lastly, the levels of education are transformed into lower educated, college educated (Bachelor), and higher educated (Master, PhD). Because exclusion of respondents who chose not to answer the household income question from the sample would result in a large loss of data, this parameter is not included in further analysis. Additionally, the distribution of living country shows an offset of 94.5% for the Netherlands and 5.5% for other countries, which is too skewed to include in further analysis.

5.2 Multinominal logit model

This section presents an evaluation of the results obtained from the estimation of the MNL model previously described. These results are shown in Table 16. The analysis of the results will be divided in accordance with the two experimental stages.

The effects of gender, age, and level of education are estimated as interactions with the main effects in the model. Based on the expectation that the majority of interaction parameters between the socio-demograhic characteristics and the context effects would be insignificant due to the generally small size of context effect parameter estimations, it was decided not to include these interactions in the model. Excluding these interactions would additionally help to reduce the number of to be estimated parameters.

To further limit the number of parameters, it is assumed that the effects of socio-demographic characteristics are linear across different levels. As a result, the effects of the various attribute levels can be estimated using single parameters. Specifically, for gender, the variable used to calculate interactions takes the value of -1 for males and 1 for females. The age variable is assigned -1 for respondents younger than 40, 0 for respondents aged between 40 and 65, and 1 for respondents older than 65. Lastly, the education variable takes the value of -1 for lower educated respondents, 0 for college educated respondents, and 1 for higher educated respondents.

The McFadden ρ^2 value of the estimated MNL model is 0.388, indicating an excellent model fit (McFadden, 1979). The Likelihood Ratio Statistic (LRS) of 20,593,47 at a critical χ^2 statistic of 113.15 at 90 degrees of freedom, indicates that the MNL model outperforms the null model.

5.2.1 Experiment stage 1 - Parking location choice

The first half of Table 16 presents the estimation results of the first stage of the experiment, where respondents were asked to choose between two hypothetical parking alternatives and a "neither" option. The estimation of the alternative-specific constant 1 reveals that the decision to choose neither of the parking alternatives is negative and statistically significant at the 1% level. This implies that respondents are more likely to select one of the defined parking alternatives.

Concerning the types of parking facilities, the results indicate that respondents tend to prefer parking options with a parking garage type. The estimate of this variable is positive and significant at the 1% level, with a value of 0.342. On-street and surface-level parking facility options, on the other hand, have negative effects on utility of an alternative, with on-street parking being the least preferred.

As for the hourly fee attribute, the large negative part worth utility of -0.863 per Euro is not surprising, and it is statistically significant at the 1% level. This result is consistent with the findings of a variety of academic literature, such as Golias et al. (2002), which reported that parking cost is the main (negative) factor influencing the parking location choice of individuals.

The estimates for the search time and egress time attributes are also negative and statistically significant at the 1% level, indicating that an alternative is less likely to be chosen with an increasing time value. Of the two, egress time has a greater negative part worth utility of -0.159 per minute, indicating a stronger effect. This tendency has been confirmed by the studies of Axhausen and Polak (1991) and Lau et al. (2005), among others.

To conduct a more comprehensive analysis of the effects of the context variables, namely trip purpose and delay, the part-worth utilities of these context attributes were computed along with the main effects. The computed results for trip purpose and delay are presented in Table 17 and Table 18, respectively, taking into account the attribute levels presented to the participants in the choice contexts.

While none of the effects of trip purpose, except for the interactions between visiting a friend and fee, as well as between shopping and fee, shopping and search time, and shopping and egress time, reach statistical significance at the 10% level, Table 17 reveals some intriguing distribution patterns of estimates.

Regarding the effects of trip purpose on the neither alternative specific constant, we observe a more negative estimate when visiting a city center for a dentist appointment or to do some shopping. This can likely be attributed to the fact that the duration of meeting with a friend is less defined compared to the other two activity types, making it more challenging to choose between the defined alternatives and thus increasing the attractiveness of looking for another facility. Although the on-street parking type has a negative effect on utility for all three trip purposes, it appears to become more appealing

Table 16: Estimation MNL model

		Pw Util.	Pw Util. distribution	Std. Error	|z|>Z*
Parameters in utility function					
1st stage - Parking location choice					
Main effects					
Constant 1 (neither)		-6.152***		0.175	0.00
Type of parking facility	On-street	-0.206[a]		-	-
	Surface level	-0.136***		0.045	0.00
	Garage	0.342***		0.043	0.00
Fee (/€)		-0.863***,[b]		0.031	0.00
Search time (/min)		-0.091***,[b]		0.016	0.00
Egress time (/min)		-0.159***,[b]		0.011	0.00
Context effects trip purpose					
Dentist (fixed)	Constant 1	-0.107[a]		-	-
	On-street parking	0.077[a]		-	-
	Surface level parking	-0.024[a]		-	-
	Parking garage	-0.053[a]		-	-
	Fee (/€)	-0.371[a,b]		-	-
	Search time (/min)	0.034[a,b]		-	-
	Egress time (/min)	0.048[a,b]		-	-
Friend (flexible)	Constant 1	0.160		0.124	0.19
	On-street parking	0.003[a]		-	-
	Surface level parking	-0.003		0.034	0.94
	Parking garage	0.000		0.032	0.99
	Fee (/€)	0.089***,[b]		0.030	0.00
	Search time (/min)	0.007[b]		0.015	0.64
	Egress time (/min)	0.007[b]		0.010	0.53
Shopping (free)	Constant 1	-0.053		0.119	0.65
	On-street parking	-0.080[a]		-	-
	Surface level parking	0.027		0.033	0.41
	Parking garage	0.053		0.032	0.10
	Fee (/€)	0.282***,[b]		0.051	0.00
	Search time (/min)	-0.041[b]		0.028	0.14
	Egress time (/min)	-0.054***,[b]		0.018	0.00
Context effects delay					
Delay (/min)	Constant 1	0.090***,[c]		0.023	0.00
	On-street parking	0.015[a,c]		-	-
	Surface level parking	0.030***,[c]		0.006	0.00
	Parking garage	-0.045***,[c]		0.006	0.00
	Fee (/€)	0.023***,[c,b]		0.003	0.00
	Search time (/min)	-0.004***,[c,b]		0.002	0.01
	Egress time (/min)	0.004***,[c,b]		0.001	0.00
Interaction effects gender[d]					
Gender	Constant 1	-0.438***		0.086	0.00
	On-street parking	0.003[a]		-	-
	Surface level parking	0.053**		0.023	0.02
	Parking garage	-0.056**		0.022	0.01
	Fee (/€)	-0.023**,[b]		0.012	0.05
	Search time (/min)	-0.017***,[b]		0.006	0.01
	Egress time (/min)	-0.014***,[b]		0.004	0.00

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Table 16 – continued from previous page

		Pw Util.	*Pw Util. distribution*	*Std. Error*	*|z|>Z**
Interaction effects age[e]					
Age	Constant 1	0.786***		0.159	0.00
	On-street parking	-0.031[a]		-	-
	Surface level parking	0.021		0.043	0.63
	Parking garage	0.010		0.041	0.81
	Fee (/€)	0.034[b]		0.022	0.12
	Search time (/min)	0.012[b]		0.012	0.29
	Egress time (/min)	0.038***[b]		0.008	0.00
Interaction effects education[f]					
Education	Constant 1	-1.222***		0.131	0.00
	On-street parking	-0.061[a]		-	-
	Surface level parking	0.030		0.039	0.44
	Parking garage	0.031		0.038	0.42
	Fee (/€)	-0.104***[b]		0.019	0.00
	Search time (/min)	-0.043***[b]		0.011	0.00
	Egress time (/min)	-0.038***[b]		0.007	0.00
2nd stage - Adapted parking choice					
Main effects					
Constant 2 (parking advise)		-0.837***		0.045	0.00
Type of parking facility	On-street	-0.225[a]		-	-
	Surface level	0.086*		0.044	0.05
	Garage	0.139***		0.041	0.00
Fee (/€)		-1.185***[b]		0.062	0.00
Search time (/min)		-0.226***[b]		0.026	0.00
Egress time (/min)		-0.250***[b]		0.020	0.00
Diff in travelt (/min)		-0.035**[b]		0.018	0.05
Context effects trip purpose					
Dentist (fixed)	Constant 2	0.061[a]		-	-
	On-street parking	0.038[a]		-	-
	Surface level parking	-0.013[a]		-	-
	Parking garage	-0.025[a]		-	-
	Fee (/€)	-0.509[a,b]		-	-
	Search time (/min)	0.135[a,b]		-	-
	Egress time (/min)	-0.045[a,b]		-	-
	Diff in travelt (/min)	-0.004[a,b]		-	-
Friend (flexible)	Constant 2	-0.044		0.031	0.16
	On-street parking	-0.021[a]		-	-
	Surface level parking	0.050*		0.029	0.08
	Parking garage	-0.029		0.031	0.34
	Fee (/€)	0.101[b]		0.063	0.11
	Search time (/min)	-0.053**[b]		0.025	0.03
	Egress time (/min)	0.039**[b]		0.019	0.04
	Diff in travelt (/min)	-0.008[b]		0.012	0.52
Shopping (free)	Constant 2	-0.017		0.031	0.58
	On-street parking	-0.017[a]		-	-
	Surface level parking	-0.037		0.029	0.19
	Parking garage	0.054*		0.030	0.08
	Fee (/€)	0.408***[b]		0.108	0.00
	Search time (/min)	-0.083*[b]		0.043	0.05
	Egress time (/min)	0.006[b]		0.033	0.85
	Diff in travelt (/min)	0.012[b]		0.012	0.32

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Table 16 – continued from previous page

		Pw Util.	*Pw Util. distribution*	*Std. Error*	$\lvert z \rvert > Z*$
Context effects delay					
Delay (/min)	Constant 2	$0.042^{***,c}$		0.005	0.00
	On-street parking	$0.017^{a,c}$		-	-
	Surface level parking	$-0.010^{*,c}$		0.005	0.06
	Parking garage	-0.007^{c}		0.005	0.22
	Fee (/€)	$0.022^{***,c,b}$		0.006	0.00
	Search time (/min)	$0.007^{**,c,b}$		0.003	0.01
	Egress time (/min)	$0.008^{***,c,b}$		0.002	0.00
	Diff in travelt (/min)	$-0.012^{***,c,b}$		0.002	0.00
Interaction effects gender[d]					
Gender	Constant 2	-0.024		0.022	0.26
	On-street parking	-0.004^{a}		-	-
	Surface level parking	0.061^{***}		0.020	0.00
	Parking garage	-0.057^{***}		0.021	0.01
	Fee (/€)	$-0.066^{***,b}$		0.024	0.01
	Search time (/min)	$-0.019^{*,b}$		0.010	0.05
	Egress time (/min)	$-0.019^{**,b}$		0.008	0.01
	Diff in travelt (/min)	0.008^{b}		0.008	0.36
Interaction effects age[e]					
Age	Constant 2	-0.031		0.039	0.43
	On-street parking	0.062^{a}		-	-
	Surface level parking	-0.053		0.036	0.14
	Parking garage	-0.009		0.038	0.82
	Fee (/€)	$0.129^{***,b}$		0.043	0.00
	Search time (/min)	$0.060^{***,b}$		0.018	0.00
	Egress time (/min)	$0.087^{***,b}$		0.014	0.00
	Diff in travelt (/min)	$0.088^{***,b}$		0.015	0.00
Interaction effects education[f]					
Education	Constant 2	0.059		0.038	0.12
	On-street parking	-0.007^{a}		-	-
	Surface level parking	0.022		0.035	0.54
	Parking garage	-0.015		0.037	0.69
	Fee (/€)	$-0.276^{***,b}$		0.039	0.00
	Search time (/min)	$-0.055^{***,b}$		0.017	0.00
	Egress time (/min)	$-0.045^{***,b}$		0.013	0.00
	Diff in travelt (/min)	$-0.051^{***,b}$		0.015	0.00

***,**,* →Parameter is significant at the 1%, 5%, 10% level.
a. Part worth utility has been computed manually.
b. Parameter is continuous; part worth utility per unit.
c. Context effect is continuous; part worth utility per unit.
d. Female × 1; Male × -1.
e. 65+ × 1; 40-65 × 0; <40 × -1.
f. Higher × 1; College × 0; Lower × -1.

as the flexibility in arrival time decreases for the reason to visit the city center. This could be attributed to a greater desire for easily accessible parking spots in situations where there is more time pressure. Conversely, parking garage exhibits a trend opposite to that of on-street parking, which can be similarly explained. Surface level parking, on the other hand, has relatively equal negative estimates for all three trip purposes.

The estimates for hourly parking fees increase with greater flexibility in the arrival time for every trip purpose, with values of -1.234 for a dentist appointment, -0.774 for meeting a friend, and -0.581 for shopping. This finding contradicts the results of Van Der Goot (1982) in their study on parking place choices. One possible explanation for this distribution is that respondents are more accustomed to paying higher parking fees for shopping in their daily lives compared to meeting up with a friend or going to the dentist. Although a small negative linear trend is visible for search time, the estimated parameter do not vary all that much between the trip purposes. Egress time shows a negative linear trend, and is most negative for shopping, indicating that respondents were less willing to walk in this context compared to meeting a friend or going to the dentist.

In contrast to trip purpose, all part-worth utilities of the delay context effects in Table 16 are statistically significant at the 1% level. Before discussing the effects of delay, it is important to note that the effects presented in Table 16 are based on a single minute of delay, while the computed results in Table 18 are based on the actual delay levels (none, 5, and 10 minutes) presented to the respondents in the survey.

Let's start by evaluating the distribution of the part-worth utility of alternative specific constant 1. The estimated parameter increases with increasing delay, indicating that individuals with longer delays are more likely to choose the neither alternative compared to those without delay. It is possible that respondents found it more challenging to consider any of the defined parking alternatives acceptable when a delay component was introduced in the choice context. Regarding the type of parking facilities, a similar trend to that observed for trip purpose is noticeable: The more easily accessible parking alternatives (i.e., on-street parking and surface level parking) become more preferred options as time pressure increases. On the other hand, the parking garage facility type exhibits the opposite trend. As for the hourly parking fee, an expected increasing effect can be observed with increasing delay, suggesting that respondents are less concerned about hourly costs when they experience delays during their trips. Both search time and egress time show relatively equal effects across the three delay levels.

Similarly to the contextual effects, the socio-demographic characteristics are also presented in a computed format. The results pertaining to gender are displayed in Table 19, those regarding age in Table 20, and the level of education in Table 21.

As indicated in Table 16, all main effect parameters significantly differed between men and women in the sample with at least 95% confidence. Table 19 reveals that women in the sample exhibited a higher inclination to select one of the offered parking alternatives over the "neither" option compared to men. While both men and women demonstrated a relatively similar preference for on-street parking, men showed a lesser preference for surface-level parking facilities and a greater preference for parking garages compared to women. According to Yanjie et al. (2008), parking garages are often perceived as less secure than surface-level and on-street parking. Additionally, women generally feel less safe in public environments compared to men Bozoganova (2015), which could explain the observed preference differences concerning these two facility types. Furthermore, the results indicate that women express greater concern for hourly parking fees compared to men. This finding aligns with the research conducted by Mo et al. (2008) and Tsamboulas (2001). Moreover, women display less preference for search time and egress time compared to men.

Based on Table 16, the only significant preference differences among age groups are observed for the "neither" alternative specific constant 1 and egress time. This is also illustrated by the computed results presented in Table 20, where almost all other attributes show relatively similar values across the different age groups. Notably, the parameter for constant 1 suggests that as age increases, individuals are more likely to select the "neither" alternative. This phenomenon may be attributed to a decline in working memory with advancing age, which can make decision-making more challenging (Del Missier et al., 2015). Although not statistically significant, the fee attribute shows a positive effect for age, indicating that older respondents were less concerned with hourly parking fees. This finding is inconsistent with that of Anastasiadou et al. (2009). Interestingly, the estimate for egress time increases with age, indicating that older respondents are less bothered by longer walking distances from the parking facility to their final destination.

Regarding education, Table 16 shows significant interactions with all first-stage parameters except parking facility type. The interaction with constant 1 is negative, indicating that higher-educated respondents were more likely to select one of the offered parking alternatives rather than the "neither" option compared to lower-educated respondents. The interaction with fee is also negative, suggesting that respondents in higher-educated categories are more concerned with hourly parking fees than lower-educated respondents. This finding contrasts with the findings of Anastasiadou et al. (2009), who state that lower-educated individuals are less familiar with paid parking and, therefore, more opposed to it. It is expected however, this effect is minor in the Netherlands. Search time and egress time have a comparable negative effect, revealing that higher-educated respondent groups value these times more than lower-educated groups. This finding is consistent with the results of the study of Salomon (1986).

5.2.2 Experiment stage 2 - Adapted parking choice

When examining the second half of Table 16, it is evident that the specific constant 2 for the Smart Parking System (SPS) option has a significant negative estimate of -0.785 at the 1% level. This implies that respondents were less inclined to choose the SPS option than the previously chosen parking (Status Quo (SQ)) option. There are various ways to explain this tendency of respondents to stick with their initial parking choice. One of them is the First Instinct Fallacy, a theoretical framework that describes the inclination of individuals to overestimate the effectiveness of sticking with their first instinct in choice situations to avoid feeling dissatisfied if they alter their choice for the worse (Kruger et al., 2005). Another explanation is cognitive dissonance, a psychological framework described in *A Theory of Cognitive Dissonance* by Festinger (1957). This theory explains that people can subconsciously revise their opinion after considering alternatives and making a choice in a choice scenario, influencing their next decision by favoring the alternative they already chose. A decrease in interest in selecting the parking alternative could also be attributed to a lack of trust in technology or the information communicated by it. As described in Section 5.1.2 of this report, respondents indicated that they were about 18% more likely to diverge to another parking lot when it is full if they observe it themselves rather than if it is communicated to them via a PGIS. Similar observations have been made by Choocharukul (2008) and Madanat et al. (1995), among others.

With respect to parking facility types, surface level parking and parking garage have comparable estimates of 0.114 and 0.127, respectively. On-street parking has a negative contribution to utility with an estimate of -0.241. Interestingly, surface level parking had a negative effect in the first stage of the experiment. The hourly parking fee has a parameter estimate of -1.370, which is significant at the 1% level. Notably, decisions by respondents are more sensitive to price in SPS choice scenarios compared to regular parking location choice situations. Like in the first stage of the experiment, the estimates of search and egress time are comparable in size. Of the two, egress time has the largest negative effect on choice utility. Finally, the effect of added travel time has a relatively small estimate of -0.080 compared to the other time related parameters included in the experiment.

In the second experiment stage, the context effects of trip purpose are mostly insignificant, except for the interactions between visiting a friend and surface level parking, visiting a friend and search time, visiting a friend and egress time, shopping and parking garage, shopping and fee, and shopping and search time. Similar to the first stage, the effect distributions have been visualized in Table 17, where most distributions are either neutral, or a tendency comparable to that described for stage 1 can be observed.

Table 17: Effects trip purpose

Variable	Dentist	Friend	Shopping
Stage 1 - Parking location choice			
Constant 1	-6.259	-5.991	-6.205
On-street parking	-0.128	-0.203	-0.286
Surface level parking	-0.160	-0.138	-0.109
Parking garage	0.289	0.342	0.394
Fee	-1.234	-0.774	-0.581
Search time	-0.057	-0.084	-0.132
Egress time	-0.112	-0.153	-0.214
Stage 2 - Adapted parking choice			
Constant 2	-0.777	-0.881	-0.854
On-street parking	-0.187	-0.246	-0.242
Surface level parking	0.073	0.136	0.049
Parking garage	0.114	0.110	0.193
Fee	-1.693	-1.084	-0.777
Search time	-0.090	-0.278	-0.308
Egress time	-0.296	-0.212	-0.244
Added travel time	-0.039	-0.043	-0.023

Table 18: Effects delay

	no delay	5 min delay	10 min delay
Stage 1 - Parking location choice			
Constant 1	-6.152	-5.703	-5.255
On-street parking	-0.206	-0.129	-0.051
Surface level parking	-0.136	0.014	0.164
Parking garage	0.342	0.114	-0.113
Fee	-0.863	-0.750	-0.636
Search time	-0.091	-0.113	-0.136
Egress time	-0.159	-0.140	-0.120
Stage 2 - Adapted parking choice			
Constant 2	-0.837	-0.629	-0.420
On-street parking	-0.225	-0.140	-0.056
Surface level parking	0.086	0.034	-0.017
Parking garage	0.139	0.106	0.073
Fee	-1.185	-1.075	-0.966
Search time	-0.226	-0.191	-0.157
Egress time	-0.250	-0.212	-0.173
Added travel time	-0.035	-0.094	-0.153

Table 19: Effects gender

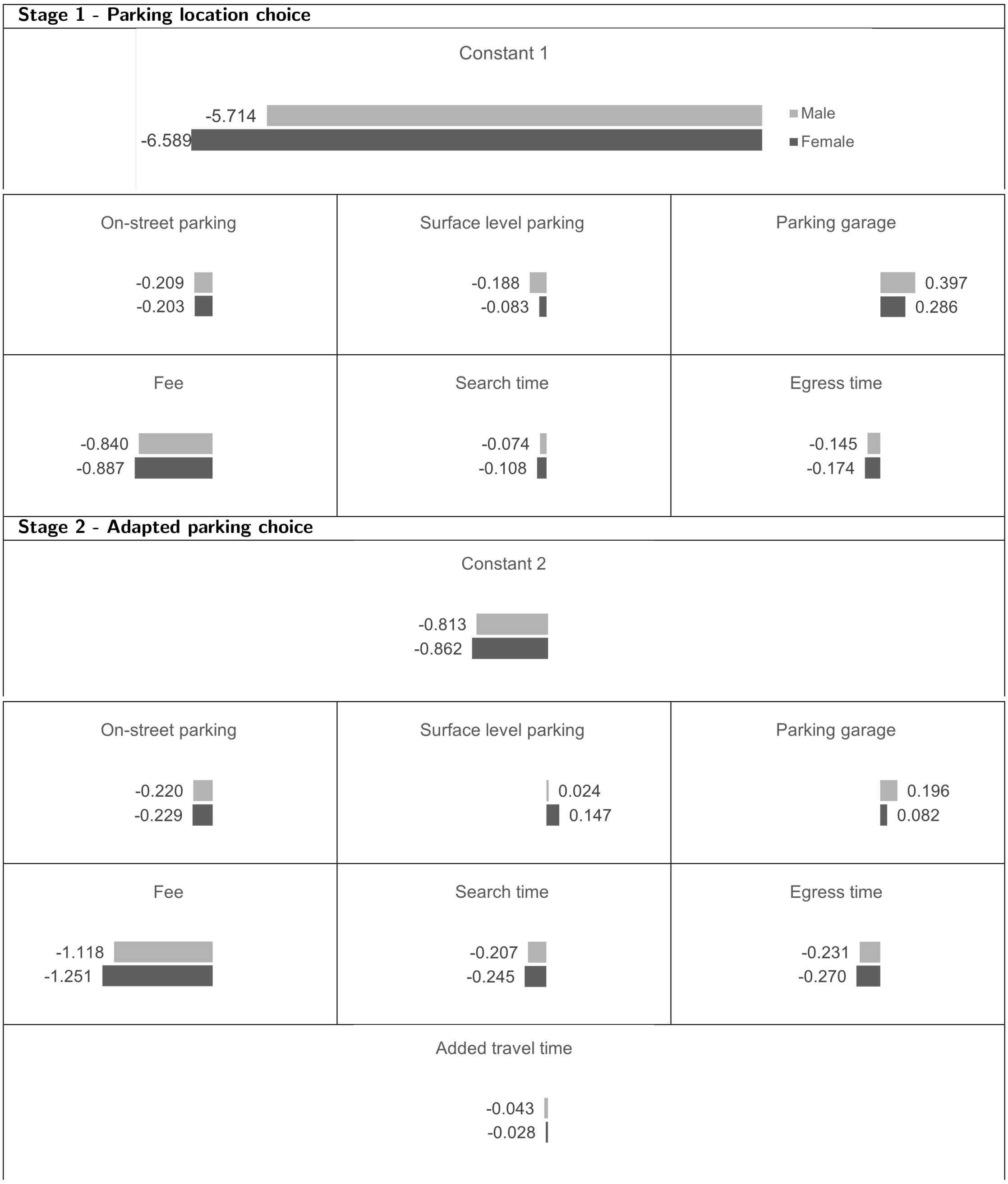

Table 20: Effects age

	< 40	40-65	65+
Stage 1 - Parking location choice			
Constant 1	-6.937	-6.152	-5.366
On-street parking	-0.175	-0.206	-0.236
Surface level parking	-0.156	-0.136	-0.115
Parking garage	0.332	0.342	0.351
Fee	-0.897	-0.863	-0.829
Search time	-0.103	-0.091	-0.079
Egress time	-0.197	-0.159	-0.122
Stage 2 - Adapted parking choice			
Constant 2	-0.806	-0.837	-0.868
On-street parking	-0.286	-0.225	-0.163
Surface level parking	0.139	0.086	0.033
Parking garage	0.148	0.139	0.130
Fee	-1.313	-1.185	-1.056
Search time	-0.285	-0.226	-0.166
Egress time	-0.337	-0.250	-0.164
Added travel time	-0.123	-0.035	0.053

Table 21: Effects level of education

	Lower	College	Higher
Stage 1 - Parking location choice			
Constant 1	-4.930	-6.152	-7.374
On-street parking	-0.145	-0.206	-0.267
Surface level parking	-0.166	-0.136	-0.106
Parking garage	0.311	0.342	0.372
Fee	-0.760	-0.863	-0.967
Search time	-0.048	-0.091	-0.134
Egress time	-0.121	-0.159	-0.198
Stage 2 - Adapted parking choice			
Constant 2	-0.896	-0.837	-0.778
On-street parking	-0.218	-0.225	-0.231
Surface level parking	0.064	0.086	0.107
Parking garage	0.154	0.139	0.124
Fee	-0.909	-1.185	-1.461
Search time	-0.170	-0.226	-0.281
Egress time	-0.205	-0.250	-0.296
Added travel time	0.016	-0.035	-0.086

Regarding delay, all interactions, except for the parking garage facility type, show a significant effect. Notably, the distribution of the constant 2 estimates in Table 18 is of interest. With increasing delay, the negative estimate for constant 2 increases, indicating that respondents are more likely to select the SPS advice. It is worth mentioning the increasingly negative part-worth utility of surface level parking with increasing delay, which is contrary to the trend observed in the first experimental stage. All other distributions are neutral or comparable to those in stage 1.

Regarding the socio-demographic characteristics, we find that the interactions with the SPS advice alternative specific constant 2 are not significant. This implies that respondents of different genders, ages, or education levels do not appear to assign different values to the negative base utility for SPS advice. Moving on to the other interactions and their distributions for gender, we observe similar trends as described in the previous stage. The interaction between gender and the difference in travel time is not statistically significant at the 10% level, indicating that men and women evaluate the difference in travel time between the SQ parking alternative and the SPS advice alternative equally.

In the second stage, age exhibits different effects compared to the first stage. Here, the interactions with fee, search time, egress time, and the difference in travel time are all statistically significant at the 1% level. The parameter for fee is positive, suggesting that older respondents are less concerned with hourly parking prices than younger respondents when evaluating the SPS advice alternative. The effects of search time, egress time, and the difference in travel time are all positive, indicating that older respondents place less value on time compared to younger respondents. Interestingly, the computed part-worth utility for added travel time is positive for the 65 and older age category.

For education, we observe similar effects as in the first stage of the experiment. The interaction parameter for added travel time is negative, indicating that higher-educated respondents, like in the case of other time-related attributes, value this attribute more than the two lower-educated groups.

5.2.3 Stage comparison

From the estimation of the MNL model (Table 16), it appears that the estimates of comparable attributes differ in the two experiment stages. Although there is a slight difference in the choice scenarios, they remain fairly similar. According to utility theory, which states that respondents select the alternative with the highest utility when presented with a choice situation, the observed components of behavior should be equal and remain equal with an equal set of respondents in an equal choice scenario. A difference in the parameter estimations in stages 1 and 2 might be, therefore, somewhat surprising. To test whether there is indeed a difference in the observed components of the two stages, an additional MNL model has been estimated. In this MNL, the input data has been formatted as in Table 22, in which the effect of the parameters in the second stage are included twice, once in a combined estimation with the first stage and once independently of the first stage.

Table 22: Data format stage 1 and 2 difference test

Q	A	$i \in a$	Con. 1	k_1	k_2	...	k_i	Con. 2	k_{1b}	k_{2b}	...	k_{ib}
$q_i \in Q$	$a_i \in A$	$i_1 \in a_i$	0	.	.	...	.	0	0	0	...	0
$q_i \in Q$	$a_i \in A$	$i_2 \in a_i$	0	.	.	...	.	0	0	0	...	0
$q_i \in Q$	$a_i \in A$	$i_3 \in a_i$	1	.	.	...	.	0	0	0	...	0
$q_i \in Q$	$a_i' \in A$	$i_1 \in a_i'$	0	.	.	...	.	0	.	.	...	.
$q_i \in Q$	$a_i' \in A$	$i_2 \in a_i'$	0	.	.	...	.	1	.	.	...	.
			β_0	β_1	β_2	...	β_i	δ_0	δ_1	δ_2	...	δ_i

The results of the model estimation can be found in Table 23. Because the model measures deviation of the second experiment stage to that of the first, the first part of the results in Table 23 equal those of the first stage in Table 16. The parameters in the second part of the table are of interest to determine whether a significant difference between the estimations of similar parameters in the first and second stages is present. If these parameter estimates have a |z|>Z∗ value of less than 0.10, a significant difference between the stage 1 and 2 estimations is present. The original stage 2 values in Table 16 can be computed again by summing the related estimates in parts 1 and 2. From the results, it becomes clear that the parameters of the main effects in the second stage of the experiment (type of parking facility, fee, search time, and egress time) differ significantly from their corresponding parameters in the first stage. All parameter estimates of the context effects of trip purpose except that between visiting a friend and search time have a |z|>Z∗ larger than 0.10, indicating that these estimates are not significantly different from those in the first stage. This is most likely due to the general lack in significant effects from trip purpose on the main effect parameters in the first place. For delay, all effects except those with fee and egress time are significant on the 5% level. All effects of gender in the second stage do not seem to differ significantly from the effects in the first stage. For age, interactions with fee, search time and egress time differ in the second stage, and for education, only the interaction effect with fee differs significantly.

This difference in parameter estimates in seemingly similar choice situations can be attributed to the following:

> *While ... stated preference and choice studies involve expressing an overall evaluation of a series of attribute profiles, respectively choosing between two or more attribute profiles, the focus of stated adaptation experiments shifts towards expressing the likelihood and nature of possible behavioral change.* (van Bladel et al., 2008)

Since the same principles of experimental design were followed in both stages of the experiment, and only the nature of the dependent variable differs, the responses in the second stage task represent transition probabilities from current to new behavior rather than choices between alternatives in the first task. Although both stages are coded into the same dependent variable, the estimations of stage 1 and stage 2 do not explain the same choice behavior. This, combined with the observation that there are significant differences between several parameters in the first and second stages of the experiment, justifies discussing the estimation results of the second stage independently of those in the first stage.

5.3 Latent class model

The NLOGIT 6 package (Econometric Software Inc., 2016) was employed to estimate a series of LCMs. As discussed in Chapter 3, LCM allows for the correction of panel effects in the data and facilitates the identification of heterogeneity among groups of respondents. The LCMs were estimated with up to three classes. The McFadden ρ^2 values for the 2-class and 3-class LCMs, as reported by NLOGIT, are 0.439 and 0.449, respectively, indicating a better goodness of fit compared to the MNL model with a ρ^2 of 0.381. However, the 2-class and 3-class LCMs have higher Bayesian Information Criterion (BIC) values of 37,757.42 and 37,235.34, respectively, compared to the MNL model with a BIC of 33,386.05, indicating inferior performance. Because of the varying number of choice entries per respondent in the sample and the resulting varying panel effect per respondent, the LCMs are analyzed and described in this chapter despite their lesser performance. The two-class model has a slightly lower BIC, while the three-class model exhibits slightly better goodness of fit. Therefore, both class models are extensively described in this section, with the complete NLOGIT 6 output provided in Appendix D. Unfortunately, NLOGIT 6 encountered suspected capacity issues during the estimation of the class membership models. An attempt was made to run an LCM in the R environment

Table 23: Estimation MNL model stage 1 and 2 difference test

		Pw Util.	*Pw Util. distribution*	*Std. Error*	*|z|>Z**
Parameters in utility function					
Part 1 - Equal to 1st stage of MNL model					
Main effects					
Constant 1 (neither)		-6.152***		0.175	0.00
Type of parking facility	On-street	-0.206[a]		-	-
	Surface level	-0.136***		0.045	0.00
	Garage	0.341***		0.043	0.00
Fee (/€)		-0.863***,[b]		0.031	0.00
Search time (/min)		-0.091***,[b]		0.016	0.00
Egress time (/min)		-0.159***,[b]		0.011	0.00
Context effects trip purpose					
Dentist (fixed)	Constant 1	-0.107[a]		-	-
	On-street parking	0.077[a]		-	-
	Surface level parking	-0.024[a]		-	-
	Parking garage	-0.053[a]		-	-
	Fee (/€)	-0.371[a,b]		-	-
	Search time (/min)	0.034[a,b]		-	-
	Egress time (/min)	0.048[a,b]		-	-
Friend (flexible)	Constant 1	0.161		0.124	0.19
	On-street parking	0.003[a]		-	-
	Surface level parking	-0.003		0.034	0.95
	Parking garage	0.000		0.032	0.99
	Fee (/€)	0.089***,[b]		0.030	0.00
	Search time (/min)	0.007[b]		0.015	0.64
	Egress time (/min)	0.007[b]		0.010	0.53
Shopping (free)	Constant 1	-0.053		0.119	0.65
	On-street parking	-0.080[a]		-	-
	Surface level parking	0.028		0.033	0.40
	Parking garage	0.053*		0.032	0.10
	Fee (/€)	0.282***,[b]		0.051	0.00
	Search time (/min)	-0.041[b]		0.028	0.14
	Egress time (/min)	-0.054***,[b]		0.018	0.00
Context effects delay					
Delay (/min)	Constant 1	0.090***,[c]		0.023	0.00
	On-street parking	0.015[a,c]		-	-
	Surface level parking	0.030***,[c]		0.006	0.00
	Parking garage	-0.045***,[c]		0.006	0.00
	Fee (/€)	0.023***,[c,b]		0.003	0.00
	Search time (/min)	-0.004***,[c,b]		0.002	0.01
	Egress time (/min)	0.004***,[c,b]		0.001	0.00
Interaction effects gender[d]					
Gender	Constant 1	-0.438***		0.086	0.00
	On-street parking	0.003[a]		-	-
	Surface level parking	0.053**		0.023	0.02
	Parking garage	-0.056**		0.022	0.01
	Fee (/€)	-0.023**,[b]		0.012	0.05
	Search time (/min)	-0.017***,[b]		0.006	0.01
	Egress time (/min)	-0.014***,[b]		0.004	0.00

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Table 23 – continued from previous page

		Pw Util.	*Pw Util. distribution*	*Std. Error*	*|z|>Z∗*
Interaction effects age[e]					
Age	Constant 1	0.786***		0.159	0.00
	On-street parking	-0.031[a]		-	-
	Surface level parking	0.020		0.043	0.63
	Parking garage	0.010		0.041	0.81
	Fee (/€)	0.034[b]		0.022	0.12
	Search time (/min)	0.012[b]		0.012	0.29
	Egress time (/min)	0.038***[b]		0.008	0.00
Interaction effects education[f]					
Education	Constant 1	-1.222***		0.131	0.00
	On-street parking	-0.061[a]		-	-
	Surface level parking	0.030		0.039	0.45
	Parking garage	0.031		0.038	0.42
	Fee (/€)	-0.103***[b]		0.019	0.00
	Search time (/min)	-0.043***[b]		0.011	0.00
	Egress time (/min)	-0.038***[b]		0.007	0.00
Part 2 - Difference in stages 1 and 2 of MNL model					
Main effects					
Constant 2 (parking advise)		-0.837***		0.045	0.00
Type of parking facility	On-street	-0.019[a]		-	-
	Surface level	0.221***		0.063	0.00
	Garage	-0.203***		0.060	0.00
Fee (/€)		-0.321***[b]		0.069	0.00
Search time (/min)		-0.135***[b]		0.030	0.00
Egress time (/min)		-0.091***[b]		0.023	0.00
Diff in travelt (/min)		-0.035**[b]		0.018	0.05
Context effects trip purpose					
Dentist (fixed)	Constant 2	0.061[a]		-	-
	On-street parking	-0.040[a]		-	-
	Surface level parking	0.012[a]		-	-
	Parking garage	0.028[a]		-	-
	Fee (/€)	-0.138[a,b]		-	-
	Search time (/min)	0.101[a,b]		-	-
	Egress time (/min)	-0.093[a,b]		-	-
	Diff in travelt (/min)	-0.004[a,b]		-	-
Friend (flexible)	Constant 2	-0.044		0.031	0.16
	On-street parking	-0.044[a]		-	-
	Surface level parking	0.053		0.045	0.24
	Parking garage	-0.030		0.044	0.50
	Fee (/€)	0.012[b]		0.070	0.86
	Search time (/min)	-0.060**[b]		0.029	0.04
	Egress time (/min)	0.032[b]		0.022	0.13
	Diff in travelt (/min)	-0.008[b]		0.012	0.52
Shopping (free)	Constant 2	-0.017		0.031	0.58
	On-street parking	-0.017[a]		-	-
	Surface level parking	-0.065		0.043	0.14
	Parking garage	0.001		0.044	0.97
	Fee (/€)	0.126[b]		0.120	0.29
	Search time (/min)	-0.042[b]		0.051	0.41
	Egress time (/min)	0.060[b]		0.038	0.11
	Diff in travelt (/min)	0.012[b]		0.012	0.32

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Table 23 – continued from previous page

		Pw Util.	*Pw Util. distribution*	*Std. Error*	*|z|>Z**
Context effects delay					
Delay (/min)	Constant 2	0.042^{***,c}		0.005	0.00
	On-street parking	0.001^{a,c}		-	-
	Surface level parking	-0.040^{***,c}		0.008	0.00
	Parking garage	0.039^{***,c}		0.008	0.00
	Fee (/€)	-0.001^{c,b}		0.007	0.91
	Search time (/min)	0.011^{***,c,b}		0.003	0.00
	Egress time (/min)	0.004^{*,c,b}		0.002	0.09
	Diff in travelt (/min)	-0.012^{***,c,b}		0.002	0.00
Interaction effects gender[d]					
Gender	Constant 2	-0.024		0.022	0.26
	On-street parking	-0.007^{a}		-	-
	Surface level parking	0.008		0.030	0.78
	Parking garage	-0.001		0.031	0.96
	Fee (/€)	-0.043^{b}		0.027	0.10
	Search time (/min)	-0.002^{b}		0.012	0.87
	Egress time (/min)	-0.005^{b}		0.009	0.57
	Diff in travelt (/min)	0.008^{b}		0.008	0.36
Interaction effects age[e]					
Education	Constant 2	-0.031		0.039	0.43
	On-street parking	0.092^{a}		-	-
	Surface level parking	-0.074		0.056	0.19
	Parking garage	-0.019		0.056	0.74
	Fee (/€)	0.094^{*,b}		0.048	0.05
	Search time (/min)	0.047^{**,b}		0.021	0.03
	Egress time (/min)	0.049^{***,b}		0.016	0.00
	Diff in travelt (/min)	0.088^{***,b}		0.015	0.00
Interaction effects education[f]					
Education	Constant 2	0.059		0.038	0.12
	On-street parking	0.054^{a}		-	-
	Surface level parking	-0.008		0.053	0.88
	Parking garage	-0.046		0.053	0.39
	Fee (/€)	-0.172^{***,b}		0.044	0.00
	Search time (/min)	-0.012^{b}		0.020	0.54
	Egress time (/min)	-0.007^{b}		0.015	0.62
	Diff in travelt (/min)	-0.051^{***,b}		0.015	0.00

***,**,* → Parameter is significant at the 1%, 5%, 10% level.
a. Part worth utility has been computed manually.
b. Parameter is continuous; part worth utility per unit.
c. Context effect is continuous; part worth utility per unit.
d. Female × 1; Male × -1.
e. 65+ × 1; 40-65 × 0; <40 × -1.
f. Higher × 1; College × 0; Lower × -1.

(R Core Team, 2022); however, it was not successful in running an LCM with the data presented in this report. Consequently, no membership models will be presented in this section.

5.3.1 2-class latent class model

Prior to discussing the model estimation results, let us evaluate the performance of the model. According to NLOGIT, the McFadden ρ^2 goodness-of-fit statistic for the two-class LCM is 0.439, indicating an excellent model fit. The LRS, which is twice the difference between the log-likelihood of the estimated and restricted model, is 27,960.90, surpassing the critical χ^2 value of 128.80 at 104 degrees of freedom. Thus, the estimated model outperforms the restricted model. Table 24 presents an overview of the estimation results for the two-level LCM, while Table 25 showcases the distribution. Similar to the description of the MNL, the discussion of the estimation results will be divided for the first and second experiment stages. This discussion is followed by a section on class preferences.

Experiment stage 1 - Parking location choice

Starting with the main effects, a noticeable difference between the class estimates for the alternative-specific constant 1 parameter is observed. For class 1, this parameter has a significant estimate of -3.671, compared to a significant estimate of -16.774 for class 2. This means respondents in class 2 were less eager to select the neither alternative. As for the type of parking facility, the respective parameters are more comparable in size. Class 2 seems to have less of a negative preference for on-street parking, and besides having a negative part worth utility of -0.179 for surface level parking. The preference of the two classes for parking garages is roughly similar. The fee has estimate values of -0.508 for class 1 and -1.903 for class 2, both significant at the 1% level. The estimates of search time and egress time are significant and work in the expected negative direction for both classes. Interestingly, the fee, search time, and egress time estimates are much less extreme for class 1 compared to class 2.

The interaction effects of trip purpose are mostly insignificant for both classes. However, for Class 2, there is a significant estimate of -2.120 at a 5% significance level for the interaction between visiting a friend and constant 1, indicating that respondents in this class are even less likely to choose the "neither" option when visiting a friend. Additionally, the interaction between visiting a friend and hourly parking fee for Class 1 is significant at a 1% significance level, and it works opposite to the main effect, indicating that fee is a less important factor when respondents in Class 1 meet up with a friend. The interactions between friend and search time and friend and egress time are also negative and significant on 95% and 90% confidence intervals respectively for Class 2, but its effects are relatively small.

Regarding the interactions with doing some shopping, there is a significant interaction with parking garage for Class 1, with a significant estimate of 0.144 at a 1% significance level. This suggests that respondents in Class 1 prefer parking in a parking garage when visiting the city center to do some shopping. The interactions between shopping and fee are significant for both classes, and the directionality of these effects is opposite to that of the main effect for fee, indicating that fee is less important when visiting the city center for some shopping. However, for both classes, shopping enhances the negative effect of search time and egress time on utility.

Regarding the interactions of delay, especially for Class 2, there are significant estimates for constant 1 (0.266), surface level parking (0.054), parking garage (-0.062), fee (0.076), search time (0.007) and egress time (0.014). Although all effects are relatively small, the estimates for parking facility type suggest a preference for the more easily accessible parking options on-street and on surface level facilities. Interestingly, the interactions of delay with both search time and egress time are positive instead of negative, indicating that increasing search and egress times decrease utility to a lesser extend with increasing delay. For Class 1, only parking garage shows a significant estimate of -0.036.

Experiment stage 2 - Adapted parking choice

The impact of Constant 2 on utility is statistically significant at a 99% confidence level, with values of -0.750 and -0.283 for classes 1 and 2, respectively. This implies that respondents in class 1 are

Table 24: Estimation LC model - 2 classes

		Class 1			**Class 2**		
Class probability		0.528 (53%)			0.472 (47%)		
		Pw Util.	*Std. Error*	$\lvert z\rvert > Z*$	*Pw Util.*	*Std. Error*	$\lvert z\rvert > Z*$
Parameters in utility function							
1st stage - Parking location choice							
Main effects							
Constant 1 (neither)		-3.671***	0.186	0.00	-16.774***	0.853	0.00
Type of parking	On-street	-0.421[a]	-	-	-0.226[a]	-	-
	Surface level	0.039	0.054	0.47	-0.179**	0.074	0.02
	Parking garage	0.382***	0.053	0.00	0.405***	0.070	0.00
Fee (/€)		-0.508***,[b]	0.037	0.00	-1.903***,[b]	0.093	0.00
Search t (/min)		-0.086***,[b]	0.021	0.00	-0.322***,[b]	0.036	0.00
Egress t (/min)		-0.082***,[b]	0.015	0.00	-0.427***,[b]	0.029	0.00
Context effects trip purpose							
Dentist (fixed)	Constant 1	-0.319[a]	-	-	1.640[a]	-	-
	On-street	0.216[a]	-	-	0.049[a]	-	-
	Surface level	-0.098[a]	-	-	0.054[a]	-	-
	Parking garage	-0.118[a]	-	-	-0.103[a]	-	-
	Fee (/€)	-0.357[a,b]	-	-	-0.216[a,b]	-	-
	Search t (/min)	0.097[a,b]	-	-	0.220[a,b]	-	-
	Egress t (/min)	0.070[a,b]	-	-	0.151[a,b]	-	-
Friend (flexible)	Constant 1	0.185	0.133	0.16	-2.120**	0.898	0.02
	On-street	-0.041[a]	-	-	-0.044[a]	-	-
	Surface level	0.066	0.048	0.17	-0.056	0.073	0.44
	Parking garage	-0.026	0.047	0.59	0.101	0.065	0.12
	Fee (/€)	0.123***,[b]	0.039	0.00	-0.127[b]	0.098	0.19
	Search t (/min)	-0.017[b]	0.023	0.46	-0.092**,[b]	0.038	0.02
	Egress t (/min)	-0.008[b]	0.015	0.61	-0.056*,[b]	0.031	0.07
Shopping (free)	Constant 1	0.134	0.135	0.32	0.480	0.660	0.47
	On-street	-0.175[a]	-	-	-0.005[a]	-	-
	Surface level	0.032	0.048	0.051	0.003	0.069	0.97
	Parking garage	0.144***	0.048	0.00	0.003	0.063	0.097
	Fee (/€)	0.234***,[b]	0.069	0.00	0.344**,[b]	0.156	0.03
	Search t (/min)	-0.080*,[b]	0.041	0.05	-0.128**,[b]	0.062	0.04
	Egress t (/min)	-0.062**,[b]	0.027	0.02	-0.095*,[b]	0.052	0.07

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Table 24 – continued from previous page

		Class 1			**Class 2**		
		Pw Util.	*Std. Error*	$\|z\|>Z*$	*Pw Util.*	*Std. Error*	$\|z\|>Z*$
Context effects delay							
Delay (/min)	Constant 1	0.028^{c}	0.025	0.27	$0.266^{*,c}$	0.153	0.08
	On-street	$0.026^{a,c}$	-	-	$0.009^{a,c}$	-	-
	Surface level	0.011^{c}	0.008	0.20	$0.054^{***,c}$	0.011	0.00
	Parking garage	$-0.036^{***,c}$	0.008	0.00	$-0.062^{***,c}$	0.011	0.00
	Fee (/€)	$0.001^{c,b}$	0.004	0.77	$0.076^{***,c,b}$	0.009	0.00
	Search t (/min)	$0.000^{c,b}$	0.003	0.95	$0.007^{*,c,b}$	0.004	0.08
	Egress t (/min)	$0.002^{c,b}$	0.002	0.30	$0.014^{***,c,b}$	0.003	0.00
2nd stage - Adapted parking choice							
Main effects							
Constant 2 (parking advise)		-0.750^{***}	0.064	0.00	-0.283^{***}	0.040	0.00
Type of parking	On-street	-0.331^{a}	-	-	-0.523^{a}	-	-
	Surface level	0.180^{***}	0.062	0.00	0.371^{***}	0.042	0.00
	Parking garage	0.151^{**}	0.058	0.01	0.152^{***}	0.038	0.00
Fee (/€)		$-0.125^{**,b}$	0.059	0.03	$-0.296^{***,b}$	0.042	0.00
Search t (/min)		$0.061^{*,b}$	0.031	0.05	$0.094^{***,b}$	0.020	0.00
Egress t (/min)		0.008^{b}	0.023	0.72	$0.052^{***,b}$	0.015	0.00
Diff travel t (/min)		$-0.094^{***,b}$	0.024	0.00	$-0.097^{***,b}$	0.015	0.00
Context effects trip purpose							
Dentist (fixed)	Constant 2	0.009^{a}	-	-	0.051^{a}	-	-
	On-street	0.142^{a}	-	-	0.168^{a}	-	-
	Surface level	-0.113^{a}	-	-	-0.163^{a}	-	-
	Parking garage	-0.029^{a}	-	-	-0.006^{a}	-	-
	Fee (/€)	$0.041^{a,b}$	-	-	$-0.086^{a,b}$	-	-
	Search t (/min)	$-0.009^{a,b}$	-	-	$0.116^{a,b}$	-	-
	Egress t (/min)	$0.013^{a,b}$	-	-	$0.084^{a,b}$	-	-
	Diff travel t (/min)	$-0.025^{a,b}$	-	-	$-0.028^{a,b}$	-	-
Friend (flexible)	Constant 2	-0.027	0.052	0.60	-0.107^{***}	0.033	0.00
	On-street	-0.114^{a}	-	-	-0.115^{a}	-	-
	Surface level	0.007	0.051	0.89	0.074^{**}	0.034	0.03
	Parking garage	0.106^{**}	0.052	0.04	0.041	0.035	0.24
	Fee (/€)	-0.017^{b}	0.064	0.79	0.023^{b}	0.046	0.62
	Search t (/min)	-0.007^{b}	0.035	0.85	$-0.058^{***,b}$	0.022	0.01
	Egress t (/min)	0.002^{b}	0.024	0.92	-0.013^{b}	0.016	0.40
	Diff travel t (/min)	0.030^{b}	0.020	0.14	$0.024^{*,b}$	0.013	0.07

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Table 24 – continued from previous page

		Class 1			Class 2		
		Pw Util.	*Std. Error*	*|z|>Z**	*Pw Util.*	*Std. Error*	*|z|>Z**
Shopping (free)	Constant 2	0.018	0.053	0.74	0.055*	0.034	0.10
	On-street	-0.029[a]	-	-	-0.053[a]	-	-
	Surface level	0.106**	0.050	0.03	0.088***	0.033	0.01
	Parking garage	-0.077	0.053	0.14	-0.035	0.035	0.31
	Fee (/€)	-0.024[b]	0.111	0.83	0.062[b]	0.078	0.42
	Search t (/min)	0.015[b]	0.060	0.80	-0.058[b]	0.039	0.13
	Egress t (/min)	-0.016[b]	0.041	0.71	-0.071***[,b]	0.027	0.01
	Diff travel t (/min)	-0.005[b]	0.020	0.82	0.003[b]	0.013	0.79
Context effects delay							
Delay (/min)	Constant 2	0.025***[,c]	0.009	0.01	0.025***[,c]	0.006	0.00
	On-street	0.012[a,c]	-	-	0.056[a,c]	-	-
	Surface level	-0.010[c]	0.009	0.29	-0.046***[,c]	0.006	0.00
	Parking garage	-0.002[c]	0.009	0.83	-0.010[c]	0.006	0.11
	Fee (/€)	-0.001[c,b]	0.006	0.81	-0.003[c,b]	0.004	0.42
	Search t (/min)	-0.007**[,c,b]	0.003	0.04	-0.007***[,c,b]	0.002	0.00
	Egress t (/min)	0.000[c,b]	0.002	0.88	-0.002[c,b]	0.002	0.23
	Diff travel t (/min)	0.006[c,b]	0.004	0.12	-0.001[c,b]	0.002	0.69

***,**,* $\rightarrow$Parameter is significant at the 1%, 5%, 10% level.

a. Part worth utility has been computed manually.

b. Parameter is continuous; part worth utility per unit.

c. Context effect is continuous; part worth utility per unit.

Table 25: Estimation LC model - 2 classes (distribution)

	Class 1	Class 2
	Pw Util. dist.	*Pw Util. dist.*
Parameters in utility function		
1st stage - Parking location choice		
Main effects		
Constant 1		
On-street parking		
Surface level parking		
Parking garage		
Fee		
Search t (/min)		
Egress t (/min)		
Context effects trip purpose - Dentist		
Constant 1		
On-street parking		
Surface level parking		
Parking garage		
Fee (/€)		
Search t (/min)		
Egress t (/min)		
Context effects trip purpose - Friend		
Constant 1		
On-street parking		
Surface level parking		
Parking garage		
Fee (/€)		
Search t (/min)		
Egress t (/min)		
Context effects trip purpose - Shopping		
Constant 1		
On-street parking		
Surface level parking		
Parking garage		
Fee (/€)		
Search t (/min)		
Egress t (/min)		

Continued on next page

Table 25 – continued from previous page

	Class 1	Class 2
	Pw Util. dist.	*Pw Util. dist.*
Context effects delay (/min)		
Constant 1		
On-street parking		
Surface level parking		
Parking garage		
Fee (/€)		
Search t (/min)		
Egress t (/min)		
2nd stage - Adapted parking choice		
Main effects		
Constant 2		
On-street parking		
Surface level parking		
Parking garage		
Fee (/€)		
Search t (/min)		
Egress t (/min)		
Diff travel t (/min)		
Context effects trip purpose - Dentist		
Constant 2		
On-street parking		
Surface level parking		
Parking garage		
Fee (/€)		
Search t (/min)		
Egress t (/min)		
Diff travel t (/min)		
Context effects trip purpose - Friend		
Constant 2		
On-street parking		
Surface level parking		
Parking garage		
Fee (/€)		
Search t (/min)		
Egress t (/min)		
Diff travel t (/min)		

Continued on next page

Table 25 – continued from previous page

	Class 1	Class 2
	Pw Util. dist.	*Pw Util. dist.*
Context effects trip purpose - Shopping		
Constant 2		
On-street parking		
Surface level parking		
Parking garage		
Fee (/€)		
Search t (/min)		
Egress t (/min)		
Diff travel t (/min)		
Context effects delay (/min)		
Constant 2		
On-street parking		
Surface level parking		
Parking garage		
Fee (/€)		
Search t (/min)		
Egress t (/min)		
Diff travel t (/min)		

less inclined to select the offered SPS option compared to those in class 2. The effect of parking facility type is similarly dispersed for the two classes, although the effects of on-street and surface level parking are more pronounced for class 2. The fee estimate of -0.125 is significant at the 5% level for class 1, while the -0.296 fee estimate for class 2 is significant at the 1% level and both act in the expected direction. Both classes' search time estimates are statistically significant and counterintuitively enhance utility. This implies that respondents in both classes are more likely to select an option with increasing search time. Class 2 exhibits a similar effect for egress time. The travel time parameter estimates differ significantly between the two classes, adversely influencing utility at a comparable rate.

In the second stage of the experiment, as in the first stage, only a few significant interaction effects between trip purpose and other variables are evident. Class 2 displays a significant effect of -0.107 between visiting a friend and constant 2, indicating that respondents in this class are less likely to follow the SPS advice in this scenario. In addition to the constant, visiting a friend has significant interactions with surface level parking and search time in the second-class estimates. For class 1, a significant interaction of 0.106 can be observed between visiting a friend and parking garages, indicating that respondents in this class prefer this type of facility when the choice context involves visiting a friend. For doing some shopping, an interaction effect of 0.106 can be seen with surface level parking, which is favored by class 1 over other parking alternatives. This same trend is visible for class 2. Furthermore, class 2 shows a negative effect of -0.071 for egress time. The interactions between delay and constant 2 are 0.025 for the two classes. Interestingly, this means that respondents are more likely to select the SPS alternatives with increasing delay. As in the first stage of the experiment, an interaction between delay and surface level parking is observed for class 2. This time, however, the effect is negative, and only the on-street parking interaction is positive. Lastly, delay shows a comparable interaction with search time for both classes.

Class preference interpretation

Based on the observed main effects in stage 1, it can be inferred that the estimate of constant 1 is approximately five times higher for class 2 compared to class 1. In conjunction with the more extreme estimations for fee, search time, and egress time in class 2, it suggests that respondents in class 2 had greater confidence in evaluating alternatives and exhibited stronger preferences. This distinction forms the basis for differentiating between the two classes.

When we extend this observation to the second stage of the experiment, we find that class 1 respondents, who displayed lower confidence in their decision-making during stage 1, demonstrate a more extreme tendency to disregard the offered SPS advice. This is evident from the increased extremity of the estimate for constant 2 in class 1, as well as the smaller or comparable estimates for all other main effects. This pattern can likely be attributed to the strengthened effect of cognitive dissonance as the difficulty of choosing between alternatives increases (Festinger, 1957). Moreover, the awareness of respondents in class 2 regarding the impact of delay in the first stage of the experiment also appears to have contributed to the formation of these two distinct classes.

5.3.2 3-class latent class model

The McFadden ρ^2 statistic of the 3-class LCM estimated in NLOGIT 6 is 0.449, which, according to McFadden (1979), indicates an excellent fit for the model. Similar to the 2-class model, the 3-class LCM demonstrates superior performance compared to the restricted model based on the LRS test. The results of this model estimation are presented in Table 26. As with the previously discussed 2-class LCM, the results of the two experiment stages will be sequentially discussed, followed by a discussion of class composition.

Table 26: Estimation LC model - 3 classes

		Class 1			**Class 2**			**Class 3**		
Class probability		0.316 (32%)			0.314 (31%)			0.369 (37%)		
		Pw Util.	*Std. Error*	$\|z\|>Z*$	*Pw Util.*	*Std. Error*	$\|z\|>Z*$	*Pw Util.*	*Std. Error*	$\|z\|>Z*$
Parameters in utility function										
1st stage - Parking location choice										
Main effects										
Constant 1 (neither)		-13.769***	0.992	0.00	-15.165***	0.794	0.00	-2.898***	0.195	0.00
Type of parking	On-street	-0.181[a]	-	-	-0.255[a]	-	-	-0.451[a]	-	-
	Surface level	-0.053	0.117	0.04	-0.191**	0.079	0.02	0.061	0.060	0.30
	Parking garage	0.233**	0.111	0.04	0.447***	0.074	0.00	0.390***	0.060	0.00
Fee (/€)		-1.576***[b]	0.117	0.00	-1.765***[b]	0.095	0.00	-0.416***[b]	0.041	0.00
Search time (/min)		-0.333***[b]	0.051	0.00	-0.267***[b]	0.037	0.00	-0.071***[b]	0.024	0.00
Egress time (/min)		-0.394***[b]	0.039	0.00	-0.366***[b]	0.030	0.00	-0.066***[b]	0.016	0.00
Context effects trip purpose										
Dentist (fixed)	Constant 1	0.725[a]	-	-	1.698[a]	-	-	-0.307[a]	-	-
	On-street	0.153[a]	-	-	0.021[a]	-	-	0.253[a]	-	-
	Surface level	-0.004[a]	-	-	0.042[a]	-	-	-0.120[a]	-	-
	Parking garage	-0.148[a]	-	-	-0.063[a]	-	-	-0.134[a]	-	-
	Fee (/€)	-0.144[a,b]	-	-	-0.239[a,b]	-	-	-0.353[a,b]	-	-
	Search time (/min)	0.172[a,b]	-	-	0.220[a,b]	-	-	0.099[a,b]	-	-
	Egress time (/min)	0.165[a,b]	-	-	0.148[a,b]	-	-	0.059[a,b]	-	-
Friend (flexible)	Constant 1	-1.596*	0.956	0.095	-1.372**	0.655	0.04	0.203	0.144	0.16
	On-street	-0.090[a]	-	-	-0.012[a]	-	-	-0.059[a]	-	-
	Surface level	0.063	0.111	0.57	-0.045	0.077	0.56	0.062	0.054	0.25
	Parking garage	0.028	0.100	0.78	0.057	0.070	0.42	-0.003	0.054	0.95
	Fee (/€)	-0.040[b]	0.137	0.77	-0.111	0.102	0.28	0.122***[b]	0.042	0.00
	Search time (/min)	-0.044[b]	0.055	0.43	-0.092**[b]	0.040	0.02	-0.020	0.026	0.45
	Egress time (/min)	-0.048[b]	0.044	0.28	-0.050[b]	0.032	0.12	-0.007	0.017	0.70
Shopping (free)	Constant 1	0.871	0.635	0.17	-0.326	0.621	0.60	0.105	0.145	0.47
	On-street	-0.062[a]	-	-	-0.010[a]	-	-	-0.194[a]	-	-
	Surface level	-0.059	0.098	0.55	0.003	0.073	0.96	0.057	0.054	0.29
	Parking garage	0.121	0.093	0.20	0.006	0.066	0.92	0.137**	0.054	0.01
	Fee (/€)	0.184[b]	0.201	0.36	0.350**[b]	0.160	0.03	0.231***[b]	0.075	0.00
	Search time (/min)	-0.129[b]	0.091	0.16	-0.128**[b]	0.064	0.05	-0.079*[b]	0.047	0.09
	Egress time (/min)	-0.118*[b]	0.066	0.07	-0.098*[b]	0.052	0.06	-0.053*[b]	0.030	0.08

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Table 26 – continued from previous page

		Class 1			Class 2			Class 3		
		Pw Util.	*Std. Error*	$\|z\|>Z*$	*Pw Util.*	*Std. Error*	$\|z\|>Z*$	*Pw Util.*	*Std. Error*	$\|z\|>Z*$
Context effects delay										
Delay (/min)	Constant 1	0.529^{***,c}	0.107	0.00	0.201^{*,c}	0.120	0.10	0.002^{c}	0.027	0.94
	On-street	0.019^{a,c}	-	-	0.006^{a,c}	-	-	0.030^{a,c}	-	-
	Surface level	0.024^{c}	0.017	0.15	0.053^{***,c}	0.012	0.00	0.009^{c}	0.009	0.34
	Parking garage	-0.043^{***,c}	0.016	0.01	-0.058^{***,c}	0.012	0.00	-0.039^{***,c}	0.010	0.00
	Fee (/€)	0.067^{***,c,b}	0.012	0.00	0.070^{***,c,b}	0.009	0.00	-0.004^{c,b}	0.004	0.35
	Search time (/min)	0.014^{**,c,b}	0.006	0.01	0.003^{c,b}	0.004	0.49	0.002^{c,b}	0.003	0.56
	Egress time (/min)	0.022^{***,c,b}	0.005	0.00	0.011^{***,c,b}	0.003	0.00	0.000^{c,b}	0.002	1.00
2nd stage - Adapted parking choice										
Main effects										
Constant 2 (parking advise)		-1.244***	0.182	0.00	-0.307***	0.044	0.00	-0.827***	0.076	0.00
Type of parking	On-street	0.424^{a}	-	-	-0.543^{a}	-	-	-0.299^{a}	-	-
	Surface level	-0.553***	0.166	0.00	0.370***	0.046	0.00	0.145**	0.073	0.05
	Parking garage	0.129	0.111	0.24	0.173***	0.042	0.00	0.154**	0.069	0.02
Fee (/€)		-3.927^{***,b}	0.388	0.00	-0.192^{***,b}	0.041	0.00	-0.106^{b}	0.067	0.11
Search time (/min)		-1.064^{***,b}	0.122	0.00	0.101^{***,b}	0.021	0.00	0.087^{**,b}	0.037	0.02
Egress time (/min)		-0.916^{***,b}	0.110	0.00	0.069^{***,b}	0.016	0.00	0.022^{b}	0.027	0.41
Diff in travelt (/min)		-0.211^{***,b}	0.050	0.00	-0.096^{***,b}	0.017	0.00	-0.087^{***,b}	0.028	0.00
Context effects trip purpose										
Dentist (fixed)	Constant 2	0.084^{a}	-	-	0.059^{a}	-	-	0.007^{a}	-	-
	On-street	-0.055^{a}	-	-	0.152^{a}	-	-	0.190^{a}	-	-
	Surface level	0.057^{a}	-	-	-0.151^{a}	-	-	-0.084^{a}	-	-
	Parking garage	-0.002^{a}	-	-	-0.001^{a}	-	-	-0.106^{a}	-	-
	Fee (/€)	-1.015^{a,b}	-	-	-0.047^{a,b}	-	-	-0.040^{a,b}	-	-
	Search time (/min)	0.142^{a,b}	-	-	0.069^{a,b}	-	-	-0.039^{a,b}	-	-
	Egress time (/min)	0.130^{a,b}	-	-	0.089^{a,b}	-	-	0.009^{a,b}	-	-
	Diff in travelt (/min)	-0.120^{a,b}	-	-	-0.021^{a,b}	-	-	-0.021^{a,b}	-	-
Friend (flexible)	Constant 2	0.195*	0.115	0.09	-0.126***	0.037	0.00	-0.022	0.062	0.72
	On-street	-0.068^{a}	-	-	-0.108^{a}	-	-	-0.134^{a}	-	-
	Surface level	0.213**	0.103	0.04	0.028	0.037	0.45	-0.006	0.060	0.93
	Parking garage	-0.145	0.097	0.14	0.080**	0.038	0.04	0.140**	0.061	0.02
	Fee (/€)	-0.050^{b}	0.490	0.92	0.015^{b}	0.046	0.75	0.013^{b}	0.072	0.85
	Search time (/min)	-0.048^{b}	0.132	0.72	-0.040^{*,b}	0.024	0.10	0.003^{b}	0.042	0.94
	Egress time (/min)	-0.023^{b}	0.100	0.82	-0.018^{b}	0.017	0.27	0.000^{b}	0.028	0.99
	Diff in travelt (/min)	0.013^{b}	0.046	0.78	0.012^{b}	0.015	0.40	0.024^{b}	0.024	0.32

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Table 26 – continued from previous page

		Class 1			Class 2			Class 3		
		Pw Util.	*Std. Error*	$\|z\|>Z*$	*Pw Util.*	*Std. Error*	$\|z\|>Z*$	*Pw Util.*	*Std. Error*	$\|z\|>Z*$
Shopping (free)	Constant 2	-0.278**	0.121	0.02	0.067*	0.037	0.07	0.015	0.062	0.80
	On-street	0.123[a]	-	-	-0.044[a]	-	-	-0.056[a]	-	-
	Surface level	-0.269***	0.103	0.01	0.122***	0.036	0.00	0.089	0.058	0.12
	Parking garage	0.146	0.102	0.15	-0.079**	0.038	0.04	-0.033	0.062	0.59
	Fee (/€)	1.065[b]	0.790	0.18	0.033[b]	0.076	0.67	0.027[b]	0.127	0.83
	Search time (/min)	-0.094[b]	0.218	0.67	-0.029[b]	0.042	0.49	0.035[b]	0.070	0.61
	Egress time (/min)	-0.107[b]	0.183	0.56	-0.071**[,b]	0.029	0.01	-0.009[b]	0.049	0.86
	Diff in travelt (/min)	0.107**[,b]	0.047	0.02	0.009[b]	0.014	0.53	-0.003[b]	0.024	0.90
Context effects delay										
Delay (/min)	Constant 2	0.086***[,c]	0.023	0.00	0.026***[,c]	0.007	0.00	0.025**[,c]	0.011	0.02
	On-street	-0.068[a,c]	-	-	0.057[a,c]	-	-	0.006[a,c]	-	-
	Surface level	0.071***[,c]	0.022	0.00	-0.045***[,c]	0.007	0.00	-0.002[c]	0.011	0.88
	Parking garage	-0.00[c]3	0.018	0.89	-0.011*[,c]	0.007	0.08	-0.005[c]	0.011	0.65
	Fee (/€)	0.088*[,c,b]	0.050	0.08	-0.002[c,b]	0.004	0.59	0.001[c,b]	0.007	0.86
	Search time (/min)	0.072***[,c,b]	0.015	0.00	-0.007***[,c,b]	0.002	0.00	-0.009**[,c,b]	0.004	0.02
	Egress time (/min)	0.041***[,c,b]	0.011	0.00	-0.001[c,b]	0.002	0.51	0.001[c,b]	0.003	0.68
	Diff in travelt (/min)	-0.018**[c,b]	0.008	0.03	0.001[c,b]	0.003	0.57	0.005[c,b]	0.004	0.21

***,**,* →Parameter is significant at the 1%, 5%, 10% level.

a. Part worth utility has been computed manually.

b. Parameter is continuous; part worth utility per unit.

c. Context effect is continuous; part worth utility per unit.

Table 27: Estimation LC model - 3 classes (distribution)

	Class 1	Class 2	Class 3
	Pw Util. dist.	*Pw Util. dist.*	*Pw Util. dist.*
Parameters in utility function			
1st stage - Parking location choice			
Main effects			
Constant 1			
On-street parking			
Surface level parking			
Parking garage			
Fee (/€)			
Search t (/min)			
Egress t (/min)			
Context effects trip purpose - Dentist			
Constant 1			
On-street parking			
Surface level parking			
Parking garage			
Fee (/€)			
Search t (/min)			
Egress t (/min)			
Context effects trip purpose - Friend			
Constant 1			
On-street parking			
Surface level parking			
Parking garage			
Fee (/€)			
Search t (/min)			
Egress t (/min)			
Context effects trip purpose - Shopping			
Constant 1			
On-street parking			
Surface level parking			
Parking garage			
Fee (/€)			
Search t (/min)			
Egress t (/min)			

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Table 27 – continued from previous page

	Class 1	Class 2	Class 2
	Pw Util. dist.	*Pw Util. dist.*	*Pw Util. dist.*
Context effects delay (/min)			
Constant 1			
On-street parking			
Surface level parking			
Parking garage			
Fee (/€)			
Search t (/min)			
Egress t (/min)			
2nd stage - Adapted parking choice			
Main effects			
Constant 2			
On-street parking			
Surface level parking			
Parking garage			
Fee (/€)			
Search t (/min)			
Egress t (/min)			
Diff travel t (/min)			
Context effects trip purpose - Dentist			
Constant 2			
On-street parking			
Surface level parking			
Parking garage			
Fee (/€)			
Search t (/min)			
Egress t (/min)			
Diff travel t (/min)			
Context effects trip purpose - Friend			
Constant 2			
On-street parking			
Surface level parking			
Parking garage			
Fee (/€)			
Search t (/min)			
Egress t (/min)			
Diff travel t (/min)			

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Table 27 – continued from previous page

	Class 1	Class 2	Class 2
	Pw Util. dist.	*Pw Util. dist.*	*Pw Util. dist.*
Context effects trip purpose - Shopping			
Constant 2			
On-street parking			
Surface level parking			
Parking garage			
Fee (/€)			
Search t (/min)			
Egress t (/min)			
Diff travel t (/min)			
Context effects delay (/min)			
Constant 2			
On-street parking			
Surface level parking			
Parking garage			
Fee (/€)			
Search t (/min)			
Egress t (/min)			
Diff travel t (/min)			

Experiment stage 1 - Parking location choice

The first set of attributes and their associated estimates in Table 26 describe the main effects in the first stage of the experiment. The alternative specific constant 1 for the neither choice shows large negative estimates of -13.769 and -15.165 for class 1 and class 2, respectively, compared to a smaller estimate of -2.898 for class 3. All three estimates are significant at the 1% level. Among the characteristics of parking facilities, only parking garage exhibits a significant positive effect for class 1 and 3. For Class 2, both surface level and parking garage are significant, with surface level parking having a negative effect of -0.191 (at 5%) and parking garage having a positive effect of 0.447 (at 1%) on utility. The fee has estimates of -1.576, -1.765, and -0.416 for the three classes, all significant at the 1% level. Both search and egress times have a significant negative estimate for all classes, where egress time has a more extreme value for classes 1 and 2.

The majority of interaction effects based on trip purpose are, like in the MNL model and 2-class LCM, insignificant for the 3-class model. Class 1 does not exhibit any significant interaction at 5%. For class 2, the interactions between visiting a friend and constant 1, as well as search time, are significant at the 5% level and have a negative effect on utility. Meeting up with a friend interacts significantly with fee and has a positive effect of 0.122 on utility for Class 3. This class is therefore less worried about price when visiting a friend. The interactions between doing some shopping and fee, and shopping and search time has a significant effect on utility for class 2 and 3, at the 10% level. Respondents in class 3 tend to favor parking garages more in a shopping context. For this group, the interaction between shopping and fee is valued at 0.231, significant at 1%.

Regarding the interaction effects between delay and constant 1, only the coefficients of class 1 and 2 are significant, with respective values of 0.529 and 0.201. Of the interactions with parking facility type, surface level parking has a significant positive effect on utility for class 2, and parking garage has a comparable negative effect for all three classes. The interaction effect of delay on fee is positive and significant at the 1% level for classes 1 and 2. This effect is comparable in size but nonexistent for class 3. Delay has a significant interaction with search time for class 1 of 0.014, but none for the other two classes. Egress time is significantly affected by delay for classes 1 and 2, with both having a positive effect on utility.

Experiment stage 2 - Adapted parking choice

The estimated alternative specific constant 2 for the SPS model is significant at the 1% level and negative for all three classes, with values of -1.244 for class 1, -0.307 for class 2, and -0.827 for class 3. In terms of the parking facility type attributes, surface level parking is significant for all three classes. Notably, the estimate for class 1 is the only negative attribute with a value of -0.553, whereas the attribute estimates for class 2 and 3 are 0.370 and 0.145, respectively. The parking garage estimate is not significant at the 10% level for class 1 but is significant, positive, and of comparable size for the other two classes.

The effect of the fee attribute for class 1 is quite extreme, with an estimate of -3.927 compared to the estimate of -0.192 for the second class, whilst the fee estimate is not significant for the third class. This means that fees in offered alternatives are most negatively evaluated by class 1, whilst fee is not a relevant attribute in the decisions made by class 3. The search and egress time parameter estimates for class 1 are negative and significant at the 1% level, but surprisingly large compared to the other two classes, which have positive estimates ranging from 0.069 to 0.101, if significant. The last main effect of the second stage, the difference in travel time, has a negative estimated value of -0.211 for class one, significant at the 1% level. This value is roughly double that of the other two classes.

For class 1, only the interactions between visiting a friend and constant 2, friend and surface level parking, shopping and constant 2, shopping and surface level parking, and shopping and difference in travel time are significant at the 10% level among trip purpose interactions. On the other hand, class 2 exhibits a wider range of significant estimates, such as friend and constant 2 (-0.126), friend and parking garage (0.080), shopping and constant 2 (0.067), shopping and surface level parking (0.122), shopping and parking garage(-0.079), and shopping and egress time (-0.071). Meanwhile, the only significant estimation for class 3 is the interaction between meeting a friend and parking garage.

The interaction between delay and constant 2 is significant across all three classes. The estimate for class 1 is 0.086, while for class 2 and class 3, it is 0.026 and 0.025, respectively. The interaction between delay and surface level parking is significant for classes 1 and 2, with estimates of 0.071 and -0.045, respectively. Search time is also found to have significant estimates for all three classes, with values of 0.072, -0.007, and -0.009 for class 1, 2, and 3, respectively. The interaction effect of delay on egress time is only significant for class 1, as is the case for difference in travel time.

Class preference interpretation
As depicted in Table 27, classes 1 and 2 exhibit similar parameter distributions in the initial stage of the experiment. For both classes, the neither alternative specific constant and hourly parking fee estimations are the most influential determinants of alternative utility in terms of main effects. Class 2 displays more prominent interactions stemming from trip purpose, while the interactions arising from delay are comparable for both classes in the first stage. On the other hand, the parameter estimations for class 3 are relatively moderate.

Moving on to the second stage of the experiment, class 1 maintains its extreme valuation of the explanatory parameters, including the negative SPS advice alternative specific constant. Fee continues to be the primary factor influencing alternative utility through main and context effects. Notably, class 2 now demonstrates moderate part-worth utilities for the main effects, which align more closely with class 3 rather than class 1. However, the SPS advice alternative specific constant in class 2 has a roughly three times lower negative value compared to class 3. Class 2 exhibits context effects similar to class 3. Similar to the first stage, class 3 showcases a relatively moderate valuation of attributes in the second stage.

In summary, it is evident that class 1 consistently exhibits extreme valuations for the main explanatory attributes, with a strong focus on the fee attribute. Class 3 consistently maintains a moderate valuation of attributes throughout the experiment, without a strong emphasis on the fee attribute. Class 2, on the other hand, shows a preference pattern that is comparable to class 1 in the first stage but aligns more closely with class 3 in the second stage, with the exception of a larger quantity of significant context effects.

5.4 Conclusion

In conclusion, the descriptive analysis of the socio-demographic characteristics indicates that the study sample is not representative of the entire Dutch traveling population in terms of gender, age, and level of education. Therefore, caution should be exercised when generalizing the results to the broader population. To achieve more accurate generalizability, future studies should consider respondent weighting, although such adjustments were beyond the scope of this study. To address low-frequency distributions, certain variables were recoded, resulting in three levels for age groups and education levels. The household income characteristic was excluded from further analysis to avoid potential data loss. Moreover, the distribution of living country showed a skewed representation, making it unsuitable for further examination.

The MNL model analysis yielded promising results. The model demonstrated excellent fit and outperformed the null model. The analysis focused on two stages: parking location choice and adapted parking choice. In the first stage, respondents displayed a clear preference for parking with a garage type, while on-street and surface-level parking options were less favored. The significant negative utility of the hourly fee confirmed its influence on parking location choice, indicating the importance of cost. Longer search time and egress time had a negative impact, suggesting a preference for shorter durations. Trip purpose generally showed no significant effects, except for specific interactions. However, delay had a noteworthy influence, affecting the likelihood of selecting the neither option and shaping preferences for different parking facility types, fees, and times.

In the second stage, respondents exhibited reluctance to switch from their initial parking choice to the SPS option. Factors such as the First Instinct Fallacy, cognitive dissonance, or a lack of trust in technology could explain this behavior. Of the parking facility types, surface-level parking and parking garage options had positive effects, while on-street parking had a negative effect. The hourly fee remained a significant factor, indicating a heightened sensitivity to price in adapted parking scenarios. The impact of search time and egress time persisted in this stage as well.

The analysis also explored how preferences of respondents differ between people of a different gender, age and education level. Gender displayed significant differences between male and female respondents for all main parameters, with women being more likely to select one of the offered parking alternatives in the first stage and showing greater concern for fee, while displaying less preference for larger search and egress times than men. Age differences mainly manifested in the neither alternative and egress time, indicating that older respondents were more inclined to choose the neither option and less bothered by longer walking distances. Education levels exhibited significant interactions, with higher-educated individuals showing a smaller likelihood of selecting one of the parking alternatives in stage 1, expressing more concern for fees, and placing higher value on search time and egress time compared to lower-educated respondents.

The estimation of the MNL model revealed differences in parameter estimates between the two experiment stages. This is somewhat surprising since respondents should exhibit consistent behavior in similar choice scenarios. To further investigate this, an additional MNL model was estimated, including the effect of SPS advice on the parameters estimated for stage 1. The results showed significant effects, demonstrating differences between the first and second stages, particularly in the main effects of parking facility type, fee, search time, and egress time. The effects of trip purpose were not significantly different, likely due to their limited influence on the main effects. Gender effects remained consistent, while age and education showed differences in interaction effects. These disparities in parameter estimates can be attributed to the nature of the experimental design, as the second stage focused on expressing the likelihood and nature of behavioral change rather than simple choice between alternatives. Consequently, the estimations of stage 1 and stage 2 do not explain the same choice behavior, warranting separate analysis for the second stage results.

The LCM analysis revealed distinct patterns among respondents. In the 2-class LCM model, class 2 exhibited stronger preferences and greater confidence in evaluating alternatives compared to class 1. This distinction was evident in the estimations for fees, search time, and egress time. Class 1 respondents, who had lower confidence in their decision-making, demonstrated a stronger tendency to disregard the provided SPS advice in the second stage. This pattern could be attributed to a stronger effect of cognitive dissonance. The 3-class LCM model showed similar parameter distributions for classes 1 and 2 in the initial stage, with the neither alternative constant and hourly parking fee estimations playing significant roles. Class 2 displayed more interactions related to trip purpose, while delay effects were comparable for classes 1 and 2. In the second stage, class 1 maintained extreme valuations, while class 2 aligned more closely with class 3 but with a lower negative value for the SPS advice constant. Class 3 consistently demonstrated a moderate valuation of attributes throughout the experiment.

6 Conclusions, limitations, and recommendations

In the opening section of this chapter, a comprehensive overview of the primary findings presented in this report is provided. Section 6.2 presents a summary of the key limitations pertaining to the present research, while Section 6.3 elucidates the practical and academic implications derived from this study.

6.1 Conclusions

Smart parking has the potential to enhance parking facility efficiency and decrease the traffic generated by parking. Currently, the incorporation of this technology in urban centers is limited, and there is a lack of information regarding the impact of smart parking on parking choice behavior. Hence, this study aims to assess the efficacy of in-vehicle Smart Parking System (SPS) advice by examining the hypothetical behavioral changes resulting from the SPS advice treatment. To explore compliance behavior with SPS advice, the following research question was formulated:

"How do personal, parking facility, and trip-related attributes influence driver compliance with advice provided by in-vehicle smart parking systems?"

To address this research question, a literature review and a stated adaptation experiment comprising two consecutive choice tasks were undertaken. The literature review aimed to gain a comprehensive understanding of the concept of smart parking and identify factors that may influence driver compliance with SPS advice.

From the literature review, two trip characteristics were deemed pertinent for examining compliance: trip purpose and the delay encountered en route to the final destination. These factors were incorporated into the choice contexts within the stated adaptation experiment. Additionally, the experiment included five parking facility attributes: parking facility type, hourly parking fee, search time, egress time, and travel time difference. Furthermore, four personal characteristics were identified: gender, age, income, and education.

In this study, the theoretical framework of utility theory was employed to analyze choice behavior. Within this framework, it is assumed that individuals assess choice alternatives based on their personal preferences and select the alternative that offers the highest utility or preference. The utility of an alternative is determined by how individuals value its attributes. By systematically manipulating these attributes, the relative importance of each attribute for individual participants can be ascertained. This was accomplished through an orthogonal stated adaptation experiment comprising 144 profiles retrieved from Ngene. These profiles described two consecutive choice tasks. In the first task, participants were asked to choose between two parking alternatives and a neither option, while in the second task, respondents had to choose between their previously chosen alternative and an alternative advised by the SPS. The experiment was administered to 1619 participants through an online survey, and the resulting data was analyzed using a Multinominal Logit Model (MNL) model, as well as 2-class and 3-class Latent Class Model (LCM) models with NLOGIT 6. However, due to suspected capacity issues encountered during the estimation of the class membership models in the LCM estimation, only the MNL model incorporates personal characteristics.

Based on the results obtained from all the estimated models, it can be concluded that respondents generally have a negative base attitude towards the SPS advice alternative. This sentiment is believed to stem from the combined influence of three psychological frameworks: cognitive dissonance, the first instinct fallacy, and a general distrust in technology. The models also revealed that all the parking facility characteristics included in the experiment have an impact on the choice between a previously selected alternative and the offered SPS advice alternative. Among the trip characteristics, trip purpose does not seem to considerably affect the decision to comply, while any delay experienced en route enhances the attractiveness of the SPS advice. None of the socio-demographic characteristics seem to have a direct effect on the base attractiveness of the SPS advice alternative, although they do have an effect on the evaluation of the characteristics of the alternative.

In the 2-class LCM, the two groups of respondents comprised approximately half of the participants. One group displayed confidence in their regular parking choice behavior, and interestingly, this confidence led to a higher appreciation of the offered SPS advice compared to the other group. For this confident group, the hourly parking fee contributed the most to the overall utility of the explanatory parameters. The observation that the group of respondents who were less confident in their initial choice were less likely to comply with SPS advice might be attributed to the stronger influence of cognitive dissonance.

The 3-class LCM identified three classes, encompassing 31% to 37% of the respondents. One class consistently exhibited extreme valuations for the primary explanatory attributes, with a strong focus on the fee attribute. The second class consistently maintained moderate valuations of attributes throughout the experiment, without a strong emphasis on the fee attribute. Meanwhile, the remaining group of respondents exhibited a preference pattern similar to the extreme class in their regular parking choice behavior, but aligned more closely with the moderate class in the choice between the previously selected parking alternative and the SPS advice.

In conclusion, the study effectively addressed all of the research questions outlined previously. The findings revealed that respondents in the sample displayed a fundamental reluctance towards the provided SPS advice. Among the trip attributes, delay exerted a positive influence on compliance, whereas type of parking facility, hourly fee, search time, egress time, and difference in travel time had a negative impact on compliance with the SPS advice. The study has made a valuable contribution to scientific literature by addressing the research gap with regards to drivers' reactions and responses to the advice provided by SPS technologies.

6.2 Limitations

Like any study, the research presented in this report has several limitations that highlight the need for caution when interpreting findings without validation.

Firstly, the identification of explanatory attributes in the literature was constrained by the limited availability of academic sources specifically focused on the effects of SPS advice on drivers' parking choices. As a result, the identification of potentially relevant attributes had to rely on literature from related fields such as parking choice behavior and compliance with various forms of Variable Message Signage (VMS). Consequently, the set of attributes derived from this review may not fully capture the context of SP, and there may be other unobserved attributes that could have a significant impact on compliance with SP advice.

Due to apparent capacity-related issues encountered during the estimation of the LCM models, none of the personal characteristics identified in the literature review were incorporated into the LCM analysis. However, as the MNL results proofs, it is highly probable that these characteristics exert an influence on driver compliance with SPS advice, and that, therefore, class membership could be predicted on the basis of socio-demographic characteristics.

Additionally, this research is constrained by its focus on the specific parking context in the Netherlands where especially parking facility attributes differ non-European contexts. As a result, the findings may not have direct applicability to other countries or regions with distinct environments, cultural norms, and urban and transportation planning frameworks. Moreover, when comparing the sample used in this study with the ODiN 2021 sample, it became evident that the respondents in this study do not represent the broader Dutch traveling population adequately in terms of gender, age, and level of education. Consequently, the results cannot be readily generalized for the Netherlands as a whole.

Lastly, while there are ample theoretical indications that the Stated Adaptation (SA) experimental setup used in this study, which consists of two consecutive choice tasks, is capable of effectively capturing real-world behavior, this has not yet been validated. Although unlikely given the ubiquity of parking in people's daily lives, it is possible that respondents encountered challenges in constructing a mental model of the initial choice scenario. This difficulty could potentially get worse with the introduction of the modified choice scenario in the second task. As a consequence, inaccuracies in the data may arise, leading to unreliable analysis results.

6.3 Recommendations

As reiterated throughout this report, SPS technology holds immense potential in improving parking efficiency and, consequently, reducing unnecessary driving distances in search of parking spaces and its associated emissions and frustrations. In light of this, policymakers and parking facility operators should actively explore the feasibility and implementation options of SPSs. It is crucial that any adopted system takes into consideration driver preferences to promote compliant behavior and maximize the effectiveness of the technology.

Regarding compliance with SPS advice, the findings of this study suggest several recommendations for practice and policy. Firstly, recommended alternative parking facilities should not only meet but surpass the quality and convenience of the initial parking option such that the overall parking performance and productivity increases. Study participants showed base negative preference for the SPS advice alternatives, so it is crucial to address these concerns and ensure that the recommended facilities are attractive and desirable choices.

To encourage compliance among a segment of system users, dynamic parking pricing strategies could be employed. As demonstrated by this and other studies in academic literature, it is evident that parking fees strongly influence parking location choices. By implementing dynamic pricing mechanisms that adjust parking fees based on demand, availability, or the collective ambition to achieve broader societal goals like reduced congestion and greenhouse gas emissions, drivers may be incentivized to choose the recommended SPS advice alternative. This approach aligns with the concept of demand-responsive pricing, where prices are adjusted in real-time to manage parking demand and encourage efficient use of parking resources (Litman & Burwell, 2006).

However, for a larger portion of drivers, it is vital that the recommended SPS parking alternative significantly contributes to reducing their overall travel time. Time efficiency is a crucial factor for many drivers, and the SPS should prioritize providing parking options that minimize travel times to drivers' final destinations. Therefore, the process of allocating drivers to available parking spots based on their routing, and especially their final destination, assumes great importance in ensuring effective implementation of SPSs. This can be achieved through the integration of real-time traffic and navigation data, enabling the SPS to offer personalized and efficient parking recommendations tailored to individual drivers' routes and destinations.

Moreover, it is worth noting that there are variations in the evaluation of SPS choice alternatives based on socio-demographic characteristics. This study has shown that factors such as gender, age, and level of education can influence individuals' parking preferences and decision-making. Therefore, exploring personalized SPS advice based on driver characteristics could further enhance compliance. This could involve incorporating socio-demographic data and preferences into the SPS algorithm to generate tailored recommendations that align with individual drivers' needs and preferences. This concept could be elaborated upon by introducing a self-learning system that aims to perfect personal parking allocation based on past preferences and behaviors of the system user over time.

In conclusion, in order to improve compliance with SPS advice, recommended alternative parking facilities should surpass initial options, dynamic pricing strategies should be considered, travel time reduction should be prioritized, and personalized SPS advice based on driver characteristics should be explored. By implementing these recommendations, policymakers and practitioners can promote greater compliance with SPS recommendations and enhance the effectiveness and efficiency of parking management in urban areas.

For future research, it is imperative to move beyond the hypothetical context presented in this report and transition into real-world implementation to further advance our understanding of driver compliance with SPS advice. Conducting a study in an actual SPS pilot setting would provide an opportunity to validate, refute, or expand upon the findings of this study based on observed behavior in a practical context.

Furthermore, it would be valuable to conduct similar studies in different regions around the world, going beyond the Dutch or European context. This approach would enable us to gain insights into the implementation of SPSs in diverse cultural, economic, and infrastructural settings. By examining compliance with SPS advice in non-Dutch or non-European contexts, we can identify variations and similarities in compliance behavior and explore the factors that influence compliance across different regions.

Moreover, it would be beneficial to investigate compliance with SPS advice in a time when the general public is more familiar with the concept of smart parking. As SPSs become more prevalent and integrated into urban environments, societal attitudes and norms regarding parking may evolve. Therefore, exploring compliance behavior in a context where the general public is well-acquainted with SPSs would provide valuable insights into the impact of social environments on compliance behavior. This examination of social dynamics would add depth to our understanding of the factors that influence compliance with SPSs.

In conclusion, future research should focus on conducting studies in real-world SPS pilot settings to validate and expand upon the findings of this study. Additionally, investigating compliance in different global contexts and exploring the impact of social environments on compliance behavior would contribute to a more comprehensive understanding of the factors influencing compliance with SPSs.

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A Experiment design generation in NGene

Listing A1: NGene code

```
? design
Design
;alts = alt1, alt2, alt3
;rows = 81
;orth = sim
;model:
U(alt1) = b01 + b2 * A[0,1,2] + b3 * B[0,1,2] + b4 * C[0,1,2] + b5 * D[0,1,2] + b6
      * E[0,1,2] + b7 * F[0,1,2] + b8 * G[0,1,2] + b9 * H[0,1,2] + b10 * I[0,1,2] +
      b11 * J[0,1,2] + b12 * K[0,1,2] + b13 * L[0,1,2] + b14 * M[0,1,2] + b15 * N
     [0,1,2] + b16 * O[0,1,2] + b17 * A * C + b18 * A * D + b19 * A * E + b20 * A *
      F + b21 * A * G + b22 * A * H + b23 * A * I + b24 * A * J + b25 * A * K + b26
      * A * L + b27 * A * M + b28 * A * N + b29 * A * O + b30 * B * C + b31 * B * D
      + b32 * B * E + b33 * B * F + b34 * B * G + b35 * B * H + b36 * B * I + b37 *
      B * J + b38 * B * K + b39 * B * L + b40 * B * M + b41 * B * N + b42 * B * O /
U(alt2) = b02 + b2 * A + b3 * B + b4 * C + b5 * D + b6 * E + b7 * F + b8 * G + b9
     * H + b10 * I + b11 * J + b12 * K + b13 * L + b14 * M + b15 * N + b16 * O /
U(alt3) = b2 * A + b3 * B + b4 * C + b5 * D + b6 * E + b7 * F + b8 * G + b9 * H +
     b10 * I + b11 * J + b12 * K + b13 * L + b14 * M + b15 * N + b16 * O

$
```

Table A1: Orthogonal fractional factorial design (evaluation 40676)

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O
1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2	1	1	1	2	2	1	1	2	2	1	1	2	2	1	1
3	2	2	2	1	1	0	0	0	0	2	2	1	2	1	1
4	1	0	0	2	2	2	2	1	1	1	1	0	1	2	2
5	0	1	1	0	0	2	2	0	0	0	0	2	1	1	1
6	2	2	2	1	1	1	1	2	2	1	1	0	0	0	0
7	1	0	0	1	1	0	0	2	2	2	2	2	1	2	2
8	0	2	2	2	2	2	2	1	1	0	0	1	2	0	0
9	0	2	2	2	2	2	2	2	2	2	2	2	2	2	2
10	2	0	0	1	1	0	0	1	1	0	0	1	1	0	0
11	1	2	2	1	1	1	1	0	0	0	0	2	0	1	1
12	0	1	1	0	0	2	2	2	2	1	1	0	1	0	0
13	2	2	2	0	0	2	2	1	1	1	1	1	0	1	1
14	0	1	1	1	1	1	1	0	0	2	2	0	1	2	2
15	1	0	0	2	2	1	1	2	2	2	2	1	0	0	0
16	2	1	1	0	0	0	0	1	1	0	0	2	2	2	2
17	2	1	0	1	2	2	0	2	0	1	0	1	2	1	2
18	0	0	1	2	1	0	2	0	2	0	1	0	0	2	1
19	2	2	0	0	2	0	1	0	1	1	2	0	1	1	0
20	1	0	2	2	0	1	0	1	0	2	1	2	2	0	1
21	1	2	1	0	2	1	0	1	2	2	0	0	0	1	2
22	0	1	2	2	0	0	1	2	1	0	2	1	1	2	1
23	2	1	0	1	0	1	2	1	0	1	2	2	0	2	0
24	1	0	1	0	1	2	1	0	1	2	1	1	2	0	2
25	1	1	2	1	2	0	2	2	1	2	0	0	0	0	1
26	2	2	1	2	1	2	0	1	2	0	2	2	1	1	0
27	0	0	2	1	0	2	1	0	2	1	0	2	1	0	2
28	2	2	0	0	1	1	2	2	0	0	1	1	2	2	0
29	1	0	1	1	0	1	2	2	1	0	2	0	2	1	2
30	0	1	0	0	1	2	1	1	2	2	0	1	0	2	1
31	2	2	1	2	0	0	1	1	0	1	2	1	0	0	2
32	0	1	2	0	2	1	0	0	1	2	1	2	1	2	0
33	0	1	2	2	1	2	0	2	0	0	1	2	0	0	2
34	1	2	1	1	2	0	2	0	2	1	0	1	1	2	0
35	1	2	0	1	0	2	1	2	1	2	0	2	2	1	0
36	2	0	2	0	1	1	2	1	2	0	2	0	1	0	1
37	0	0	1	1	2	2	0	1	0	2	1	0	0	1	0
38	2	1	0	2	1	0	2	0	1	1	2	2	2	0	1
39	0	0	2	0	2	0	1	0	2	0	1	1	2	1	2
40	1	2	0	2	0	1	0	2	0	1	0	0	1	2	1
41	2	2	0	0	2	0	1	1	0	2	1	2	1	0	1
42	0	0	2	2	0	1	0	0	1	1	2	0	2	1	0
43	2	1	0	1	2	2	0	0	2	0	1	0	2	2	1
44	1	0	1	2	1	0	2	2	0	1	0	1	0	1	2
45	1	0	1	0	1	2	1	1	0	1	2	2	2	2	0
46	0	1	0	1	0	1	2	0	1	2	1	1	0	0	2
47	2	1	2	2	0	0	1	1	2	2	0	0	1	1	2
48	1	2	1	0	2	1	0	2	1	0	2	1	0	2	1
49	2	1	2	0	2	1	0	0	1	2	1	2	1	2	0
50	0	2	1	2	0	0	1	1	0	1	2	1	0	0	2
51	1	1	0	0	1	2	1	1	2	2	0	1	0	2	1
52	0	0	1	1	0	1	2	2	1	0	2	0	2	1	2
53	0	2	0	0	1	1	2	2	0	0	1	1	2	2	0
54	2	0	2	1	0	2	1	0	2	1	0	2	1	0	2
55	1	2	1	2	1	2	0	1	2	0	2	2	1	1	0
56	2	1	2	1	2	0	2	2	1	2	0	0	0	0	1
57	2	0	1	0	1	2	1	0	1	2	1	1	2	0	2
58	1	1	0	1	0	1	2	1	0	1	2	2	0	2	0

Continued on next page

Table A1 – continued from previous page

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O
59	1	1	2	2	0	0	1	2	1	0	2	1	1	2	1
60	0	2	1	0	2	1	0	1	2	2	0	0	0	1	2
61	2	0	2	2	0	1	0	1	0	2	1	2	2	0	1
62	1	2	0	0	2	0	1	0	1	1	2	0	1	1	0
63	2	0	1	2	1	0	2	0	2	0	1	0	0	2	1
64	0	1	0	1	2	2	0	2	0	1	0	1	2	1	2
65	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
66	2	2	2	0	0	2	2	0	0	2	2	0	0	2	2
67	2	1	1	0	0	0	0	2	2	2	2	1	2	0	0
68	0	0	0	2	2	1	1	1	1	0	0	2	0	2	2
69	2	1	1	2	2	1	1	0	0	0	0	0	2	0	0
70	1	0	0	0	0	0	0	2	2	1	1	2	0	1	1
71	0	0	0	2	2	2	2	0	0	2	2	1	1	1	1
72	1	2	2	1	1	0	0	1	1	1	1	0	2	2	2
73	1	2	2	2	2	2	2	1	1	0	0	1	2	0	0
74	0	0	0	1	1	0	0	2	2	2	2	2	1	2	2
75	0	2	2	1	1	1	1	2	2	1	1	0	0	0	0
76	2	1	1	0	0	2	2	0	0	0	0	2	1	1	1
77	2	0	0	2	2	2	2	1	1	1	1	0	1	2	2
78	1	2	2	1	1	0	0	0	0	2	2	1	2	1	1
79	0	1	1	2	2	1	1	2	2	1	1	2	2	1	1
80	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
81	1	2	1	1	2	0	2	2	0	0	1	2	1	0	2
82	2	1	2	2	1	2	0	0	2	1	0	1	0	2	0
83	0	0	2	0	1	1	2	2	1	2	0	2	1	1	0
84	1	2	0	1	0	2	1	1	2	0	2	0	2	0	1
85	0	0	1	1	2	2	0	0	1	1	2	2	0	0	1
86	1	1	0	2	1	0	2	1	0	2	1	0	2	1	0
87	0	0	2	0	2	0	1	2	0	1	0	0	2	2	1
88	2	2	0	2	0	1	0	0	2	0	1	1	1	1	2
89	0	2	1	2	1	2	0	2	1	2	0	0	1	0	1
90	2	1	2	1	2	0	2	1	2	0	2	2	0	1	0
91	1	2	0	0	1	1	2	0	2	1	0	2	2	0	2
92	2	0	2	1	0	2	1	2	0	0	1	1	1	2	0
93	2	1	0	0	1	2	1	2	1	0	2	0	0	1	2
94	0	0	1	1	0	1	2	1	2	2	0	1	2	2	1
95	1	1	2	0	2	1	0	1	0	1	2	1	1	0	2
96	0	2	1	2	0	0	1	0	1	2	1	2	0	2	0
97	2	2	1	0	2	1	0	2	1	0	2	1	0	2	1
98	1	1	2	2	0	0	1	1	2	2	0	0	1	1	2
99	1	1	0	1	0	1	2	0	1	2	1	1	0	0	2
100	0	0	1	0	1	2	1	1	0	1	2	2	2	2	0
101	2	0	1	2	1	0	2	2	0	1	0	1	0	1	2
102	1	1	0	1	2	2	0	0	2	0	1	0	2	2	1
103	2	0	2	2	0	1	0	0	1	1	2	0	2	1	0
104	0	2	0	0	2	0	1	1	0	2	1	2	1	0	1
105	0	2	0	2	0	1	0	2	0	1	0	0	1	2	1
106	1	0	2	0	2	0	1	0	2	0	1	1	2	1	2
107	0	1	0	2	1	0	2	0	1	1	2	2	2	0	1
108	2	0	1	1	2	2	0	1	0	2	1	0	0	1	0
109	1	0	2	0	1	1	2	1	2	0	2	0	1	0	1
110	2	2	0	1	0	2	1	2	1	2	0	2	2	1	0
111	0	2	1	1	2	0	2	0	2	1	0	1	1	2	0
112	1	1	2	2	1	2	0	2	0	0	1	2	0	0	2
113	1	2	1	2	0	0	1	0	1	2	1	2	0	2	0
114	0	1	2	0	2	1	0	1	0	1	2	1	1	0	2
115	2	0	1	1	0	1	2	1	2	2	0	1	2	2	1
116	0	1	0	0	1	2	1	2	1	0	2	0	0	1	2

Continued on next page

Table A1 – continued from previous page

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O
117	1	0	2	1	0	2	1	2	0	0	1	1	1	2	0
118	2	2	0	0	1	1	2	0	2	1	0	2	2	0	2
119	0	1	2	1	2	0	2	1	2	0	2	2	0	1	0
120	2	2	1	2	1	2	0	2	1	2	0	0	1	0	1
121	0	2	0	2	0	1	0	0	2	0	1	1	1	1	2
122	2	0	2	0	2	0	1	2	0	1	0	0	2	2	1
123	0	1	0	2	1	0	2	1	0	2	1	0	2	1	0
124	1	0	1	1	2	2	0	0	1	1	2	2	0	0	1
125	0	2	0	1	0	2	1	1	2	0	2	0	2	0	1
126	1	0	2	0	1	1	2	2	1	2	0	2	1	1	0
127	1	1	2	2	1	2	0	0	2	1	0	1	0	2	0
128	2	2	1	1	2	0	2	2	0	0	1	2	1	0	2
129	0	2	2	1	1	0	0	1	1	1	1	0	2	2	2
130	1	0	0	2	2	2	2	0	0	2	2	1	1	1	1
131	2	0	0	0	0	0	0	2	2	1	1	2	0	1	1
132	1	1	1	2	2	1	1	0	0	0	0	0	2	0	0
133	2	0	0	2	2	1	1	1	1	0	0	2	0	2	2
134	0	1	1	0	0	0	0	2	2	2	2	1	2	0	0
135	1	2	2	0	0	2	2	0	0	2	2	0	0	2	2
136	2	1	1	1	1	1	1	1	1	1	1	1	1	1	1
137	1	1	1	0	0	0	0	1	1	0	0	2	2	2	2
138	2	0	0	2	2	1	1	2	2	2	2	1	0	0	0
139	2	1	1	1	1	1	1	0	0	2	2	0	1	2	2
140	0	2	2	0	0	2	2	1	1	1	1	1	0	1	1
141	1	1	1	0	0	2	2	2	2	1	1	0	1	0	0
142	0	2	2	1	1	1	1	0	0	0	0	2	0	1	1
143	0	0	0	1	1	0	0	1	1	0	0	1	1	0	0
144	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2

B Python code for data transformation

Listing B1 shows the installation of the Pandas and Numpy packages commonly used to alter two-dimensional data structures, known as dataframe (df); as well as the reading/loading of the df as exported from the LimeSurvey environment.

Listing B1: Reading data

```
#%% —— pip install pandas ——
import pandas as pd
import numpy as np

#%% —— Read data ——
path_to_file = 'C:/XXX/results-survey169147.csv'
df = pd.read_csv(path_to_file, sep=',', dtype=str)
```

Data cleaning on the basis of entry completeness, possession of drivers licence and comments described in chapter 3.6 commences with the code in listing B2. Besides the cleaning, it also describes the addition of the *trustw* variable, which has also been elaborated upon in chapter 3.6.

Listing B2: Data cleaning

```
#%% —— data cleaning ——
#remove incomplete entries'
df['G5Q01'].replace('', np.nan, inplace=True)
df.dropna(subset=['G5Q01'], inplace=True)

#remove entries without driverslicense
df = df.loc[df['G1Q01'] == 'A1']

#remove entries with a traveltime > 120min
df['G2Q03']=df['G2Q03'].astype(int)
df = df.loc[df['G2Q03'] <= 120]

#remove entries based on comments
  #test entries
df = df.loc[df['id'] != '375']
df = df.loc[df['id'] != '379']
df = df.loc[df['id'] != '381']

  #filled out survey twice
df = df.loc[df['id'] != '2064']
df = df.loc[df['id'] != '2135']
df = df.loc[df['id'] != '2155']
df = df.loc[df['id'] != '2221']

  #Misinterpreted added traveltime variable
df = df.loc[df['id'] != '51']
df = df.loc[df['id'] != '485']
df = df.loc[df['id'] != '544']
df = df.loc[df['id'] != '943']
df = df.loc[df['id'] != '1065']
df = df.loc[df['id'] != '1205']
df = df.loc[df['id'] != '1651']
df = df.loc[df['id'] != '2209']
df = df.loc[df['id'] != '2221']
df = df.loc[df['id'] != '2297']

#Provide entries with choice answer values of SUM(A1)=/=0, SUM(A2)=/=0, SUM(A3)<6
    with a 1 'trustw' constant value.
```

```
df['trustw'] = 0
df['A1sum'] = (df.iloc[:,np.r_[23:598:1,609:1185:1]] == 'A1').sum(axis=1)
df['A2sum'] = (df.iloc[:,np.r_[23:598:1,609:1185:1]] == 'A2').sum(axis=1)
df['A3sum'] = (df.iloc[:,np.r_[23:598:1]] == 'A3').sum(axis=1)

df = df.reset_index(drop=True)
for index in range(0, len(df)):
    if df['A1sum'][index] == 0: df['trustw'][index] = 0
    else: df['trustw'][index] = 1
    if df['A2sum'][index] == 0: df['trustw'][index] = 0
    else: df['trustw'][index] = 1
    if df['A3sum'][index] >= 6: df['trustw'][index] = 0
    else: df['trustw'][index] = 1

df = df.drop(['A1sum','A2sum','A3sum'], axis=1)
```

Listing B3 shows the python coding used to re-code the nominal variables in the df into variables with less levels as described in chapter 4

Listing B3: Recoding nominal variables

```
#%% −− Recode nominal variables to lesser levels −−
#recode age to 3 levels
df['G5Q02']=df['G5Q02'].replace(['A1','A5'],['A2','A4'])
df['G5Q02']=df['G5Q02'].replace(['A2','A3','A4','A6'],['A1','A2','A3','A4'])


#recode income to 3 levels
df['G5Q03']=df['G5Q03'].replace(['A1','A2','A4','A7','A8'],['A3','A3','A5','A6','
    A6'])
df['G5Q03']=df['G5Q03'].replace(['A3','A5','A6','A9'],['A1','A2','A3','A4'])


#recode education to 3 levels
df['G5Q04']=df['G5Q04'].replace(['A1','A2'],['A3','A3'])
df['G5Q04']=df['G5Q04'].replace(['A3','A4','A5','A6','A7'],['A1','A2','A3','A4','
    A5'])

#recode country to 2 levels
df['G5Q05']=df['G5Q05'].replace(['A3','A4','A5','A6'],'A2')

#recode city center visits to 3 levels
df['G2Q02']=df['G2Q02'].replace(['A1','A3','A5'],['A2','A4','A6'])
df['G2Q02']=df['G2Q02'].replace(['A2','A4','A6'],['A1','A2','A3'])

#recode ccv fixed to 3 levels
df['G2Q04[1]']=df['G2Q04[1]'].replace(['A1','A2','A4','A6'],['A3','A3','A5','A7'])
df['G2Q04[1]']=df['G2Q04[1]'].replace(['A3','A5','A7'],['A1','A2','A3'])

#recode ccv flexible to 3 levels
df['G2Q04[2]']=df['G2Q04[2]'].replace(['A1','A2','A4','A6'],['A3','A3','A5','A7'])
df['G2Q04[2]']=df['G2Q04[2]'].replace(['A3','A5','A7'],['A1','A2','A3'])

#recode ccv no appointment to 3 levels
df['G2Q04[3]']=df['G2Q04[3]'].replace(['A1','A2','A4','A6'],['A3','A3','A5','A7'])
df['G2Q04[3]']=df['G2Q04[3]'].replace(['A3','A5','A7'],['A1','A2','A3'])

#recode parking habit to 3 levels
df['G2Q05']=df['G2Q05'].replace('A1','A2')
df['G2Q05']=df['G2Q05'].replace(['A2','A3','A4'],['A1','A2','A3'])
```

```
#save updated dataset as df
df.to_csv('C:/XXX/results-survey169147_df.csv', index=False)
print('Cleaning and recoding of data completed. Results saved in df')
```

Listings B4 and B5 describe the data reformatting process required to change the data from a wide to a long format. The first step in doing so is separating respondent specific data (i.e. socio-demographics and behavioral characteristics) from the choice data and storing this into two separate dfs whilst disregarding some of the columns that are irrelevant for the analyses (listing B4). Besides this, both the initial and additional choice tasks questions are renamed to their respective task number. Next, a while loop is used to separate the choice df into 144 temporary dfs; one for every unique choice task (listing B5). In this separation process, the initial and additional choice tasks (now both part of the same temporary set) are checked for repeated samples by counting the occurrence of the unique respondent IDs. If the number of occurrences is larger than 1, that entry is removed from the df. This process is necessary because of the rare occasion in which a single respondent preformed the same choice task twice (once in the choice tasks that were initially presented and again in the additional choice tasks). After this final cleanup, the data is reformatted into the long format. Next, a choice and reference column are added to the temporary dfs, after which a merger between them takes place and the df is saved.

Listing B4: Separating choice and respondent data

```
#%% -- select relevant columns & separate data --
df1 = df.iloc [:,np.r_[0,2,3,5:19:1,598:609:1,1187]] #personal data incl comments
df1.to_csv('C:/XXX/results-survey169147_df1.csv', index=False)
print('Selection of personal data completed. Results saved in df1')

df2 = df.iloc [:,np.r_[0,8,1188,22:598:1,609:1185:1]] #choice data
df2.set_axis(['id', 'travelt', 'trustw', 'eq1', '1', '1.1', '1.2', 'eq2', '2', '
    2.1', '2.2', ..., 'eq144', '144', '144.1', '144.2', 'eq1', '1', '1.1', '1.2',
    'eq2', '2', '2.1', '2.2', ..., 'eq144', '144', '144.1', '144.2'], axis=1,
    inplace=True)
df2.to_csv('C:/XXX/results-survey169147_df2.csv', index=False)
print('Selection of choice data completed. Results saved in df2')
```

Listing B5: Creating choice dataframes

```
#%% -- Preparing choice datatable --
#create while loop
count = 1
count2 = float(1)
while (count <= 144):
#%% -- create temporary dataframes --
    if(count == 1):
        df = pd.concat([df2.iloc [:,np.r_[0,1,2,4:7:1]],df2.iloc[:,np.r_
            [0,1,2,580:583:1]]],axis=0)
        df['1'].replace('', np.nan, inplace=True)
        df.dropna(subset=['1'], inplace=True)
    elif(count == 2):
        df = pd.concat([df2.iloc [:,np.r_[0,1,2,8:11:1]],df2.iloc[:,np.r_
            [0,1,2,584:587:1]]],axis=0)
        df['2'].replace('', np.nan, inplace=True)
        df.dropna(subset=['2'], inplace=True)

    ...

    elif(count == 144):
        df = pd.concat([df2.iloc [:,np.r_[0,1,2,576:579:1]],df2.iloc[:,np.r_
            [0,1,2,1152:1155:1]]],axis=0)
```

```
        df['144'].replace('', np.nan, inplace=True)
        df.dropna(subset=['144'], inplace=True)

#%% −−− remove repeated samples −−−
    df['rep'] = df.groupby('id').cumcount().add(1)
    df = df.loc[df['rep'] != 2]
    df = df.drop(['rep'], axis=1)

#%% −−− restructure to long format −−−
    df = df.set_index(['id','travelt','trustw']).stack().rename_axis(index={None:'
        setnr'}).rename('chosen_alt').reset_index()

#%% −−− add multiple entries −−−
    df['setnr'] = df['setnr'].astype(float)

    def numalt(row):
        if row['setnr'] == count2:
            return 3
        else:
            return 2
    df['numalt'] = df.apply(lambda row: numalt(row), axis=1)
    count2 = count2 + 1

    #create lists of column contents
    id_list = df['id'].tolist()
    id_s = pd.Series(id_list)
    travelt_list = df['travelt'].tolist()
    travelt_s = pd.Series(travelt_list)
    trustw_list = df['trustw'].tolist()
    trustw_s = pd.Series(trustw_list)
    setnr_list = df['setnr'].tolist()
    setnr_s = pd.Series(setnr_list)
    numalt_list = df['numalt'].tolist()
    numalt_s = pd.Series(numalt_list)
    chosen_alt_list = df['chosen_alt'].tolist()
    chosen_alt_s = pd.Series(chosen_alt_list)

    #restructure df with multiple entries
    df = pd.DataFrame({
        'id':id_s,
        'travelt': travelt_s,
        'trustw': trustw_s,
        'setnr': setnr_s,
        'numalt': numalt_s,
        'chosen_alt': chosen_alt_s
        })

    df = pd.DataFrame([
        row
        for row in df.to_dict(orient='records')
        for _ in range(row['numalt'])
        ])

#%% −−− add choice column
    df['calt'] = df.groupby(['id','setnr']).cumcount().add(1)
    df = df.astype(str)

    df['chosen_alt'] = df['chosen_alt'].replace(['A1'],'1')
    df['chosen_alt'] = df['chosen_alt'].replace(['A2'],'2')
    df['chosen_alt'] = df['chosen_alt'].replace(['A3'],'3')
    df['choice'] = np.where(df['chosen_alt'] == df['calt'], '1', '0')
```

```
    df = df.drop(['chosen_alt','calt'],axis=1)

#%% —— add reference column for merge with choicesets
    df = df.astype(str)
    df ['ref'] = df.groupby('id').cumcount().add(1).astype(str)

#%% —— end loop ——
    if(count==1):
        df3 = df
    else: df3 = pd.concat([df3,df], axis=0)
    count = count + 1

df3['id']=df3['id'].astype(int)
df3['setnr']=df3['setnr'].astype(float)
df3 = df3.sort_values(['id','setnr'], ascending=True)

df3.to_csv('C:/XXX/results-survey169147_df3.csv', index=False)
print('Restructuring of data completed. Results saved in df3')
```

At this stage, the df only contains information on what choices have been made out of the alternatives, but no information yet about what the alternatives entail. Therefore, listing B5 describes the merger between the choice glsdf and a glsdf containing information on the choice alternatives made in MS Excel. This merger is possible because the choice tasks in both of the glsdfs have a set number, and all alternatives have a reference. Because LimeSurvey did not output the internal computations on the added travel time, this had to be done once more after the merger.

Listing B6: Add alternative data to choice dataframe

```
    #%% —— merge with choicesets ready for analysis ——
#load mergefile
path_to_file = 'C:/Users/s160511/OneDrive - TU Eindhoven/Documents/Afstuderen/
    Responsen/choicesets_MNL.csv'
mergefile = pd.read_csv(path_to_file, sep=',', dtype=str)
mergefile['setnr'] = mergefile['setnr'].astype(float).astype(str)
#merge
df = df3.astype(str)
df = pd.merge(df, mergefile, how='left', on=['setnr', 'ref'])

#remove reference column
df = df.drop(['ref'], axis=1)

#compute xtravelt
df['travelt']=df['travelt'].astype(int)
df['xtt']=df['xtt'].astype(float)
df['xtravelt_comp']= (df.travelt * df.xtt).round().astype(int)

conditions = [
    (df['xtravelt_comp'] > 5),
    (df['xtravelt_comp'] >= -5) & (df['xtravelt_comp'] <= 5),
    (df['xtravelt_comp'] < -5)
    ]

values = [5, df['xtravelt_comp'], -5]

df['xttc'] = np.select(conditions,values)

#include interactions
df['a1_xttc'] = df['a1'].astype(int) * df['xttc'].astype(int)
df['a2_xttc'] = df['a2'].astype(int) * df['xttc'].astype(int)
df['d_xttc'] = df['d'].astype(int) * df['xttc'].astype(int)
```

```
#remove unneccessary xtravelt columns
df = df.drop(['travelt','xtt','xtravelt_comp'], axis=1)

df5 = df
df5.to_csv('C:/XXX/results-survey169147_df5.csv', index=False)
print('Merge with alternative df completed. Results saved in df5')
```

In listing B7 columns describing the case number of a choice task, numeric labeling of each choice alternative within a choice task, the total number of entries for each respondent, and a constant to determine the Log Likelihood function of the null model (LL0) have been added to the df. This process has been repeated 3 more times for data structures B, C, and D. To finalize the data transformation, all nominal variables have been effect coded using the code in listing B8 and the df containing respondent specific data is merged with the choice df on the basis of respondent ID using listing B9.

Listing B7: Create 4 data structures

```
#create dataset type Full normal:
#add case, count, nument and LL0 columns
path_to_file = 'C:/XXX/results-survey169147_df5.csv'
df = pd.read_csv(path_to_file, sep=',', dtype=str)

df['case'] = 1
count = 1
for index in range(1, len(df)):
    if df['setnr'][index] == df['setnr'][index - 1]:
        df['case'][index] = count
    else:
        count = count + 1
        df['case'][index] = count

df ['count'] = df.groupby('case').cumcount().add(1).astype(str)
df['nument'] = (df.groupby(['id'])['case'].transform('nunique'))
df ['LL0'] = 0

#adjust column order
df=df.iloc[:,np.r_[0,1,36,34,2,3,35,37,4,5:15:1,33,15:33:1]]

df5A=df
df5A.to_csv('C:/XXX/results-survey169147_df5A.csv', index=False)
print('Restructing of data completed. Results saved in df5A')

# -- create dataset type 3lvl task:
path_to_file = 'C:/XXX/results-survey169147_df5.csv'
df = pd.read_csv(path_to_file, sep=',', dtype=str)
df['numalt'] = df['numalt'].astype(int)

df = df.loc[df['numalt'] == 3]
df.reset_index(drop=True, inplace=True)

#add case, count, nument and LL0 columns
df['case'] = 1
count = 1
for index in range(1, len(df)):
    if df['setnr'][index] == df['setnr'][index - 1]:
        df['case'][index] = count
    else:
        count = count + 1
        df['case'][index] = count
```

```
df ['count'] = df.groupby('case').cumcount().add(1).astype(str)
df['nument'] = (df.groupby(['id'])['case'].transform('nunique'))
df ['LL0'] = 0

#adjust column order and remove irrelevent columns
df=df.iloc[:,np.r_[0,1,36,34,2,3,35,37,4,5,7:20:1,21:26:1,27:32:1]]

df5B=df
df5B.to_csv('C:/XXX/results-survey169147_df5B.csv', index=False)
print('Restructing of data completed. Results saved in df5B')

# --- create dataset type 2lvl task:
path_to_file = 'C:/XXX/results-survey169147_df5.csv'
df = pd.read_csv(path_to_file, sep=',', dtype=str)
df['numalt'] = df['numalt'].astype(int)

df = df.loc[df['numalt'] == 2]
df.reset_index(drop=True, inplace=True)

#add case, count, nument and LL0 columns
df['case'] = 1
count = 1
for index in range(1, len(df)):
    if df['setnr'][index] == df['setnr'][index - 1]:
        df['case'][index] = count
    else:
        count = count + 1
        df['case'][index] = count

df ['count'] = df.groupby('case').cumcount().add(1).astype(str)
df['nument'] = (df.groupby(['id'])['case'].transform('nunique'))
df ['LL0'] = 0

#adjust column order and remove irrelevent columns
df=df.iloc[:,np.r_[0,1,36,34,2,3,35,37,4,6:15:1,33,15:33:1]]

df5C=df
df5C.to_csv('C:/XXX/results-survey169147_df5C.csv', index=False)
print('Restructing of data completed. Results saved in df5C')

# --- create dataset type all as separate parameters
df=df5A.iloc[:,np.r_[0:10:1,11:19:1,20:25:1,26:31:1,32:37:1]]
df.loc[df['numalt'] == '2', ['a1','a2','d','t1','t2','f','st','et','a1_t1','a1_t2'
    ,'a1_f','a1_st','a1_et','a2_t1','a2_t2','a2_f','a2_st','a2_et','d_t1','d_t2','
    d_f','d_st','d_et']] = 0
df.rename(columns={'a1':'a1A','a2':'a2A','d':'dA','t1':'t1A','t2':'t2A','f':'fA','
    st':'stA','et':'etA','a1_t1':'a1_t1A','a1_t2':'a1_t2A','a1_f':'a1_fA','a1_st':
    'a1_stA','a1_et':'a1_etA','a2_t1':'a2_t1A','a2_t2':'a2_t2A','a2_f':'a2_fA','
    a2_st':'a2_stA','a2_et':'a2_etA','d_t1':'d_t1A','d_t2':'d_t2A','d_f':'d_fA','
    d_st':'d_stA','d_et':'d_etA'}, inplace = True)
dfA = df

df = df5C.iloc[:,np.r_[0,4,6,9:37:1]]
df.rename(columns={'a1':'a1B','a2':'a2B','d':'dB','t1':'t1B','t2':'t2B','f':'fB','
    st':'stB','et':'etB','a1_t1':'a1_t1B','a1_t2':'a1_t2B','a1_f':'a1_fB','a1_st':
    'a1_stB','a1_et':'a1_etB','a2_t1':'a2_t1B','a2_t2':'a2_t2B','a2_f':'a2_fB','
    a2_st':'a2_stB','a2_et':'a2_etB','d_t1':'d_t1B','d_t2':'d_t2B','d_f':'d_fB','
    d_st':'d_stB','d_et':'d_etB'}, inplace = True)
dfB = df

df = pd.merge(dfA, dfB, how='left', on=['id','setnr','count'])
df.fillna(0, inplace=True)
```

```
df5D=df

df5D.to_csv('C:/XXX/results-survey169147_df5D.csv', index=False)
print('Restructing of data completed. Results saved in df5D')
```

Listing B8: Effect-code nominal variables

```
#%% --- Prep and Effectcode socio-demographic data (df1_2) ---
path_to_file = 'C:/XXX/results-survey169147_df1_1.csv'
df1_1 = pd.read_csv(path_to_file, sep=',', dtype=str)

# select Socio-demographic data (without pc)
df1_2 = df1_1.iloc [:,np.r_[0,1,14:19:1]]
df1_2.to_csv('C:/XXX/results-survey169147_df1_2.csv', index=False)
print('Selection of socio-demographic data completed. Results saved in df1_2')

df=df1_2

#drivers license
df['d_d']=df['d_d'].replace('A1',-1)

#gender
df['d_g']=df['d_g'].replace(['A1','A2','A3','A4'],[-1,1,0,0])

#age
df['d_a1'] = 0
df['d_a2'] = 0

for index in range(0, len(df)):
    if df['d_a'][index] == 'A1':
        df['d_a1'][index] = -1
        df['d_a2'][index] = -1
    elif df['d_a'][index] == 'A2':
        df['d_a1'][index] = 1
        df['d_a2'][index] = 0
    elif df['d_a'][index] == 'A3':
        df['d_a1'][index] = 0
        df['d_a2'][index] = 1
    else:
        df['d_a1'][index] = 0
        df['d_a2'][index] = 0

#income
df['d_i1'] = 0
df['d_i2'] = 0

for index in range(0, len(df)):
    if df['d_i'][index] == 'A1':
        df['d_i1'][index] = -1
        df['d_i2'][index] = -1
    elif df['d_i'][index] == 'A2':
        df['d_i1'][index] = 1
        df['d_i2'][index] = 0
    elif df['d_i'][index] == 'A3':
        df['d_i1'][index] = 0
        df['d_i2'][index] = 1
    else:
        df['d_i1'][index] = 0
        df['d_i2'][index] = 0

#education
df['d_e1'] = 0
```

```
df['d_e2'] = 0

for index in range(0, len(df)):
    if df['d_e'][index] == 'A1':
        df['d_e1'][index] = -1
        df['d_e2'][index] = -1
    elif df['d_e'][index] == 'A2':
        df['d_e1'][index] = 1
        df['d_e2'][index] = 0
    elif df['d_e'][index] == 'A3':
        df['d_e1'][index] = 0
        df['d_e2'][index] = 1
    else:
        df['d_e1'][index] = 0
        df['d_e2'][index] = 0

#country
df['d_c']=df['d_c'].replace(['A1','A2','A7'],[-1,1,0])
df = df.drop(['d_a','d_i','d_e'], axis=1)

df1_2ec = df

#%% --- Perp and Effectcode behavioral data (df1_3) ---
# Select behavioral data
df1_3 = df1_1.iloc [:,np.r_[0,2:14:1]]
df1_3.to_csv('C:/XXX/results-survey169147_df1_3.csv', index=False)
print('Selection of behavioral data completed. Results saved in df1_3')

df=df1_3

#cc visit
df['b_v1'] = 0
df['b_v2'] = 0

for index in range(0, len(df)):
    if df['b_v'][index] == 'A1':
        df['b_v1'][index] = -1
        df['b_v2'][index] = -1
    elif df['b_v'][index] == 'A2':
        df['b_v1'][index] = 1
        df['b_v2'][index] = 0
    else:
        df['b_v1'][index] = 0
        df['b_v2'][index] = 1

#cc visit fixed appointment
df['b_vfi1'] = 0
df['b_vfi2'] = 0

for index in range(0, len(df)):
    if df['b_vfi'][index] == 'A1':
        df['b_vfi1'][index] = -1
        df['b_vfi2'][index] = -1
    elif df['b_vfi'][index] == 'A2':
        df['b_vfi1'][index] = 1
        df['b_vfi2'][index] = 0
    else:
        df['b_vfi1'][index] = 0
        df['b_vfi2'][index] = 1

#cc visit flex appointment
df['b_vfl1'] = 0
```

```
df['b_vfl2'] = 0

for index in range(0, len(df)):
    if df['b_vfl'][index] == 'A1':
        df['b_vfl1'][index] = -1
        df['b_vfl2'][index] = -1
    elif df['b_vfl'][index] == 'A2':
        df['b_vfl1'][index] = 1
        df['b_vfl2'][index] = 0
    else:
        df['b_vfl1'][index] = 0
        df['b_vfl2'][index] = 1

#cc visit no appointment
df['b_vno1'] = 0
df['b_vno2'] = 0

for index in range(0, len(df)):
    if df['b_vno'][index] == 'A1':
        df['b_vno1'][index] = -1
        df['b_vno2'][index] = -1
    elif df['b_vno'][index] == 'A2':
        df['b_vno1'][index] = 1
        df['b_vno2'][index] = 0
    else:
        df['b_vno1'][index] = 0
        df['b_vno2'][index] = 1

#park at same facility
df['b_sp1'] = 0
df['b_sp2'] = 0

for index in range(0, len(df)):
    if df['b_sp'][index] == 'A1':
        df['b_sp1'][index] = -1
        df['b_sp2'][index] = -1
    elif df['b_sp'][index] == 'A2':
        df['b_sp1'][index] = 1
        df['b_sp2'][index] = 0
    else:
        df['b_sp1'][index] = 0
        df['b_sp2'][index] = 1

df = df.drop(['b_vfi','b_vfl','b_vno','b_sp'], axis=1)
df['b_v']=df['b_v'].replace(['A1','A2','A3'],[0,1,2])
df1_3ec = df

#%% Prep extra choice tasks (df1_4)
df1_4 = df1_1.iloc [:,np.r_[0,24]]
```

Listing B9: Merge dataframes into single dataframe

```
#%% -- Merge socio-demographic, behavioral data and extra choicetasks with
    Choicedata
#merge df5 with df1_2ec
df1_2ec['id'] = df1_2ec['id'].astype(str)
df1_3ec['id'] = df1_3ec['id'].astype(str)
df1_4['id'] = df1_4['id'].astype(str)

dftemp = pd.merge(df1_2ec,df1_3ec,how='left', on=['id'])
df = dftemp
dftemp = pd.merge(df,df1_4,how='left', on=['id'])
```

```
df = df5A.astype(str)
df6A = pd.merge(df, dftemp, how='left', on=['id'])
df6A.to_csv('C:/XXX/results-survey169147_df6A.csv', index=False)
print('Data merger completed. Results saved in df6A')

df = df5B.astype(str)
df6B = pd.merge(df, dftemp, how='left', on=['id'])
df6B.to_csv('C:/XXX/results-survey169147_df6B.csv', index=False)
print('Data merger completed. Results saved in df6B')

df = df5C.astype(str)
df6C = pd.merge(df, dftemp, how='left', on=['id'])
df6C.to_csv('C:/XXX/results-survey169147_df6C.csv', index=False)
print('Data merger completed. Results saved in df6C')

df = df5D.astype(str)
df6D = pd.merge(df, dftemp, how='left', on=['id'])
df6D.to_csv('C:/XXX/results-survey169147_df6D.csv', index=False)
print('Data merger completed. Results saved in df6D')
```

Listing B10: Filter respondents that did not want to provide personal information from set label

```
#filter out respondentents that didnt want to provide personal info.
df7 = pd.merge(df6D, dfsd, how='left', on=['id'])
df7 = df7.loc[df7['G5Q01'] != 'A4']
df7 = df7.loc[df7['G5Q02'] != 'A6']
df7 = df7.loc[df7['G5Q04'] != 'A6']
df7 = df7.loc[df7['G5Q05'] != 'A7']

df7 = df7.drop(['G5Q01','G5Q02','G5Q03','G5Q04','G5Q05'], axis=1)

df7.to_csv('C:/Users/s160511/OneDrive - TU Eindhoven/Documents/Afstuderen/
    Responsen/results-survey169147_df7.csv', index=False)
print('Data merger completed. Results saved in df7')

dfsocdemlc =pd.merge(df7, df1, how='left', on=['id'])
dfsocdemlc = dfsocdemlc.loc[dfsocdemlc['trustw'] == '1']
dfsocdemlc.to_csv('C:/Users/s160511/OneDrive - TU Eindhoven/Documents/Afstuderen/
    Responsen/results-survey169147_df_socdemlc.csv', index=False)
```

C Estimations multinominal logit models

Listing C1: MNL model estimation Data structure A; Full sample

```
|-> Reset $
|-> Read; File=XXX\results-survey169147 df6A.csv$
Last observation read from data file was   76808
|-> Nlogit
    ; lhs = choice, numalt, count
    ; rhs = con1, con2, t1, t2, f, st, et, xttc, a1_con1, a1_con2, a1_t1, a1_t2, a1_f, a1_st,
         a1_et, a1_xttc, a2_con1, a2_con2, a2_t1, a2_t2, a2_f, a2_st, a2_et, a2_xttc, d_con1,
         d_con2, d_t1, d_t2, d_f, d_st, d_et, d_xttc
    ; Choices = 1,2,3
    ; shares
    ; CheckData
    $
+-------------------------------------------------------+
| Inspecting the data set before estimation.            |
| These errors mark observations which will be skipped. |
| Row Individual = 1st row then group number of data block |
+-------------------------------------------------------+
No bad observations were found in the sample

Iterative procedure has converged
Normal exit:   6 iterations. Status=0, F=    .1846486D+05

-----------------------------------------------------------------------------
Discrete choice (multinomial logit) model
Dependent variable                Choice
Log likelihood function     -18464.85989
Estimation based on N =  30459, K =  32
Inf.Cr.AIC  =  36993.7 AIC/N =    1.215
---------------------------------------
            Log likelihood R-sqrd R2Adj
ASCs  only  model must be fit separately
            Use NLOGIT ;...;RHS=ONE$
Note: R-sqrd = 1 - logL/Logl(constants)
Warning:  Model does not contain a full
set of ASCs. R-sqrd is problematic. Use
model setup with ;RHS=one to get LogL0.
---------------------------------------
Response data are given as proportions.
Number of obs.= 30459, skipped    0 obs
--------+--------------------------------------------------------------------
        |                  Standard            Prob.       95% Confidence
  CHOICE|  Coefficient       Error       z     |z|>Z*         Interval
--------+--------------------------------------------------------------------
    CON1|   -6.91126***      .12657   -54.60  .0000    -7.15933   -6.66319
    CON2|    -.66923***      .03160   -21.18  .0000     -.73118    -.60729
      T1|     .04349*        .02348     1.85  .0639     -.00252     .08951
      T2|     .22173***      .02242     9.89  .0000      .17780     .26567
       F|    -.91776***      .02300   -39.90  .0000     -.96284    -.87268
      ST|    -.14995***      .01128   -13.30  .0000     -.17205    -.12785
      ET|    -.19703***      .00786   -25.06  .0000     -.21244    -.18163
    XTTC|    -.09922***      .01250    -7.94  .0000     -.12372    -.07473
 A1_CON1|     .08733         .09796      .89  .3726     -.10466     .27932
 A1_CON2|    -.03378         .02734    -1.24  .2167     -.08737     .01981
   A1_T1|     .04542**       .02045     2.22  .0263      .00534     .08549
   A1_T2|    -.00646         .02067     -.31  .7547     -.04698     .03406
    A1_F|     .05561**       .02456     2.26  .0236      .00747     .10376
   A1_ST|    -.02228*        .01222    -1.82  .0683     -.04624     .00167
   A1_ET|     .00439         .00843      .52  .6025     -.01213     .02091
 A1_XTTC|    -.00185         .01084     -.17  .8644     -.02309     .01939
 A2_CON1|     .10799         .09593     1.13  .2603     -.08002     .29600
 A2_CON2|     .01071         .02714      .39  .6932     -.04249     .06391
   A2_T1|     .01592         .01976      .81  .4203     -.02280     .05464
   A2_T2|     .03516*        .02040     1.72  .0847     -.00481     .07514
    A2_F|     .18690***      .04230     4.42  .0000      .10399     .26982
   A2_ST|    -.07946***      .02165    -3.67  .0002     -.12189    -.03703
   A2_ET|    -.06035***      .01489    -4.05  .0001     -.08953    -.03117
 A2_XTTC|     .00844         .01070      .79  .4302     -.01253     .02941
  D_CON1|     .12015***      .01782     6.74  .0000      .08523     .15506
```

```
   D_CON2|      .03342***        .00480      6.97   .0000        .02402     .04282
     D_T1|      .00141           .00346       .41   .6839      -.00537     .00819
     D_T2|     -.02306***        .00359     -6.43   .0000      -.03009    -.01602
      D_F|      .02191***        .00244      8.97   .0000        .01712     .02670
     D_ST|     -.00058           .00132      -.44   .6586      -.00318     .00201
     D_ET|      .00528***        .00090      5.87   .0000        .00352     .00704
   D_XTTC|     -.00426**         .00192     -2.22   .0266      -.00804    -.00049
---------+--------------------------------------------------------------------------
***, **, * ==>  Significance at 1%, 5%, 10% level.
Model was estimated on Mar 21, 2023 at 09:01:47 AM
------------------------------------------------------------------------------------
```

Listing C2: MNL model estimation Data structure A; Filter non-choice resp. (Table 12)

```
|-> Reset $
|-> Read; File=XXX\results-survey169147 df6A.csv$
Last observation read from data file was   76808
|-> Reject; trustw = 0 $
|-> Nlogit
    ; lhs = choice, numalt, count
    ; rhs = con1, con2, t1, t2, f, st, et, xttc, a1_con1, a1_con2, a1_t1, a1_t2, a1_f, a1_st,
          a1_et, a1_xttc, a2_con1, a2_con2, a2_t1, a2_t2, a2_f, a2_st, a2_et, a2_xttc, d_con1,
          d_con2, d_t1, d_t2, d_f, d_st, d_et, d_xttc
    ; Choices = 1,2,3
    ; shares
    ; CheckData
    $
+--------------------------------------------------------+
| Inspecting the data set before estimation.             |
| These errors mark observations which will be skipped.  |
| Row Individual = 1st row then group number of data block |
+--------------------------------------------------------+
No bad observations were found in the sample

Iterative procedure has converged
Normal exit:   7 iterations. Status=0, F=    .1701961D+05

------------------------------------------------------------------------------------
Discrete choice (multinomial logit) model
Dependent variable               Choice
Log likelihood function     -17019.61363
Estimation based on N =   30009, K =  32
Inf.Cr.AIC  =  34103.2 AIC/N =    1.136
----------------------------------------
            Log likelihood R-sqrd R2Adj
ASCs  only  model must be fit separately
               Use NLOGIT ;...;RHS=ONE$
Note: R-sqrd = 1 - logL/Logl(constants)
Warning:  Model does not contain a full
set of ASCs. R-sqrd is problematic. Use
model setup with ;RHS=one to get LogL0.
----------------------------------------
Response data are given as proportions.
Number of obs.= 30009, skipped    0 obs
---------+--------------------------------------------------------------------------
         |                  Standard             Prob.        95% Confidence
   CHOICE|  Coefficient       Error        z    |z|>Z*           Interval
---------+--------------------------------------------------------------------------
     CON1|    -7.87751***      .14177    -55.57   .0000      -8.15537   -7.59965
     CON2|     -.69171***      .03220    -21.48   .0000       -.75483    -.62860
       T1|      .04516*        .02427      1.86   .0628       -.00241     .09273
       T2|      .21970***      .02300      9.55   .0000        .17463     .26478
        F|    -1.01335***      .02503    -40.48   .0000      -1.06241    -.96429
       ST|     -.16551***      .01183    -13.99   .0000       -.18870    -.14232
       ET|     -.21390***      .00832    -25.71   .0000       -.23021    -.19760
     XTTC|     -.09844***      .01271     -7.74   .0000       -.12335    -.07353
  A1_CON1|     -.04045         .11112      -.36   .7158       -.25824     .17734
  A1_CON2|     -.03238         .02779     -1.17   .2440       -.08684     .02209
    A1_T1|      .05381**       .02113      2.55   .0109        .01240     .09523
    A1_T2|     -.01694         .02129      -.80   .4262       -.05868     .02479
     A1_F|      .06130**       .02676      2.29   .0220        .00884     .11375
    A1_ST|     -.02856**       .01272     -2.25   .0247       -.05348    -.00364
```

```
   A1_ET|      .00213            .00891        .24   .8114      -.01534    .01960
 A1_XTTC|     -.00283            .01104       -.26   .7980      -.02446    .01881
 A2_CON1|      .11854            .10751       1.10   .2702      -.09216    .32925
 A2_CON2|      .00552            .02755        .20   .8413      -.04848    .05951
   A2_T1|      .00757            .02037        .37   .7103      -.03235    .04748
   A2_T2|      .04863**          .02100       2.32   .0206       .00748    .08979
    A2_F|      .23276***         .04576       5.09   .0000       .14307    .32246
   A2_ST|     -.09110***         .02253      -4.04   .0001      -.13525   -.04695
   A2_ET|     -.06300***         .01569      -4.02   .0001      -.09374   -.03225
 A2_XTTC|      .00848            .01088        .78   .4356      -.01284    .02981
  D_CON1|      .14360***         .01989       7.22   .0000       .10461    .18259
  D_CON2|      .03512***         .00488       7.20   .0000       .02556    .04467
    D_T1|      .00197            .00357        .55   .5805      -.00502    .00897
    D_T2|     -.02234***         .00370      -6.04   .0000      -.02959   -.01509
     D_F|      .02534***         .00263       9.65   .0000       .02019    .03048
    D_ST|      .00050            .00138        .36   .7191      -.00222    .00321
    D_ET|      .00570***         .00095       5.97   .0000       .00383    .00757
  D_XTTC|     -.00512***         .00196      -2.61   .0090      -.00895   -.00128
--------+--------------------------------------------------------------------
***, **, * ==>  Significance at 1%, 5%, 10% level.
Model was estimated on Mar 21, 2023 at 09:01:52 AM
-----------------------------------------------------------------------------
```

Listing C3: MNL model estimation Data structure A; Filter non-visiting resp.

```
|-> Reset $
|-> Read; File=XXX\results-survey169147 df6A.csv$
Last observation read from data file was   76808
|-> Reject; b_v = 0 $
|-> Nlogit
    ; lhs = choice, numalt, count
    ; rhs = con1, con2, t1, t2, f, st, et, xttc, a1_con1, a1_con2, a1_t1, a1_t2, a1_f, a1_st,
         a1_et, a1_xttc, a2_con1, a2_con2, a2_t1, a2_t2, a2_f, a2_st, a2_et, a2_xttc, d_con1,
         d_con2, d_t1, d_t2, d_f, d_st, d_et, d_xttc
    ; Choices = 1,2,3
    ; shares
    ; CheckData
    $
+-------------------------------------------------------+
| Inspecting the data set before estimation.            |
| These errors mark observations which will be skipped. |
| Row Individual = 1st row then group number of data block |
+-------------------------------------------------------+
No bad observations were found in the sample

Iterative procedure has converged
Normal exit:   7 iterations. Status=0, F=    .1479989D+05

-----------------------------------------------------------------------------
Discrete choice (multinomial logit) model
Dependent variable               Choice
Log likelihood function     -14799.89217
Estimation based on N =   25248, K =  32
Inf.Cr.AIC  =   29663.8 AIC/N =    1.175
---------------------------------------
            Log likelihood R-sqrd R2Adj
ASCs  only  model must be fit separately
            Use NLOGIT ;...;RHS=ONE$
Note: R-sqrd = 1 - logL/Logl(constants)
Warning:  Model does not contain a full
set of ASCs. R-sqrd is problematic. Use
model setup with ;RHS=one to get LogL0.
---------------------------------------
Response data are given as proportions.
Number of obs.= 25248, skipped   0 obs
--------+--------------------------------------------------------------------
        |                  Standard            Prob.      95% Confidence
  CHOICE|  Coefficient       Error       z    |z|>Z*         Interval
--------+--------------------------------------------------------------------
    CON1|    -7.47001***     .14779   -50.54   .0000     -7.75968   -7.18034
    CON2|     -.67120***     .03509   -19.13   .0000      -.73997    -.60243
      T1|      .00923        .02641      .35   .7267      -.04253     .06099
```

```
       T2|      .26360***       .02495     10.57  .0000        .21470      .31250
        F|     -.96361***       .02626    -36.69  .0000      -1.01508     -.91214
       ST|     -.16016***       .01266    -12.65  .0000       -.18497     -.13534
       ET|     -.21211***       .00891    -23.81  .0000       -.22958     -.19465
     XTTC|     -.09790***       .01347     -7.27  .0000       -.12430     -.07150
  A1_CON1|      .12874          .11326      1.14  .2557       -.09324      .35072
  A1_CON2|     -.03729          .03021     -1.23  .2170       -.09650      .02191
    A1_T1|      .05394**        .02274      2.37  .0177        .00937      .09851
    A1_T2|      .00264          .02294       .11  .9085       -.04232      .04759
     A1_F|      .06549**        .02780      2.36  .0185        .01100      .11999
    A1_ST|     -.01983          .01364     -1.45  .1460       -.04656      .00691
    A1_ET|      .00406          .00951       .43  .6694       -.01457      .02269
  A1_XTTC|     -.00283          .01162      -.24  .8074       -.02560      .01994
  A2_CON1|      .10678          .11090       .96  .3356       -.11057      .32414
  A2_CON2|      .00831          .02990       .28  .7810       -.05029      .06691
    A2_T1|      .01661          .02195       .76  .4492       -.02642      .05964
    A2_T2|      .03335          .02262      1.47  .1404       -.01098      .07768
     A2_F|      .22030***       .04784      4.60  .0000        .12654      .31407
    A2_ST|     -.08591***       .02421     -3.55  .0004       -.13336     -.03845
    A2_ET|     -.06716***       .01681     -3.99  .0001       -.10011     -.03421
  A2_XTTC|      .01395          .01146      1.22  .2233       -.00850      .03641
   D_CON1|      .14450***       .02067      6.99  .0000        .10400      .18500
   D_CON2|      .03498***       .00530      6.60  .0000        .02459      .04537
     D_T1|      .00480          .00386      1.24  .2142       -.00277      .01236
     D_T2|     -.02807***       .00399     -7.04  .0000       -.03589     -.02025
      D_F|      .02393***       .00277      8.63  .0000        .01849      .02936
     D_ST|      .00025          .00148       .17  .8656       -.00266      .00316
     D_ET|      .00587***       .00102      5.75  .0000        .00387      .00788
   D_XTTC|     -.00488**        .00207     -2.36  .0184       -.00893     -.00082
---------+----------------------------------------------------------------------
***, **, * ==>  Significance at 1%, 5%, 10% level.
Model was estimated on Mar 21, 2023 at 09:01:56 AM
--------------------------------------------------------------------------------
```

Listing C4: MNL model estimation Data structure A; Filter non-visit & non-choice resp.

```
|-> Reset $
|-> Read; File=XXX\results-survey169147 df6A.csv$
Last observation read from data file was   76808
|-> Reject ; b_v = 0$
|-> Reject ; trustw = 0$
|-> Nlogit
    ; lhs = choice, numalt, count
    ; rhs = con1, con2, t1, t2, f, st, et, xttc, a1_con1, a1_con2, a1_t1, a1_t2, a1_f, a1_st,
          a1_et, a1_xttc, a2_con1, a2_con2, a2_t1, a2_t2, a2_f, a2_st, a2_et, a2_xttc, d_con1,
          d_con2, d_t1, d_t2, d_f, d_st, d_et, d_xttc
    ; Choices = 1,2,3
    ; shares
    ; CheckData
    $
+------------------------------------------------------+
| Inspecting the data set before estimation.           |
| These errors mark observations which will be skipped.|
| Row Individual = 1st row then group number of data block |
+------------------------------------------------------+
No bad observations were found in the sample

Iterative procedure has converged
Normal exit:   7 iterations. Status=0, F=    .1391040D+05

--------------------------------------------------------------------------------
Discrete choice (multinomial logit) model
Dependent variable               Choice
Log likelihood function     -13910.39655
Estimation based on N =  24985, K =  32
Inf.Cr.AIC  =  27884.8 AIC/N =    1.116
----------------------------------------
              Log likelihood R-sqrd R2Adj
ASCs  only  model must be fit separately
              Use NLOGIT ;...;RHS=ONE$
Note: R-sqrd = 1 - logL/Logl(constants)
Warning:  Model does not contain a full
```

```
set of ASCs. R-sqrd is problematic. Use
model setup with ;RHS=one to get LogL0.
-----------------------------------------
Response data are given as proportions.
Number of obs.= 24985, skipped    0 obs
--------+--------------------------------------------------------------------
        |                  Standard            Prob.       95% Confidence
  CHOICE|  Coefficient       Error       z    |z|>Z*          Interval
--------+--------------------------------------------------------------------
    CON1|  -8.27256***      .16172   -51.15  .0000    -8.58952   -7.95561
    CON2|   -.68999***      .03564   -19.36  .0000     -.75984    -.62013
      T1|    .00834         .02710      .31  .7582     -.04478     .06146
      T2|    .26358***      .02546    10.35  .0000      .21368     .31347
       F|  -1.04173***      .02805   -37.13  .0000    -1.09672    -.98675
      ST|   -.17450***      .01315   -13.27  .0000     -.20026    -.14873
      ET|   -.22757***      .00931   -24.43  .0000     -.24582    -.20931
    XTTC|   -.09777***      .01366    -7.16  .0000     -.12454    -.07099
 A1_CON1|    .04387         .12471      .35  .7250     -.20056     .28830
 A1_CON2|   -.03622         .03059    -1.18  .2364     -.09618     .02373
   A1_T1|    .06125***      .02330     2.63  .0086      .01558     .10692
   A1_T2|   -.00892         .02344     -.38  .7037     -.05486     .03703
    A1_F|    .07124**       .02970     2.40  .0165      .01302     .12945
   A1_ST|   -.02362*        .01405    -1.68  .0926     -.05115     .00391
   A1_ET|    .00328         .00991      .33  .7409     -.01615     .02271
 A1_XTTC|   -.00308         .01178     -.26  .7935     -.02618     .02001
 A2_CON1|    .10446         .12128      .86  .3891     -.13324     .34216
 A2_CON2|    .00350         .03026      .12  .9080     -.05581     .06281
   A2_T1|    .00934         .02247      .42  .6775     -.03469     .05337
   A2_T2|    .04379*        .02314     1.89  .0584     -.00156     .08913
    A2_F|    .25817***      .05087     5.08  .0000      .15846     .35787
   A2_ST|   -.09276***      .02495    -3.72  .0002     -.14165    -.04387
   A2_ET|   -.06833***      .01751    -3.90  .0001     -.10264    -.03402
 A2_XTTC|    .01359         .01161     1.17  .2420     -.00917     .03635
  D_CON1|    .16942***      .02251     7.53  .0000      .12529     .21355
  D_CON2|    .03640***      .00537     6.78  .0000      .02588     .04693
    D_T1|    .00537         .00395     1.36  .1740     -.00237     .01312
    D_T2|   -.02765***      .00408    -6.77  .0000     -.03565    -.01964
     D_F|    .02687***      .00293     9.17  .0000      .02112     .03261
    D_ST|    .00142         .00154      .92  .3561     -.00159     .00443
    D_ET|    .00651***      .00107     6.09  .0000      .00441     .00860
  D_XTTC|   -.00543***      .00210    -2.59  .0096     -.00955    -.00132
--------+--------------------------------------------------------------------
***, **, * ==>  Significance at 1%, 5%, 10% level.
Model was estimated on Mar 21, 2023 at 09:01:59 AM
-----------------------------------------------------------------------------
```

Listing C5: MNL model estimation Data structure B; Full sample

```
|-> Reset $
|-> Read; File=XXX\results-survey169147 df6B.csv$
Last observation read from data file was   47670
|-> Nlogit
    ; lhs = choice
    ; rhs = con1, t1, t2, f, st, et, a1_con1, a1_t1, a1_t2, a1_f, a1_st, a1_et, a
        2_con1, a2_t1, a2_t2, a2_f, a2_st, a2_et, d_con1, d_t1, d_t2, d_f, d_st, d
        _et
    ; Choices = 1,2,3
    ; shares
    ; CheckData
    $
+------------------------------------------------------+
| Inspecting the data set before estimation.           |
| These errors mark observations which will be skipped. |
| Row Individual = 1st row then group number of data block |
+------------------------------------------------------+
No bad observations were found in the sample

Iterative procedure has converged
Normal exit:   6 iterations. Status=0, F=    .1092545D+05
```

```
Discrete choice (multinomial logit) model
Dependent variable                 Choice
Log likelihood function     -10925.44582
Estimation based on N =  15890, K =  24
Inf.Cr.AIC  =  21898.9 AIC/N =     1.378
-----------------------------------------
             Log likelihood R-sqrd R2Adj
ASCs  only  model must be fit separately
               Use NLOGIT ;...;RHS=ONE$
Note: R-sqrd = 1 - logL/Logl(constants)
Warning:  Model does not contain a full
set of ASCs. R-sqrd is problematic. Use
model setup with ;RHS=one to get LogL0.
-----------------------------------------
Response data are given as proportions.
Number of obs.= 15890, skipped    0 obs
--------+--------------------------------------------------------------------
        |                  Standard            Prob.      95% Confidence
  CHOICE|  Coefficient       Error       z    |z|>Z*         Interval
--------+--------------------------------------------------------------------
    CON1|  -5.93940***      .13619   -43.61  .0000    -6.20632   -5.67248
      T1|   -.11898***      .03351    -3.55  .0004     -.18466    -.05329
      T2|    .33840***      .03260    10.38  .0000      .27451     .40229
       F|   -.81081***      .02501   -32.42  .0000     -.85983    -.76179
      ST|   -.10605***      .01304    -8.13  .0000     -.13161    -.08050
      ET|   -.16499***      .00889   -18.55  .0000     -.18242    -.14756
 A1_CON1|    .24840**       .10439     2.38  .0173      .04380     .45301
   A1_T1|   -.01186         .03105     -.38  .7025     -.07272     .04900
   A1_T2|    .00252         .02949      .09  .9320     -.05529     .06032
    A1_F|    .07415***      .02607     2.84  .0045      .02305     .12526
   A1_ST|    .01072         .01429      .75  .4531     -.01728     .03872
   A1_ET|    .00778         .00940      .83  .4078     -.01064     .02620
 A2_CON1|   -.01984         .10217     -.19  .8461     -.22010     .18042
   A2_T1|    .02812         .02987      .94  .3465     -.03042     .08666
   A2_T2|    .02545         .02970      .86  .3916     -.03277     .08366
    A2_F|    .20805***      .04532     4.59  .0000      .11923     .29687
   A2_ST|   -.02930         .02542    -1.15  .2491     -.07914     .02053
   A2_ET|   -.05246***      .01663    -3.16  .0016     -.08505    -.01987
  D_CON1|    .07452***      .01954     3.81  .0001      .03623     .11280
    D_T1|    .02765***      .00513     5.39  .0000      .01760     .03769
    D_T2|   -.04285***      .00527    -8.12  .0000     -.05319    -.03251
     D_F|    .01931***      .00268     7.22  .0000      .01407     .02456
    D_ST|   -.00434***      .00156    -2.78  .0055     -.00740    -.00128
    D_ET|    .00333***      .00103     3.24  .0012      .00132     .00534
--------+--------------------------------------------------------------------
***, **, * ==>  Significance at 1%, 5%, 10% level.
Model was estimated on Mar 21, 2023 at 09:03:06 AM
-----------------------------------------------------------------------------
```

Listing C6: MNL model estimation Data structure B; Filter non-choice resp. (Table 13)

```
|-> Reset $
|-> Read; File=XXX\results-survey169147 df6B.csv$
Last observation read from data file was   47670
|-> Reject ; trustw = 0$
|-> Nlogit
    ; lhs = choice
    ; rhs = con1, t1, t2, f, st, et, a1_con1, a1_t1, a1_t2, a1_f, a1_st, a1_et, a
        2_con1, a2_t1, a2_t2, a2_f, a2_st, a2_et, d_con1, d_t1, d_t2, d_f, d_st, d
        _et
```

```
    ; Choices = 1,2,3
    ; shares
    ; CheckData
    $
+------------------------------------------------------+
| Inspecting the data set before estimation.           |
| These errors mark observations which will be skipped. |
| Row Individual = 1st row then group number of data block |
+------------------------------------------------------+
No bad observations were found in the sample

Iterative procedure has converged
Normal exit:   7 iterations. Status=0, F=    .9551713D+04

-----------------------------------------------------------------------------
Discrete choice (multinomial logit) model
Dependent variable               Choice
Log likelihood function     -9551.71325
Estimation based on N =  15448, K =  24
Inf.Cr.AIC  =  19151.4 AIC/N =    1.240
-----------------------------------------
            Log likelihood R-sqrd R2Adj
ASCs  only  model must be fit separately
                Use NLOGIT ;...;RHS=ONE$
Note: R-sqrd = 1 - logL/Logl(constants)
Warning:  Model does not contain a full
set of ASCs. R-sqrd is problematic. Use
model setup with ;RHS=one to get LogL0.
-----------------------------------------
Response data are given as proportions.
Number of obs.= 15448, skipped    0 obs
--------+--------------------------------------------------------------------
        |                  Standard            Prob.      95% Confidence
  CHOICE|  Coefficient       Error       z    |z|>Z*         Interval
--------+--------------------------------------------------------------------
    CON1|  -6.91769***      .15715   -44.02  .0000    -7.22570   -6.60969
      T1|   -.11585***      .03581    -3.24  .0012     -.18603    -.04567
      T2|    .34865***      .03451    10.10  .0000      .28102     .41629
       F|   -.91024***      .02773   -32.82  .0000     -.96459    -.85588
      ST|   -.11885***      .01392    -8.54  .0000     -.14614    -.09156
      ET|   -.18359***      .00963   -19.06  .0000     -.20247    -.16470
 A1_CON1|    .13624         .12178     1.12  .2632     -.10244     .37492
   A1_T1|   -.00251         .03355     -.07  .9404     -.06827     .06326
   A1_T2|   -.00181         .03136     -.06  .9541     -.06327     .05966
    A1_F|    .08211***      .02896     2.84  .0046      .02535     .13886
   A1_ST|    .00234         .01520      .15  .8776     -.02745     .03213
   A1_ET|    .00473         .01015      .47  .6415     -.01517     .02462
 A2_CON1|    .00681         .11664      .06  .9535     -.22179     .23541
   A2_T1|    .02257         .03195      .71  .4800     -.04006     .08519
   A2_T2|    .04433         .03142     1.41  .1582     -.01724     .10591
    A2_F|    .25411***      .04982     5.10  .0000      .15647     .35176
   A2_ST|   -.04650*        .02703    -1.72  .0853     -.09948     .00647
   A2_ET|   -.05762***      .01785    -3.23  .0012     -.09260    -.02264
  D_CON1|    .09693***      .02243     4.32  .0000      .05297     .14089
    D_T1|    .02925***      .00547     5.35  .0000      .01853     .03997
    D_T2|   -.04406***      .00561    -7.85  .0000     -.05506    -.03306
     D_F|    .02301***      .00294     7.83  .0000      .01725     .02877
    D_ST|   -.00379**       .00167    -2.27  .0234     -.00707    -.00051
    D_ET|    .00386***      .00112     3.45  .0006      .00166     .00606
--------+--------------------------------------------------------------------
***, **, * ==>  Significance at 1%, 5%, 10% level.
Model was estimated on Mar 21, 2023 at 09:03:08 AM
```

Listing C7: MNL model estimation Data structure B; Filter non-visiting resp.

```
|-> Reset $
|-> Read; File=XXX\results-survey169147 df6B.csv$
Last observation read from data file was   47670
|-> Reject; b_v = 0 $
|-> Nlogit
    ; lhs = choice
    ; rhs = con1, t1, t2, f, st, et, a1_con1, a1_t1, a1_t2, a1_f, a1_st, a1_et, a
       2_con1, a2_t1, a2_t2, a2_f, a2_st, a2_et, d_con1, d_t1, d_t2, d_f, d_st, d
       _et
    ; Choices = 1,2,3
    ; shares
    ; CheckData
    $
+------------------------------------------------------------+
| Inspecting the data set before estimation.                 |
| These errors mark observations which will be skipped.      |
| Row Individual = 1st row then group number of data block   |
+------------------------------------------------------------+
No bad observations were found in the sample

Iterative procedure has converged
Normal exit:   7 iterations. Status=0, F=    .8546003D+04

-----------------------------------------------------------------------------
Discrete choice (multinomial logit) model
Dependent variable               Choice
Log likelihood function     -8546.00310
Estimation based on N =  13083, K =  24
Inf.Cr.AIC  =  17140.0 AIC/N =    1.310
---------------------------------------
            Log likelihood R-sqrd R2Adj
ASCs  only  model must be fit separately
            Use NLOGIT ;...;RHS=ONE$
Note: R-sqrd = 1 - logL/Logl(constants)
Warning:  Model does not contain a full
set of ASCs. R-sqrd is problematic. Use
model setup with ;RHS=one to get LogL0.
---------------------------------------
Response data are given as proportions.
Number of obs.= 13083, skipped    0 obs
--------+--------------------------------------------------------------------
        |                Standard            Prob.       95% Confidence
  CHOICE|  Coefficient     Error       z    |z|>Z*          Interval
--------+--------------------------------------------------------------------
    CON1|  -6.49690***     .16120   -40.30  .0000    -6.81286   -6.18095
      T1|   -.15512***     .03842    -4.04  .0001     -.23042    -.07982
      T2|    .39321***     .03695    10.64  .0000      .32079     .46564
       F|   -.85539***     .02880   -29.70  .0000     -.91184    -.79895
      ST|   -.11155***     .01478    -7.55  .0000     -.14052    -.08258
      ET|   -.18040***     .01019   -17.71  .0000     -.20036    -.16044
 A1_CON1|    .29809**      .12198     2.44  .0145      .05901     .53716
   A1_T1|   -.00319        .03517     -.09  .9277     -.07212     .06574
   A1_T2|    .01335        .03319      .40  .6875     -.05170     .07840
    A1_F|    .08164***     .02969     2.75  .0060      .02344     .13984
   A1_ST|    .01230        .01605      .77  .4435     -.01916     .04375
   A1_ET|    .00501        .01066      .47  .6383     -.01588     .02590
 A2_CON1|    .01315        .11886      .11  .9119     -.21980     .24610
   A2_T1|    .03871        .03381     1.14  .2523     -.02756     .10498
```

```
   A2_T2|      .02409          .03335       .72  .4700      -.04127     .08945
    A2_F|      .22910***       .05157      4.44  .0000       .12803     .33017
   A2_ST|     -.03702          .02868     -1.29  .1968      -.09323     .01919
   A2_ET|     -.06698***       .01892     -3.54  .0004      -.10406    -.02991
  D_CON1|      .09935***       .02293      4.33  .0000       .05440     .14430
    D_T1|      .03178***       .00582      5.46  .0000       .02038     .04318
    D_T2|     -.05139***       .00596     -8.63  .0000      -.06306    -.03971
     D_F|      .02206***       .00307      7.18  .0000       .01604     .02807
    D_ST|     -.00423**        .00177     -2.39  .0168      -.00770    -.00077
    D_ET|      .00420***       .00118      3.55  .0004       .00188     .00651
--------+--------------------------------------------------------------------
***, **, * ==>  Significance at 1%, 5%, 10% level.
Model was estimated on Mar 21, 2023 at 09:03:09 AM
-----------------------------------------------------------------------------
```

Listing C8: MNL model estimation Data structure B; Filter non-visiting & non-choice resp.

```
|-> Reset $
|-> Read; File=XXX\results-survey169147 df6B.csv$
Last observation read from data file was   47670
|-> Reject ; b_v = 0$
|-> Reject ; trustw = 0$
|-> Nlogit
    ; lhs = choice
    ; rhs = con1, t1, t2, f, st, et, a1_con1, a1_t1, a1_t2, a1_f, a1_st, a1_et, a
      2_con1, a2_t1, a2_t2, a2_f, a2_st, a2_et, d_con1, d_t1, d_t2, d_f, d_st, d
      _et
    ; Choices = 1,2,3
    ; shares
    ; CheckData
    $
+-----------------------------------------------------+
| Inspecting the data set before estimation.          |
| These errors mark observations which will be skipped. |
| Row Individual = 1st row then group number of data block |
+-----------------------------------------------------+
No bad observations were found in the sample

Iterative procedure has converged
Normal exit:   7 iterations. Status=0, F=    .7703221D+04

-----------------------------------------------------------------------------
Discrete choice (multinomial logit) model
Dependent variable                 Choice
Log likelihood function      -7703.22098
Estimation based on N =  12827, K =  24
Inf.Cr.AIC  =  15454.4 AIC/N =    1.205
-----------------------------------------
             Log likelihood R-sqrd R2Adj
ASCs  only  model must be fit separately
                Use NLOGIT ;...;RHS=ONE$
Note: R-sqrd = 1 - logL/Logl(constants)
Warning:  Model does not contain a full
set of ASCs. R-sqrd is problematic. Use
model setup with ;RHS=one to get LogL0.
-----------------------------------------
Response data are given as proportions.
Number of obs.= 12827, skipped    0 obs
--------+--------------------------------------------------------------------
        |                  Standard            Prob.      95% Confidence
  CHOICE|  Coefficient       Error       z    |z|>Z*         Interval
--------+--------------------------------------------------------------------
```

```
     CON1|    -7.33495***       .18096    -40.53  .0000     -7.68963   -6.98028
       T1|     -.15472***       .04056     -3.81  .0001      -.23420    -.07523
       T2|      .40540***       .03873     10.47  .0000       .32950     .48131
        F|     -.93828***       .03127    -30.01  .0000      -.99957    -.87700
       ST|     -.12423***       .01559     -7.97  .0000      -.15478    -.09368
       ET|     -.19847***       .01086    -18.27  .0000      -.21976    -.17718
  A1_CON1|      .22692*         .13733      1.65  .0985      -.04225     .49609
    A1_T1|      .00555          .03734       .15  .8819      -.06764     .07874
    A1_T2|      .00412          .03479       .12  .9058      -.06407     .07230
     A1_F|      .08760***       .03223      2.72  .0066       .02443     .15077
    A1_ST|      .00682          .01684       .40  .6856      -.02618     .03982
    A1_ET|      .00382          .01131       .34  .7355      -.01835     .02599
  A2_CON1|      .03122          .13187       .24  .8129      -.22724     .28967
    A2_T1|      .03369          .03565       .95  .3446      -.03617     .10356
    A2_T2|      .03877          .03488      1.11  .2663      -.02958     .10712
     A2_F|      .26330***       .05556      4.74  .0000       .15440     .37220
    A2_ST|     -.04869          .03008     -1.62  .1055      -.10765     .01027
    A2_ET|     -.07063***       .02000     -3.53  .0004      -.10983    -.03143
   D_CON1|      .12681***       .02556      4.96  .0000       .07672     .17690
     D_T1|      .03321***       .00612      5.43  .0000       .02122     .04521
     D_T2|     -.05308***       .00625     -8.49  .0000      -.06534    -.04082
      D_F|      .02552***       .00331      7.72  .0000       .01904     .03200
     D_ST|     -.00339*         .00187     -1.81  .0697      -.00705     .00027
     D_ET|      .00510***       .00127      4.03  .0001       .00262     .00758
---------+--------------------------------------------------------------------
***, **, * ==>  Significance at 1%, 5%, 10% level.
Model was estimated on Mar 21, 2023 at 09:03:11 AM
------------------------------------------------------------------------------
```

Listing C9: MNL model estimation Data structure C; Full Sample

```
|-> Reset $
|-> Read; File=XXX\results-survey169147 df6C.csv$
Last observation read from data file was   29138
|-> Nlogit
    ; lhs = choice
    ; rhs = con2, t1, t2, f, st, et, xttc, a1_con2, a1_t1, a1_t2, a1_f, a1_st, a1_
        et, a1_xttc, a2_con2, a2_t1, a2_t2, a2_f, a2_st, a2_et, a2_xttc, d_con2, d
        _t1, d_t2, d_f, d_st, d_et, d_xttc
    ; Choices = 1,2
    ; shares
    ; CheckData
    $
+-------------------------------------------------------+
| Inspecting the data set before estimation.            |
| These errors mark observations which will be skipped. |
| Row Individual = 1st row then group number of data block |
+-------------------------------------------------------+
No bad observations were found in the sample

Iterative procedure has converged
Normal exit:   6 iterations. Status=0, F=    .7309702D+04

------------------------------------------------------------------------------
Discrete choice (multinomial logit) model
Dependent variable               Choice
Log likelihood function      -7309.70195
Estimation based on N =  14569, K =  28
Inf.Cr.AIC  =  14675.4 AIC/N =    1.007
---------------------------------------
             Log likelihood R-sqrd R2Adj
ASCs  only  model must be fit separately
```

```
             Use NLOGIT  ;...;RHS=ONE$
Note: R-sqrd = 1 - logL/Logl(constants)
Warning:  Model does not contain a full
set of ASCs. R-sqrd is problematic. Use
model setup with ;RHS=one to get LogL0.
----------------------------------------
Response data are given as proportions.
Number of obs.= 14569, skipped    0 obs
--------+--------------------------------------------------------------------
        |                  Standard            Prob.      95% Confidence
  CHOICE|  Coefficient       Error       z    |z|>Z*         Interval
--------+--------------------------------------------------------------------
    CON2|   -.78475***      .03601   -21.79  .0000     -.85533   -.71417
      T1|    .12643***      .03676     3.44  .0006      .05439    .19848
      T2|    .12579***      .03198     3.93  .0001      .06311    .18847
       F|  -1.33553***      .05573   -23.96  .0000    -1.44476  -1.22631
      ST|   -.25673***      .02263   -11.34  .0000     -.30109   -.21238
      ET|   -.28095***      .01721   -16.33  .0000     -.31468   -.24722
    XTTC|   -.07962***      .01373    -5.80  .0000     -.10652   -.05271
 A1_CON2|   -.04726         .03040    -1.55  .1200     -.10683    .01232
   A1_T1|    .04462         .02823     1.58  .1139     -.01070    .09994
   A1_T2|   -.02586         .03024     -.86  .3924     -.08513    .03341
    A1_F|    .08113         .06185     1.31  .1896     -.04008    .20235
   A1_ST|   -.05247**       .02422    -2.17  .0303     -.09994   -.00499
   A1_ET|    .03777**       .01846     2.05  .0407      .00159    .07396
 A1_XTTC|   -.00884         .01214     -.73  .4662     -.03263    .01494
 A2_CON2|   -.01249         .02995     -.42  .6767     -.07118    .04621
   A2_T1|   -.02353         .02792     -.84  .3993     -.07824    .03119
   A2_T2|    .04340         .02990     1.45  .1467     -.01521    .10201
    A2_F|    .36261***      .10544     3.44  .0006      .15595    .56926
   A2_ST|   -.08791**       .04187    -2.10  .0358     -.16997   -.00585
   A2_ET|    .00853         .03222      .26  .7912     -.05461    .07167
 A2_XTTC|    .01434         .01188     1.21  .2274     -.00894    .03762
  D_CON2|    .04133***      .00537     7.69  .0000      .03079    .05186
    D_T1|   -.01299**       .00528    -2.46  .0139     -.02334   -.00264
    D_T2|   -.00628         .00527    -1.19  .2330     -.01661    .00404
     D_F|    .02150***      .00588     3.66  .0003      .00998    .03302
    D_ST|    .00626**       .00259     2.41  .0159      .00117    .01134
    D_ET|    .00765***      .00190     4.03  .0001      .00393    .01137
  D_XTTC|   -.01120***      .00221    -5.07  .0000     -.01553   -.00687
--------+--------------------------------------------------------------------
***, **, * ==>  Significance at 1%, 5%, 10% level.
Model was estimated on Mar 21, 2023 at 09:03:52 AM
-----------------------------------------------------------------------------
```

Listing C10: MNL model estimation Data structure C; Filter non-choice resp. (Table 14)

```
|-> Reset $
|-> Read; File=XXX\results-survey169147 df6C.csv$
Last observation read from data file was   29138
|-> Reject ; trustw = 0$
|-> Nlogit
    ; lhs = choice
    ; rhs = con2, t1, t2, f, st, et, xttc, a1_con2, a1_t1, a1_t2, a1_f, a1_st, a1_
       et, a1_xttc, a2_con2, a2_t1, a2_t2, a2_f, a2_st, a2_et, a2_xttc, d_con2, d
       _t1, d_t2, d_f, d_st, d_et, d_xttc
    ; Choices = 1,2
    ; shares
    ; CheckData
    $
+-----------------------------------------------+
| Inspecting the data set before estimation.    |
```

```
| These errors mark observations which will be skipped.    |
| Row Individual = 1st row then group number of data block |
+----------------------------------------------------------+
No bad observations were found in the sample

Iterative procedure has converged
Normal exit:   6 iterations. Status=0, F=    .7301232D+04
```

```
Discrete choice (multinomial logit) model
Dependent variable                Choice
Log likelihood function      -7301.23171
Estimation based on N =  14561, K =  28
Inf.Cr.AIC  =  14658.5 AIC/N =     1.007
----------------------------------------
            Log likelihood R-sqrd R2Adj
ASCs  only  model must be fit separately
              Use NLOGIT ;...;RHS=ONE$
Note: R-sqrd = 1 - logL/Logl(constants)
Warning:  Model does not contain a full
set of ASCs. R-sqrd is problematic. Use
model setup with ;RHS=one to get LogL0.
----------------------------------------
Response data are given as proportions.
Number of obs.= 14561, skipped    0 obs
```

CHOICE	Coefficient	Standard Error	z	Prob. |z|>Z*	95% *Confidence* Interval	
CON2	−.78644***	.03605	−21.81	.0000	−.85710	−.71578
T1	.12452***	.03677	3.39	.0007	.05245	.19660
T2	.12529***	.03199	3.92	.0001	.06259	.18799
F	−1.33986***	.05587	−23.98	.0000	−1.44936	−1.23036
ST	−.25736***	.02265	−11.36	.0000	−.30176	−.21296
ET	−.28248***	.01725	−16.38	.0000	−.31628	−.24868
XTTC	−.08009***	.01374	−5.83	.0000	−.10702	−.05315
A1_CON2	−.04664	.03041	−1.53	.1251	−.10625	.01296
A1_T1	.04539	.02823	1.61	.1079	−.00995	.10073
A1_T2	−.02734	.03024	−.90	.3659	−.08662	.03193
A1_F	.08682	.06197	1.40	.1612	−.03463	.20828
A1_ST	−.05228**	.02424	−2.16	.0310	−.09978	−.00477
A1_ET	.03888**	.01848	2.10	.0354	.00266	.07509
A1_XTTC	−.00831	.01215	−.68	.4940	−.03212	.01550
A2_CON2	−.01481	.02999	−.49	.6213	−.07359	.04396
A2_T1	−.02345	.02794	−.84	.4013	−.07820	.03131
A2_T2	.04260	.02993	1.42	.1547	−.01607	.10127
A2_F	.37239***	.10573	3.52	.0004	.16516	.57963
A2_ST	−.08821**	.04190	−2.11	.0353	−.17034	−.00608
A2_ET	.01029	.03226	.32	.7497	−.05294	.07352
A2_XTTC	.01342	.01190	1.13	.2591	−.00989	.03674
D_CON2	.04139***	.00538	7.70	.0000	.03085	.05194
D_T1	−.01298**	.00528	−2.46	.0140	−.02333	−.00262
D_T2	−.00596	.00527	−1.13	.2587	−.01629	.00438
D_F	.02130***	.00589	3.62	.0003	.00975	.03284
D_ST	.00629**	.00260	2.42	.0154	.00120	.01137
D_ET	.00777***	.00190	4.09	.0000	.00405	.01150
D_XTTC	−.01111***	.00221	−5.03	.0000	−.01544	−.00678

***, **, * ==> Significance at *1%, 5%, 10% level*.
Model was estimated on Mar 21, 2023 at 09:03:53 AM

Listing C11: MNL model estimation Data structure C; Filter non-visiting resp.

```
|-> Reset $
|-> Read; File=XXX\results-survey169147 df6C.csv$
Last observation read from data file was   29138
|-> Reject; b_v = 0 $
|-> Nlogit
    ; lhs = choice
    ; rhs = con2, t1, t2, f, st, et, xttc, a1_con2, a1_t1, a1_t2, a1_f, a1_st, a1_
        et, a1_xttc, a2_con2, a2_t1, a2_t2, a2_f, a2_st, a2_et, a2_xttc, d_con2, d
        _t1, d_t2, d_f, d_st, d_et, d_xttc
    ; Choices = 1,2
    ; shares
    ; CheckData
    $
+--------------------------------------------------------+
| Inspecting the data set before estimation.              |
| These errors mark observations which will be skipped.   |
| Row Individual = 1st row then group number of data block |
+--------------------------------------------------------+
No bad observations were found in the sample

Iterative procedure has converged
Normal exit:   6 iterations. Status=0, F=    .6075854D+04

-----------------------------------------------------------------------------
Discrete choice (multinomial logit) model
Dependent variable               Choice
Log likelihood function      -6075.85404
Estimation based on N =  12165, K =  28
Inf.Cr.AIC  =  12207.7 AIC/N =    1.004
-----------------------------------------
           Log likelihood R-sqrd R2Adj
ASCs only  model must be fit separately
              Use NLOGIT ;...;RHS=ONE$
Note: R-sqrd = 1 - logL/Logl(constants)
Warning:  Model does not contain a full
set of ASCs. R-sqrd is problematic. Use
model setup with ;RHS=one to get LogL0.
-----------------------------------------
Response data are given as proportions.
Number of obs.= 12165, skipped    0 obs
--------+--------------------------------------------------------------------
        |                  Standard            Prob.      95% Confidence
  CHOICE|  Coefficient       Error       z    |z|>Z*         Interval
--------+--------------------------------------------------------------------
    CON2|    -.77872***      .03961   -19.66  .0000     -.85636    -.70108
      T1|     .08663**       .04066     2.13  .0331      .00693     .16632
      T2|     .16464***      .03511     4.69  .0000      .09582     .23346
       F|   -1.36183***      .06150   -22.14  .0000    -1.48237   -1.24129
      ST|    -.26613***      .02480   -10.73  .0000     -.31474    -.21753
      ET|    -.29497***      .01903   -15.50  .0000     -.33226    -.25767
    XTTC|    -.07890***      .01469    -5.37  .0000     -.10769    -.05010
 A1_CON2|    -.05323         .03339    -1.59  .1109     -.11867     .01222
   A1_T1|     .05118*        .03096     1.65  .0983     -.00950     .11187
   A1_T2|    -.01078         .03313     -.33  .7449     -.07571     .05416
    A1_F|     .10963         .06788     1.61  .1063     -.02342     .24268
   A1_ST|    -.04600*        .02653    -1.73  .0830     -.09800     .00600
   A1_ET|     .04735**       .02042     2.32  .0204      .00732     .08737
 A1_XTTC|    -.00967         .01295     -.75  .4554     -.03505     .01572
 A2_CON2|    -.01945         .03292     -.59  .5545     -.08397     .04506
   A2_T1|    -.02653         .03064     -.87  .3865     -.08658     .03351
```

```
     A2_T2|      .04069          .03281      1.24   .2149      -.02362     .10500
      A2_F|      .43782***       .11608      3.77   .0002       .21031     .66533
     A2_ST|     -.09118**        .04596     -1.98   .0473      -.18125    -.00110
     A2_ET|      .03073          .03558       .86   .3878      -.03901     .10047
   A2_XTTC|      .01854          .01269      1.46   .1441      -.00634     .04341
    D_CON2|      .04230***       .00589      7.18   .0000       .03076     .05385
      D_T1|     -.00951          .00582     -1.63   .1022      -.02091     .00189
      D_T2|     -.00914          .00577     -1.58   .1133      -.02045     .00217
       D_F|      .02024***       .00644      3.14   .0017       .00763     .03286
      D_ST|      .00755***       .00285      2.65   .0082       .00196     .01314
      D_ET|      .00769***       .00209      3.68   .0002       .00359     .01179
    D_XTTC|     -.01176***       .00236     -4.98   .0000      -.01639    -.00712
----------+-------------------------------------------------------------------
***, **, * ==>  Significance at 1%, 5%, 10% level.
Model was estimated on Mar 21, 2023 at 09:03:54 AM
------------------------------------------------------------------------------
```

Listing C12: MNL model estimation Data structure C; Filter non-visiting & non-choice resp.

```
|-> Reset $
|-> Read; File=XXX\results-survey169147 df6C.csv$
Last observation read from data file was   29138
|-> Reject ; b_v = 0$
|-> Reject ; trustw = 0$
|-> Nlogit
    ; lhs = choice
    ; rhs = con2, t1, t2, f, st, et, xttc, a1_con2, a1_t1, a1_t2, a1_f, a1_st, a1_
        et, a1_xttc, a2_con2, a2_t1, a2_t2, a2_f, a2_st, a2_et, a2_xttc, d_con2, d
        _t1, d_t2, d_f, d_st, d_et, d_xttc
    ; Choices = 1,2
    ; shares
    ; CheckData
    $
+--------------------------------------------------------+
| Inspecting the data set before estimation.             |
| These errors mark observations which will be skipped.  |
| Row Individual = 1st row then group number of data block |
+--------------------------------------------------------+
No bad observations were found in the sample

Iterative procedure has converged
Normal exit:   6 iterations. Status=0, F=    .6067460D+04

------------------------------------------------------------------------------
Discrete choice (multinomial logit) model
Dependent variable               Choice
Log likelihood function      -6067.46027
Estimation based on N =  12158, K =  28
Inf.Cr.AIC  =  12190.9 AIC/N =    1.003
----------------------------------------
            Log likelihood R-sqrd R2Adj
ASCs  only  model must be fit separately
               Use NLOGIT ;...;RHS=ONE$
Note: R-sqrd = 1 - logL/Logl(constants)
Warning:  Model does not contain a full
set of ASCs. R-sqrd is problematic. Use
model setup with ;RHS=one to get LogL0.
----------------------------------------
Response data are given as proportions.
Number of obs.= 12158, skipped    0 obs
----------+-------------------------------------------------------------------
          |                Standard              Prob.      95% Confidence
```

```
  CHOICE|  Coefficient      Error       z     |z|>Z*        Interval
--------+-------------------------------------------------------------
    CON2|   -.78103***     .03966   -19.69  .0000    -.85877    -.70329
      T1|    .08412**      .04069     2.07  .0387     .00437     .16386
      T2|    .16405***     .03513     4.67  .0000     .09519     .23290
       F|  -1.36750***     .06169   -22.17  .0000   -1.48842   -1.24659
      ST|   -.26700***     .02483   -10.75  .0000    -.31567    -.21833
      ET|   -.29696***     .01908   -15.57  .0000    -.33435    -.25957
    XTTC|   -.07944***     .01471    -5.40  .0000    -.10827    -.05061
 A1_CON2|   -.05265        .03341    -1.58  .1150    -.11813     .01282
   A1_T1|    .05218*       .03097     1.68  .0920    -.00852     .11289
   A1_T2|   -.01265        .03314     -.38  .7026    -.07760     .05229
    A1_F|    .11650*       .06805     1.71  .0869    -.01688     .24988
   A1_ST|   -.04576*       .02655    -1.72  .0848    -.09779     .00628
   A1_ET|    .04859**      .02044     2.38  .0175     .00852     .08866
 A1_XTTC|   -.00906        .01296     -.70  .4846    -.03446     .01635
 A2_CON2|   -.02224        .03297     -.67  .4999    -.08687     .04238
   A2_T1|   -.02645        .03066     -.86  .3884    -.08655     .03365
   A2_T2|    .03977        .03285     1.21  .2261    -.02462     .10415
    A2_F|    .44992***     .11648     3.86  .0001     .22162     .67822
   A2_ST|   -.09152**      .04601    -1.99  .0467    -.18170    -.00135
   A2_ET|    .03281        .03564      .92  .3573    -.03705     .10267
 A2_XTTC|    .01751        .01271     1.38  .1684    -.00741     .04243
  D_CON2|    .04242***     .00590     7.19  .0000     .03087     .05398
    D_T1|   -.00946        .00582    -1.63  .1040    -.02087     .00195
    D_T2|   -.00874        .00577    -1.51  .1300    -.02006     .00257
     D_F|    .02003***     .00645     3.11  .0019     .00739     .03267
    D_ST|    .00760***     .00286     2.66  .0078     .00200     .01320
    D_ET|    .00785***     .00209     3.75  .0002     .00375     .01196
  D_XTTC|   -.01166***     .00236    -4.93  .0000    -.01630    -.00703
--------+-------------------------------------------------------------
***, **, * ==>  Significance at 1%, 5%, 10% level.
Model was estimated on Mar 21, 2023 at 09:03:56 AM
----------------------------------------------------------------------
```

Listing C13: MNL model estimation Data structure D; Full sample

```
|-> Reset $
|-> Read; File=XXX\results-survey169147 df6D.csv$
Last observation read from data file was   76808
|-> Nlogit
    ; lhs = choice, numalt, count
    ; rhs = con1, t1A, t2A, fA, stA, etA, a1_con1, a1_t1A, a1_t2A, a1_fA, a1_stA,
       a1_etA, a2_con1, a2_t1A, a2_t2A, a2_fA, a2_stA, a2_etA, d_con1,  d_t1A, d_
       t2A, d_fA, d_stA, d_etA, con2, t1B, t2B, fB, stB, etB, xttc, a1_con2, a1_t
       1B, a1_t2B, a1_fB, a1_stB, a1_etB, a1_xttc, a2_con2, a2_t1B, a2_t2B, a2_fB
       , a2_stB, a2_etB, a2_xttc, d_con2, d_t1B, d_t2B, d_fB, d_stB,  d_etB, d_
       xttc
    ; Choices = 1,2,3
    ; shares
    ; CheckData
    $
+-----------------------------------------------------+
| Inspecting the data set before estimation.          |
| These errors mark observations which will be skipped. |
| Row Individual = 1st row then group number of data block |
+-----------------------------------------------------+
No bad observations were found in the sample

Iterative procedure has converged
Normal exit:   6 iterations. Status=0, F=    .1823492D+05
```

```
Discrete choice (multinomial logit) model
Dependent variable                Choice
Log likelihood function     -18234.92319
Estimation based on N =  30459, K =  52
Inf.Cr.AIC  =  36573.8 AIC/N =     1.201
```

```
             Log likelihood R-sqrd R2Adj
ASCs  only  model must be fit separately
              Use NLOGIT ;...;RHS=ONE$
Note: R-sqrd = 1 - logL/Logl(constants)
Warning:  Model does not contain a full
set of ASCs. R-sqrd is problematic. Use
model setup with ;RHS=one to get LogL0.
```

```
Response data are given as proportions.
Number of obs.= 30459, skipped    0 obs
```

CHOICE	Coefficient	Standard Error	z	Prob. |z|>Z*	95% *Confidence* Interval	
CON1	−5.93940***	.13619	−43.61	.0000	−6.20632	−5.67248
T1A	−.11898***	.03351	−3.55	.0004	−.18466	−.05329
T2A	.33840***	.03260	10.38	.0000	.27451	.40229
FA	−.81081***	.02501	−32.42	.0000	−.85983	−.76179
STA	−.10605***	.01304	−8.13	.0000	−.13161	−.08050
ETA	−.16499***	.00889	−18.55	.0000	−.18242	−.14756
A1_CON1	.24840**	.10439	2.38	.0173	.04380	.45301
A1_T1A	−.01186	.03105	−.38	.7025	−.07272	.04900
A1_T2A	.00252	.02949	.09	.9320	−.05529	.06032
A1_FA	.07415***	.02607	2.84	.0045	.02305	.12526
A1_STA	.01072	.01429	.75	.4531	−.01728	.03872
A1_ETA	.00778	.00940	.83	.4078	−.01064	.02620
A2_CON1	−.01984	.10217	−.19	.8461	−.22010	.18042
A2_T1A	.02812	.02987	.94	.3465	−.03042	.08666
A2_T2A	.02545	.02970	.86	.3916	−.03277	.08366
A2_FA	.20805***	.04532	4.59	.0000	.11923	.29687
A2_STA	−.02930	.02542	−1.15	.2491	−.07914	.02053
A2_ETA	−.05246***	.01663	−3.16	.0016	−.08505	−.01987
D_CON1	.07452***	.01954	3.81	.0001	.03623	.11280
D_T1A	.02765***	.00513	5.39	.0000	.01760	.03769
D_T2A	−.04285***	.00527	−8.12	.0000	−.05319	−.03251
D_FA	.01931***	.00268	7.22	.0000	.01407	.02456
D_STA	−.00434***	.00156	−2.78	.0055	−.00740	−.00128
D_ETA	.00333***	.00103	3.24	.0012	.00132	.00534
CON2	−.78448***	.03601	−21.78	.0000	−.85506	−.71390
T1B	.12713***	.03676	3.46	.0005	.05507	.19918
T2B	.12579***	.03198	3.93	.0001	.06311	.18847
FB	−1.33540***	.05573	−23.96	.0000	−1.44463	−1.22618
STB	−.25669***	.02263	−11.34	.0000	−.30105	−.21233
ETB	−.28089***	.01721	−16.32	.0000	−.31462	−.24716
XTTC	−.07963***	.01373	−5.80	.0000	−.10654	−.05273
A1_CON2	−.04749	.03040	−1.56	.1182	−.10707	.01209
A1_T1B	.04423	.02823	1.57	.1172	−.01110	.09955
A1_T2B	−.02593	.03024	−.86	.3912	−.08519	.03334
A1_FB	.08115	.06185	1.31	.1895	−.04006	.20237
A1_STB	−.05246**	.02422	−2.17	.0304	−.09994	−.00498
A1_ETB	.03779**	.01846	2.05	.0407	.00161	.07397
A1_XTTC	−.00877	.01214	−.72	.4699	−.03256	.01502
A2_CON2	−.01268	.02995	−.42	.6720	−.07138	.04602
A2_T1B	−.02390	.02792	−.86	.3919	−.07862	.03081
A2_T2B	.04326	.02990	1.45	.1480	−.01535	.10187

```
   A2_FB|      .36199***       .10544      3.43  .0006       .15533    .56865
  A2_STB|     -.08784**        .04187     -2.10  .0359      -.16990   -.00578
  A2_ETB|      .00843          .03222       .26  .7935      -.05471    .07158
 A2_XTTC|      .01440          .01188      1.21  .2254      -.00888    .03768
  D_CON2|      .04132***       .00537      7.69  .0000       .03078    .05185
   D_T1B|     -.01305**        .00528     -2.47  .0135      -.02340   -.00270
   D_T2B|     -.00626          .00527     -1.19  .2346      -.01659    .00407
    D_FB|      .02148***       .00588      3.65  .0003       .00996    .03301
   D_STB|      .00625**        .00259      2.41  .0159       .00117    .01134
   D_ETB|      .00764***       .00190      4.02  .0001       .00392    .01136
  D_XTTC|     -.01121***       .00221     -5.08  .0000      -.01554   -.00688
--------+--------------------------------------------------------------------
***, **, * ==>  Significance at 1%, 5%, 10% level.
Model was estimated on Mar 21, 2023 at 09:05:48 AM
-----------------------------------------------------------------------------
```

Listing C14: MNL model estimation Data structure D; Filter non-choice resp. (Table 15)

```
|-> Reset $
|-> Read; File=XXX\results-survey169147 df6D.csv$
Last observation read from data file was   76808
|-> Reject ; trustw = 0$
|-> Nlogit
    ; lhs = choice, numalt, count
    ; rhs = con1, t1A, t2A, fA, stA, etA, a1_con1, a1_t1A, a1_t2A, a1_fA, a1_stA,
       a1_etA, a2_con1, a2_t1A, a2_t2A, a2_fA, a2_stA, a2_etA, d_con1,  d_t1A, d_
       t2A, d_fA, d_stA, d_etA, con2, t1B, t2B, fB, stB, etB, xttc, a1_con2, a1_t
       1B, a1_t2B, a1_fB, a1_stB, a1_etB, a1_xttc, a2_con2, a2_t1B, a2_t2B, a2_fB
       , a2_stB, a2_etB, a2_xttc, d_con2, d_t1B, d_t2B, d_fB, d_stB,  d_etB, d_
       xttc
    ; Choices = 1,2,3
    ; shares
    ; CheckData
    $
+----------------------------------------------------------+
| Inspecting the data set before estimation.               |
| These errors mark observations which will be skipped.    |
| Row Individual = 1st row then group number of data block |
+----------------------------------------------------------+
No bad observations were found in the sample

Iterative procedure has converged
Normal exit:   7 iterations. Status=0, F=    .1685272D+05

-----------------------------------------------------------------------------
Discrete choice (multinomial logit) model
Dependent variable               Choice
Log likelihood function     -16852.72176
Estimation based on N =  30009, K =  52
Inf.Cr.AIC  =  33809.4 AIC/N =    1.127
-----------------------------------------
            Log likelihood R-sqrd R2Adj
ASCs  only  model must be fit separately
               Use NLOGIT ;...;RHS=ONE$
Note: R-sqrd = 1 - logL/Logl(constants)
Warning:  Model does not contain a full
set of ASCs. R-sqrd is problematic. Use
model setup with ;RHS=one to get LogL0.
-----------------------------------------
Response data are given as proportions.
Number of obs.= 30009, skipped    0 obs
--------+--------------------------------------------------------------------
```

CHOICE	Coefficient	Standard Error	z	Prob. |z|>Z*	95% *Confidence* Interval	
CON1	−6.91769***	.15715	−44.02	.0000	−7.22570	−6.60969
T1A	−.11585***	.03581	−3.24	.0012	−.18603	−.04567
T2A	.34865***	.03451	10.10	.0000	.28102	.41629
FA	−.91024***	.02773	−32.82	.0000	−.96459	−.85588
STA	−.11885***	.01392	−8.54	.0000	−.14614	−.09156
ETA	−.18359***	.00963	−19.06	.0000	−.20247	−.16470
A1_CON1	.13624	.12178	1.12	.2632	−.10244	.37492
A1_T1A	−.00251	.03355	−.07	.9404	−.06827	.06326
A1_T2A	−.00181	.03136	−.06	.9541	−.06327	.05966
A1_FA	.08211***	.02896	2.84	.0046	.02535	.13886
A1_STA	.00234	.01520	.15	.8776	−.02745	.03213
A1_ETA	.00473	.01015	.47	.6415	−.01517	.02462
A2_CON1	.00681	.11664	.06	.9535	−.22179	.23541
A2_T1A	.02257	.03195	.71	.4800	−.04006	.08519
A2_T2A	.04433	.03142	1.41	.1582	−.01724	.10591
A2_FA	.25411***	.04982	5.10	.0000	.15647	.35176
A2_STA	−.04650*	.02703	−1.72	.0853	−.09948	.00647
A2_ETA	−.05762***	.01785	−3.23	.0012	−.09260	−.02264
D_CON1	.09693***	.02243	4.32	.0000	.05297	.14089
D_T1A	.02925***	.00547	5.35	.0000	.01853	.03997
D_T2A	−.04406***	.00561	−7.85	.0000	−.05506	−.03306
D_FA	.02301***	.00294	7.83	.0000	.01725	.02877
D_STA	−.00379**	.00167	−2.27	.0234	−.00707	−.00051
D_ETA	.00386***	.00112	3.45	.0006	.00166	.00606
CON2	−.78616***	.03605	−21.81	.0000	−.85682	−.71550
T1B	.12522***	.03678	3.40	.0007	.05313	.19731
T2B	.12529***	.03199	3.92	.0001	.06258	.18799
FB	−1.33973***	.05587	−23.98	.0000	−1.44923	−1.23024
STB	−.25732***	.02265	−11.36	.0000	−.30172	−.21292
ETB	−.28242***	.01725	−16.38	.0000	−.31622	−.24862
XTTC	−.08010***	.01374	−5.83	.0000	−.10704	−.05317
A1_CON2	−.04687	.03041	−1.54	.1232	−.10648	.01273
A1_T1B	.04500	.02824	1.59	.1110	−.01035	.10034
A1_T2B	−.02741	.03024	−.91	.3648	−.08668	.03186
A1_FB	.08684	.06197	1.40	.1611	−.03461	.20830
A1_STB	−.05227**	.02424	−2.16	.0310	−.09977	−.00477
A1_ETB	.03889**	.01848	2.10	.0353	.00268	.07511
A1_XTTC	−.00823	.01215	−.68	.4978	−.03204	.01557
A2_CON2	−.01501	.02999	−.50	.6167	−.07379	.04377
A2_T1B	−.02382	.02794	−.85	.3939	−.07858	.03094
A2_T2B	.04246	.02993	1.42	.1561	−.01621	.10112
A2_FB	.37177***	.10574	3.52	.0004	.16453	.57902
A2_STB	−.08815**	.04190	−2.10	.0354	−.17028	−.00602
A2_ETB	.01019	.03226	.32	.7520	−.05304	.07343
A2_XTTC	.01349	.01190	1.13	.2569	−.00983	.03680
D_CON2	.04138***	.00538	7.69	.0000	.03084	.05193
D_T1B	−.01303**	.00528	−2.47	.0137	−.02339	−.00268
D_T2B	−.00593	.00527	−1.13	.2604	−.01627	.00440
D_FB	.02128***	.00589	3.61	.0003	.00974	.03282
D_STB	.00628**	.00260	2.42	.0155	.00120	.01137
D_ETB	.00776***	.00190	4.08	.0000	.00404	.01149
D_XTTC	−.01112***	.00221	−5.04	.0000	−.01546	−.00679

***, **, * ==> Significance at 1%, *5%, 10% level*.
Model was estimated on Mar 21, 2023 at 09:05:55 AM

Listing C15: MNL model estimation Data structure D; Filter non-visiting resp.

```
|-> Reset $
|-> Read; File=XXX\results-survey169147 df6D.csv$
Last observation read from data file was   76808
|-> Reject; b_v = 0 $
|-> Nlogit
    ; lhs = choice, numalt, count
    ; rhs = con1, t1A, t2A, fA, stA, etA, a1_con1, a1_t1A, a1_t2A, a1_fA, a1_stA,
       a1_etA, a2_con1, a2_t1A, a2_t2A, a2_fA, a2_stA, a2_etA, d_con1, d_t1A, d_t
       2A, d_fA, d_stA, d_etA, con2, t1B, t2B, fB, stB, etB, xttc, a1_con2, a1_t1
       B, a1_t2B, a1_fB, a1_stB, a1_etB, a1_xttc, a2_con2, a2_t1B, a2_t2B, a2_fB,
        a2_stB, a2_etB, a2_xttc, d_con2, d_t1B, d_t2B, d_fB, d_stB,  d_etB, d_
       xttc
    ; Choices = 1,2,3
    ; shares
    ; CheckData
    $
+-----------------------------------------------------------+
| Inspecting the data set before estimation.                |
| These errors mark observations which will be skipped.     |
| Row Individual = 1st row then group number of data block  |
+-----------------------------------------------------------+
No bad observations were found in the sample

Iterative procedure has converged
Normal exit:   7 iterations. Status=0, F=    .1462165D+05

-----------------------------------------------------------------------------
Discrete choice (multinomial logit) model
Dependent variable             Choice
Log likelihood function    -14621.64632
Estimation based on N =  25248, K =  52
Inf.Cr.AIC  =  29347.3 AIC/N =    1.162
---------------------------------------
            Log likelihood R-sqrd R2Adj
ASCs  only  model must be fit separately
               Use NLOGIT ;...;RHS=ONE$
Note: R-sqrd = 1 - logL/Logl(constants)
Warning:  Model does not contain a full
set of ASCs. R-sqrd is problematic. Use
model setup with ;RHS=one to get LogL0.
---------------------------------------
Response data are given as proportions.
Number of obs.= 25248, skipped   0 obs
```

CHOICE	Coefficient	Standard Error	z	Prob. |z|>Z*	95% *Confidence* Interval	
CON1	-6.49690***	.16120	-40.30	.0000	-6.81286	-6.18095
T1A	-.15512***	.03842	-4.04	.0001	-.23042	-.07982
T2A	.39321***	.03695	10.64	.0000	.32079	.46564
FA	-.85539***	.02880	-29.70	.0000	-.91184	-.79895
STA	-.11155***	.01478	-7.55	.0000	-.14052	-.08258
ETA	-.18040***	.01019	-17.71	.0000	-.20036	-.16044
A1_CON1	.29809**	.12198	2.44	.0145	.05901	.53716
A1_T1A	-.00319	.03517	-.09	.9277	-.07212	.06574
A1_T2A	.01335	.03319	.40	.6875	-.05170	.07840
A1_FA	.08164***	.02969	2.75	.0060	.02344	.13984
A1_STA	.01230	.01605	.77	.4435	-.01916	.04375
A1_ETA	.00501	.01066	.47	.6383	-.01588	.02590
A2_CON1	.01315	.11886	.11	.9119	-.21980	.24610
A2_T1A	.03871	.03381	1.14	.2523	-.02756	.10498

```
  A2_T2A|      .02409          .03335        .72  .4700       -.04127     .08945
   A2_FA|      .22910***       .05157       4.44  .0000        .12803     .33017
  A2_STA|     -.03702          .02868      -1.29  .1968       -.09323     .01919
  A2_ETA|     -.06698***       .01892      -3.54  .0004       -.10406    -.02991
  D_CON1|      .09935***       .02293       4.33  .0000        .05440     .14430
   D_T1A|      .03178***       .00582       5.46  .0000        .02038     .04318
   D_T2A|     -.05139***       .00596      -8.63  .0000       -.06306    -.03971
    D_FA|      .02206***       .00307       7.18  .0000        .01604     .02807
   D_STA|     -.00423**        .00177      -2.39  .0168       -.00770    -.00077
   D_ETA|      .00420***       .00118       3.55  .0004        .00188     .00651
    CON2|     -.77840***       .03961     -19.65  .0000       -.85604    -.70076
     T1B|      .08749**        .04067       2.15  .0315        .00777     .16720
     T2B|      .16463***       .03511       4.69  .0000        .09581     .23345
      FB|    -1.36165***       .06150     -22.14  .0000      -1.48219   -1.24112
     STB|     -.26607***       .02480     -10.73  .0000       -.31468    -.21747
     ETB|     -.29489***       .01903     -15.50  .0000       -.33218    -.25759
    XTTC|     -.07892***       .01469      -5.37  .0000       -.10772    -.05012
 A1_CON2|     -.05350          .03339      -1.60  .1091       -.11895     .01194
  A1_T1B|      .05071          .03097       1.64  .1015       -.00999     .11140
  A1_T2B|     -.01085          .03313       -.33  .7432       -.07579     .05408
   A1_FB|      .10964          .06788       1.62  .1063       -.02341     .24269
  A1_STB|     -.04599*         .02653      -1.73  .0830       -.09800     .00601
  A1_ETB|      .04737**        .02042       2.32  .0204        .00734     .08739
 A1_XTTC|     -.00958          .01295       -.74  .4595       -.03496     .01580
 A2_CON2|     -.01968          .03292       -.60  .5499       -.08420     .04483
  A2_T1B|     -.02698          .03064       -.88  .3786       -.08703     .03307
  A2_T2B|      .04052          .03281       1.23  .2169       -.02379     .10483
   A2_FB|      .43705***       .11608       3.77  .0002        .20954     .66457
  A2_STB|     -.09110**        .04596      -1.98  .0475       -.18118    -.00102
  A2_ETB|      .03061          .03558        .86  .3896       -.03913     .10036
 A2_XTTC|      .01861          .01269       1.47  .1425       -.00626     .04349
  D_CON2|      .04229***       .00589       7.18  .0000        .03074     .05384
   D_T1B|     -.00958*         .00582      -1.65  .0998       -.02098     .00183
   D_T2B|     -.00911          .00577      -1.58  .1144       -.02042     .00220
    D_FB|      .02022***       .00644       3.14  .0017        .00760     .03283
   D_STB|      .00754***       .00285       2.64  .0082        .00195     .01314
   D_ETB|      .00767***       .00209       3.67  .0002        .00357     .01177
  D_XTTC|     -.01177***       .00236      -4.98  .0000       -.01640    -.00714
--------+--------------------------------------------------------------------
***, **, * ==>  Significance at 1%, 5%, 10% level.
Model was estimated on Mar 21, 2023 at 09:06:01 AM
-----------------------------------------------------------------------------
```

Listing C16: MNL model estimation Data structure D; Filter non-visiting & non-choice resp.

```
|-> Reset $
|-> Read; File=XXX\results-survey169147 df6D.csv$
Last observation read from data file was   76808
|-> Reject ; b_v = 0$
|-> Reject ; trustw = 0$
|-> Nlogit
    ; lhs = choice, numalt, count
    ; rhs = con1, t1A, t2A, fA, stA, etA, a1_con1, a1_t1A, a1_t2A, a1_fA, a1_stA,
       a1_etA, a2_con1, a2_t1A, a2_t2A, a2_fA, a2_stA, a2_etA, d_con1,  d_t1A, d_
       t2A, d_fA, d_stA, d_etA, con2, t1B, t2B, fB, stB, etB, xttc, a1_con2, a1_t
       1B, a1_t2B, a1_fB, a1_stB, a1_etB, a1_xttc, a2_con2, a2_t1B, a2_t2B, a2_fB
       , a2_stB, a2_etB, a2_xttc, d_con2, d_t1B, d_t2B, d_fB, d_stB,  d_etB, d_
       xttc
    ; Choices = 1,2,3
    ; shares
    ; CheckData
    $
```

```
+-------------------------------------------------------------+
| Inspecting the data set before estimation.                  |
| These errors mark observations which will be skipped.       |
| Row Individual = 1st row then group number of data block    |
+-------------------------------------------------------------+
No bad observations were found in the sample

Iterative procedure has converged
Normal exit:   7 iterations. Status=0, F=    .1377047D+05
```

```
-----------------------------------------------
Discrete choice (multinomial logit) model
Dependent variable                Choice
Log likelihood function     -13770.47214
Estimation based on N =  24985, K =  52
Inf.Cr.AIC  =  27644.9 AIC/N =     1.106
-----------------------------------------------
            Log likelihood R-sqrd R2Adj
ASCs  only  model must be fit separately
               Use NLOGIT ;...;RHS=ONE$
Note: R-sqrd = 1 - logL/Logl(constants)
Warning:  Model does not contain a full
set of ASCs. R-sqrd is problematic. Use
model setup with ;RHS=one to get LogL0.
-----------------------------------------------
Response data are given as proportions.
Number of obs.= 24985, skipped    0 obs
```

CHOICE	Coefficient	Standard Error	z	Prob. |z|>Z*	95% *Confidence* Interval	
CON1	-7.33495***	.18096	-40.53	.0000	-7.68963	-6.98028
T1A	-.15472***	.04056	-3.81	.0001	-.23420	-.07523
T2A	.40540***	.03873	10.47	.0000	.32950	.48131
FA	-.93828***	.03127	-30.01	.0000	-.99957	-.87700
STA	-.12423***	.01559	-7.97	.0000	-.15478	-.09368
ETA	-.19847***	.01086	-18.27	.0000	-.21976	-.17718
A1_CON1	.22692*	.13733	1.65	.0985	-.04225	.49609
A1_T1A	.00555	.03734	.15	.8819	-.06764	.07874
A1_T2A	.00412	.03479	.12	.9058	-.06407	.07230
A1_FA	.08760***	.03223	2.72	.0066	.02443	.15077
A1_STA	.00682	.01684	.40	.6856	-.02618	.03982
A1_ETA	.00382	.01131	.34	.7355	-.01835	.02599
A2_CON1	.03122	.13187	.24	.8129	-.22724	.28967
A2_T1A	.03369	.03565	.95	.3446	-.03617	.10356
A2_T2A	.03877	.03488	1.11	.2663	-.02958	.10712
A2_FA	.26330***	.05556	4.74	.0000	.15440	.37220
A2_STA	-.04869	.03008	-1.62	.1055	-.10765	.01027
A2_ETA	-.07063***	.02000	-3.53	.0004	-.10983	-.03143
D_CON1	.12681***	.02556	4.96	.0000	.07672	.17690
D_T1A	.03321***	.00612	5.43	.0000	.02122	.04521
D_T2A	-.05308***	.00625	-8.49	.0000	-.06534	-.04082
D_FA	.02552***	.00331	7.72	.0000	.01904	.03200
D_STA	-.00339*	.00187	-1.81	.0697	-.00705	.00027
D_ETA	.00510***	.00127	4.03	.0001	.00262	.00758
CON2	-.78071***	.03966	-19.68	.0000	-.85845	-.70297
T1B	.08497**	.04070	2.09	.0368	.00521	.16474
T2B	.16404***	.03513	4.67	.0000	.09518	.23290
FB	-1.36732***	.06169	-22.16	.0000	-1.48823	-1.24641
STB	-.26694***	.02483	-10.75	.0000	-.31561	-.21827
ETB	-.29688***	.01908	-15.56	.0000	-.33427	-.25949
XTTC	-.07946***	.01471	-5.40	.0000	-.10829	-.05063

```
 A1_CON2|     -.05293          .03341     -1.58  .1131       -.11842     .01255
  A1_T1B|      .05171*         .03098      1.67  .0951       -.00900     .11242
  A1_T2B|     -.01273          .03314      -.38  .7009       -.07768     .05222
   A1_FB|      .11651*         .06805      1.71  .0869       -.01687     .24989
  A1_STB|     -.04575*         .02655     -1.72  .0848       -.09778     .00628
  A1_ETB|      .04861**        .02044      2.38  .0174        .00854     .08868
 A1_XTTC|     -.00897          .01296      -.69  .4888       -.03438     .01643
 A2_CON2|     -.02247          .03297      -.68  .4955       -.08710     .04215
  A2_T1B|     -.02690          .03067      -.88  .3804       -.08701     .03321
  A2_T2B|      .03959          .03285      1.21  .2281       -.02479     .10398
   A2_FB|      .44916***       .11649      3.86  .0001        .22085     .67747
  A2_STB|     -.09145**        .04601     -1.99  .0468       -.18163    -.00128
  A2_ETB|      .03269          .03564       .92  .3590       -.03717     .10255
 A2_XTTC|      .01758          .01271      1.38  .1667       -.00733     .04250
  D_CON2|      .04241***       .00590      7.19  .0000        .03085     .05397
   D_T1B|     -.00953          .00582     -1.64  .1015       -.02094     .00188
   D_T2B|     -.00872          .00577     -1.51  .1312       -.02003     .00260
    D_FB|      .02001***       .00645      3.10  .0019        .00737     .03265
   D_STB|      .00759***       .00286      2.66  .0078        .00200     .01319
   D_ETB|      .00784***       .00209      3.74  .0002        .00373     .01194
  D_XTTC|     -.01167***       .00236     -4.94  .0000       -.01631    -.00704
--------+--------------------------------------------------------------------
***, **, * ==>  Significance at 1%, 5%, 10% level.
Model was estimated on Mar 21, 2023 at 09:06:06 AM
-----------------------------------------------------------------------------
```

Listing C17: MNL estimation (Table 16)

```
|-> Reset $
|-> Read; File=C:XXX\results-survey169147 df7.csv$
Last observation read from data file was    75152
|-> Reject ; trustw=0$
|-> create ; g_con1 = d_g*con1
    ; g_t1A = d_g*t1A
    ; g_t2A = d_g*t2A
    ; g_fA = d_g*fA
    ; g_stA = d_g*stA
    ; g_etA = d_g*etA
    ; g_con2 = d_g*con2
    ; g_t1B = d_g*t1B
    ; g_t2B = d_g*t2B
    ; g_fB = d_g*fB
    ; g_stB = d_g*stB
    ; g_etB = d_g*etB
    ; g_xttc = d_g*xttc
    $
|-> create ; a_con1 = d_a2*con1
    ; a_t1A = d_a2*t1A
    ; a_t2A = d_a2*t2A
    ; a_fA = d_a2*fA
    ; a_stA = d_a2*stA
    ; a_etA = d_a2*etA
    ; a_con2 = d_a2*con2
    ; a_t1B = d_a2*t1B
    ; a_t2B = d_a2*t2B
    ; a_fB = d_a2*fB
    ; a_stB = d_a2*stB
    ; a_etB = d_a2*etB
    ; a_xttc = d_a2*xttc
    $
|-> create ; e_con1 = d_e2*con1
    ; e_t1A = d_e2*t1A
```

```
     ; e_t2A = d_e2*t2A
     ; e_fA = d_e2*fA
     ; e_stA = d_e2*stA
     ; e_etA = d_e2*etA
     ; e_con2 = d_e2*con2
     ; e_t1B = d_e2*t1B
     ; e_t2B = d_e2*t2B
     ; e_fB = d_e2*fB
     ; e_stB = d_e2*stB
     ; e_etB = d_e2*etB
     ; e_xttc = d_e2*xttc
     $

|-> Nlogit
     ; lhs = choice, numalt, count
     ; rhs = con1, t1A, t2A, fA, stA, etA, a1_con1, a1_t1A, a1_t2A, a1_fA, a1_stA,
        a1_etA, a2_con1, a2_t1A, a2_t2A, a2_fA, a2_stA, a2_etA, d_con1, d_t1A, d_t
        2A, d_fA, d_stA, d_etA, g_con1, g_t1A, g_t2A, g_fA, g_stA, g_etA, a_con1,
        a_t1A, a_t2A, a_fA, a_stA, a_etA, e_con1, e_t1A, e_t2A, e_fA, e_stA, e_etA
        , con2, t1B, t2B, fB, stB, etB, xttc, a1_con2, a1_t1B, a1_t2B, a1_fB, a1_
        stB, a1_etB, a1_xttc, a2_con2, a2_t1B, a2_t2B, a2_fB, a2_stB, a2_etB, a2_
        xttc, d_con2, d_t1B, d_t2B, d_fB, d_stB, d_etB, d_xttc, g_con2, g_t1B, g_t
        2B, g_fB, g_stB, g_etB, g_xttc, a_con2, a_t1B, a_t2B, a_fB, a_stB, a_etB,
        a_xttc, e_con2, e_t1B, e_t2B, e_fB, e_stB, e_etB, e_xttc
     ; Choices = 1,2,3
     ; shares
     ; CheckData
     $
+-------------------------------------------------------+
| Inspecting the data set before estimation.            |
| These errors mark observations which will be skipped. |
| Row Individual = 1st row then group number of data block |
+-------------------------------------------------------+
No bad observations were found in the sample

Iterative procedure has converged
Normal exit:   7 iterations. Status=0, F=    .1623017D+05

-----------------------------------------------------------------------------
Discrete choice (multinomial logit) model
Dependent variable               Choice
Log likelihood function     -16230.17365
Estimation based on N =  29418, K =  91
Inf.Cr.AIC  =  32642.3 AIC/N =     1.110
----------------------------------------
            Log likelihood R-sqrd R2Adj
ASCs  only  model must be fit separately
               Use NLOGIT ;...;RHS=ONE$
Note: R-sqrd = 1 - logL/Logl(constants)
Warning:  Model does not contain a full
set of ASCs. R-sqrd is problematic. Use
model setup with ;RHS=one to get LogL0.
----------------------------------------
Response data are given as proportions.
Number of obs.= 29418, skipped    0 obs
--------+--------------------------------------------------------------------
        |                  Standard            Prob.       95% Confidence
  CHOICE|  Coefficient       Error       z    |z|>Z*          Interval
--------+--------------------------------------------------------------------
    CON1|   -6.15164***      .17524   -35.10  .0000     -6.49511   -5.80818
     T1A|    -.13569***      .04494    -3.02  .0025      -.22377    -.04760
     T2A|     .34151***      .04310     7.92  .0000       .25703     .42599
```

FA	−.86319***	.03091	−27.92	.0000	−.92378	−.80260
STA	−.09104***	.01574	−5.78	.0000	−.12189	−.06019
ETA	−.15940***	.01085	−14.69	.0000	−.18067	−.13812
A1_CON1	.16046	.12352	1.30	.1939	−.08164	.40257
A1_T1A	−.00273	.03420	−.08	.9363	−.06976	.06429
A1_T2A	.00025	.03189	.01	.9938	−.06225	.06275
A1_FA	.08905***	.02974	2.99	.0028	.03076	.14734
A1_STA	.00724	.01549	.47	.6402	−.02312	.03760
A1_ETA	.00658	.01036	.64	.5253	−.01372	.02688
A2_CON1	−.05348	.11949	−.45	.6545	−.28768	.18072
A2_T1A	.02707	.03278	.83	.4088	−.03717	.09131
A2_T2A	.05274	.03207	1.64	.1001	−.01012	.11560
A2_FA	.28200***	.05128	5.50	.0000	.18149	.38251
A2_STA	−.04109	.02763	−1.49	.1370	−.09523	.01306
A2_ETA	−.05426***	.01822	−2.98	.0029	−.08998	−.01854
D_CON1	.08969***	.02275	3.94	.0001	.04511	.13428
D_T1A	.03000***	.00559	5.37	.0000	.01905	.04095
D_T2A	−.04544***	.00572	−7.95	.0000	−.05664	−.03423
D_FA	.02269***	.00299	7.58	.0000	.01683	.02855
D_STA	−.00446***	.00170	−2.63	.0084	−.00779	−.00114
D_ETA	.00390***	.00114	3.43	.0006	.00167	.00614
G_CON1	−.43776***	.08629	−5.07	.0000	−.60688	−.26864
G_T1A	.05264**	.02318	2.27	.0231	.00721	.09807
G_T2A	−.05572**	.02226	−2.50	.0123	−.09934	−.01209
G_FA	−.02333**	.01179	−1.98	.0478	−.04643	−.00023
G_STA	−.01709***	.00634	−2.70	.0070	−.02952	−.00466
G_ETA	−.01425***	.00427	−3.34	.0008	−.02262	−.00589
A_CON1	.78567***	.15863	4.95	.0000	.47476	1.09657
A_T1A	.02059	.04258	.48	.6288	−.06287	.10404
A_T2A	.00997	.04084	.24	.8071	−.07007	.09001
A_FA	.03426	.02176	1.57	.1154	−.00839	.07691
A_STA	.01222	.01155	1.06	.2899	−.01041	.03486
A_ETA	.03781***	.00781	4.84	.0000	.02251	.05311
E_CON1	−1.22208***	.13104	−9.33	.0000	−1.47893	−.96524
E_T1A	.03019	.03930	.77	.4424	−.04684	.10722
E_T2A	.03078	.03797	.81	.4176	−.04364	.10519
E_FA	−.10351***	.01924	−5.38	.0000	−.14122	−.06579
E_STA	−.04324***	.01066	−4.06	.0000	−.06413	−.02236
E_ETA	−.03817***	.00708	−5.39	.0000	−.05205	−.02428
CON2	−.83714***	.04473	−18.71	.0000	−.92481	−.74947
T1B	.08577*	.04438	1.93	.0533	−.00121	.17275
T2B	.13892***	.04135	3.36	.0008	.05788	.21996
FB	−1.18470***	.06186	−19.15	.0000	−1.30595	−1.06345
STB	−.22559***	.02597	−8.69	.0000	−.27649	−.17468
ETB	−.25049***	.01971	−12.71	.0000	−.28912	−.21187
XTTC	−.03527**	.01771	−1.99	.0464	−.06997	−.00056
A1_CON2	−.04371	.03096	−1.41	.1580	−.10438	.01696
A1_T1B	.05039*	.02882	1.75	.0804	−.00611	.10688
A1_T2B	−.02934	.03073	−.96	.3396	−.08957	.03088
A1_FB	.10110	.06316	1.60	.1095	−.02269	.22490
A1_STB	−.05258**	.02477	−2.12	.0338	−.10114	−.00403
A1_ETB	.03892**	.01884	2.07	.0388	.00200	.07584
A1_XTTC	−.00802	.01241	−.65	.5181	−.03233	.01630
A2_CON2	−.01688	.03060	−.55	.5812	−.07685	.04310
A2_T1B	−.03726	.02856	−1.30	.1920	−.09324	.01872
A2_T2B	.05424*	.03048	1.78	.0752	−.00551	.11398
A2_FB	.40764***	.10802	3.77	.0002	.19592	.61935
A2_STB	−.08278*	.04281	−1.93	.0532	−.16669	.00113
A2_ETB	.00622	.03286	.19	.8498	−.05818	.07062
A2_XTTC	.01218	.01215	1.00	.3161	−.01163	.03599
D_CON2	.04171***	.00549	7.60	.0000	.03095	.05246
D_T1B	−.01026*	.00539	−1.90	.0571	−.02083	.00031

```
   D_T2B|    -.00658         .00536     -1.23  .2194     -.01707    .00392
    D_FB|     .02189***      .00600      3.65  .0003      .01014    .03364
   D_STB|     .00682**       .00265      2.57  .0102      .00162    .01202
   D_ETB|     .00774***      .00194      4.00  .0001      .00395    .01154
  D_XTTC|    -.01173***      .00226     -5.19  .0000     -.01616   -.00730
  G_CON2|    -.02448         .02152     -1.14  .2554     -.06667    .01771
   G_T1B|     .06144***      .01969      3.12  .0018      .02285    .10004
   G_T2B|    -.05716***      .02087     -2.74  .0062     -.09806   -.01626
    G_FB|    -.06640***      .02378     -2.79  .0052     -.11300   -.01980
   G_STB|    -.01897*        .00984     -1.93  .0539     -.03826    .00032
   G_ETB|    -.01924**       .00760     -2.53  .0114     -.03414   -.00435
  G_XTTC|     .00773         .00841       .92  .3579     -.00875    .02421
  A_CON2|    -.03117         .03948      -.79  .4297     -.10854    .04620
   A_T1B|    -.05303         .03609     -1.47  .1416     -.12376    .01769
   A_T2B|    -.00868         .03830      -.23  .8207     -.08374    .06638
    A_FB|     .12858***      .04317      2.98  .0029      .04397    .21320
   A_STB|     .05963***      .01801      3.31  .0009      .02432    .09493
   A_ETB|     .08659***      .01388      6.24  .0000      .05940    .11379
  A_XTTC|     .08821***      .01555      5.67  .0000      .05774    .11868
  E_CON2|     .05879         .03779      1.56  .1198     -.01528    .13286
   E_T1B|     .02160         .03507       .62  .5380     -.04713    .09033
   E_T2B|    -.01481         .03715      -.40  .6902     -.08763    .05801
    E_FB|    -.27594***      .03917     -7.04  .0000     -.35272   -.19916
   E_STB|    -.05541***      .01701     -3.26  .0011     -.08875   -.02208
   E_ETB|    -.04542***      .01294     -3.51  .0004     -.07079   -.02005
  E_XTTC|    -.05109***      .01510     -3.38  .0007     -.08067   -.02150
--------+--------------------------------------------------------------------
***, **, * ==>  Significance at 1%, 5%, 10% level.
Model was estimated on May 30, 2023 at 11:55:01 AM
-----------------------------------------------------------------------------
```

Listing C18: MNL estimation stage difference test (Table 20)

```
|-> Reset $
|-> Read; File=C:XXX\results-survey169147 df7 delta.csv$
Last observation read from data file was   75152
|-> Reject ; trustw=0$
|-> create ; g_con1 = d_g*con1
    ; g_t1A = d_g*t1A
    ; g_t2A = d_g*t2A
    ; g_fA = d_g*fA
    ; g_stA = d_g*stA
    ; g_etA = d_g*etA
    ; g_con2 = d_g*con2
    ; g_t1B = d_g*t1B
    ; g_t2B = d_g*t2B
    ; g_fB = d_g*fB
    ; g_stB = d_g*stB
    ; g_etB = d_g*etB
    ; g_xttc = d_g*xttc
    $
|-> create ; a_con1 = d_a2*con1
    ; a_t1A = d_a2*t1A
    ; a_t2A = d_a2*t2A
    ; a_fA = d_a2*fA
    ; a_stA = d_a2*stA
    ; a_etA = d_a2*etA
    ; a_con2 = d_a2*con2
    ; a_t1B = d_a2*t1B
    ; a_t2B = d_a2*t2B
    ; a_fB = d_a2*fB
    ; a_stB = d_a2*stB
```

```
     ; a_etB = d_a2*etB
     ; a_xttc = d_a2*xttc
     $
|-> create ; e_con1 = d_e2*con1
     ; e_t1A = d_e2*t1A
     ; e_t2A = d_e2*t2A
     ; e_fA = d_e2*fA
     ; e_stA = d_e2*stA
     ; e_etA = d_e2*etA
     ; e_con2 = d_e2*con2
     ; e_t1B = d_e2*t1B
     ; e_t2B = d_e2*t2B
     ; e_fB = d_e2*fB
     ; e_stB = d_e2*stB
     ; e_etB = d_e2*etB
     ; e_xttc = d_e2*xttc
     $

|-> Nlogit
     ; lhs = choice, numalt, count
     ; rhs = con1, t1A, t2A, fA, stA, etA, a1_con1, a1_t1A, a1_t2A, a1_fA, a1_stA,
        a1_etA, a2_con1, a2_t1A, a2_t2A, a2_fA, a2_stA, a2_etA, d_con1, d_t1A, d_t
        2A, d_fA, d_stA, d_etA, g_con1, g_t1A, g_t2A, g_fA, g_stA, g_etA, a_con1,
        a_t1A, a_t2A, a_fA, a_stA, a_etA, e_con1, e_t1A, e_t2A, e_fA, e_stA, e_etA
        , con2, t1B, t2B, fB, stB, etB, xttc, a1_con2, a1_t1B, a1_t2B, a1_fB, a1_
        stB, a1_etB, a1_xttc, a2_con2, a2_t1B, a2_t2B, a2_fB, a2_stB, a2_etB, a2_
        xttc, d_con2, d_t1B, d_t2B, d_fB, d_stB, d_etB, d_xttc, g_con2, g_t1B, g_t
        2B, g_fB, g_stB, g_etB, g_xttc, a_con2, a_t1B, a_t2B, a_fB, a_stB, a_etB,
        a_xttc, e_con2, e_t1B, e_t2B, e_fB, e_stB, e_etB, e_xttc
     ; Choices = 1,2,3
     ; shares
     ; CheckData
     $
+--------------------------------------------------------+
| Inspecting the data set before estimation.             |
| These errors mark observations which will be skipped.  |
| Row Individual = 1st row then group number of data block |
+--------------------------------------------------------+
No bad observations were found in the sample

Iterative procedure has converged
Normal exit:   7 iterations. Status=0, F=    .1623042D+05

-----------------------------------------------------------------------------
Discrete choice (multinomial logit) model
Dependent variable                  Choice
Log likelihood function      -16230.41525
Estimation based on N =   29418, K =  91
Inf.Cr.AIC  =   32642.8 AIC/N =    1.110
---------------------------------------------
               Log likelihood R-sqrd R2Adj
ASCs  only  model must be fit separately
               Use NLOGIT ;...;RHS=ONE$
Note: R-sqrd = 1 - logL/Logl(constants)
Warning:  Model does not contain a full
set of ASCs. R-sqrd is problematic. Use
model setup with ;RHS=one to get LogL0.
---------------------------------------------
Response data are given as proportions.
Number of obs.= 29418, skipped    0 obs
--------+--------------------------------------------------------------------
        |                  Standard            Prob.       95% Confidence
```

CHOICE	Coefficient	Error	z	|z|>Z*	Interval	
CON1	−6.15171***	.17524	−35.10	.0000	−6.49517	−5.80825
T1A	−.13570***	.04494	−3.02	.0025	−.22378	−.04762
T2A	.34143***	.04310	7.92	.0000	.25696	.42591
FA	−.86321***	.03091	−27.92	.0000	−.92380	−.80262
STA	−.09099***	.01574	−5.78	.0000	−.12185	−.06014
ETA	−.15941***	.01085	−14.69	.0000	−.18069	−.13814
A1_CON1	.16052	.12352	1.30	.1938	−.08158	.40262
A1_T1A	−.00221	.03419	−.06	.9484	−.06923	.06481
A1_T2A	.00026	.03189	.01	.9935	−.06223	.06275
A1_FA	.08905***	.02974	2.99	.0028	.03076	.14735
A1_STA	.00723	.01549	.47	.6405	−.02313	.03760
A1_ETA	.00658	.01036	.64	.5253	−.01372	.02688
A2_CON1	−.05343	.11949	−.45	.6548	−.28763	.18077
A2_T1A	.02756	.03277	.84	.4005	−.03668	.09179
A2_T2A	.05278*	.03207	1.65	.0998	−.01008	.11564
A2_FA	.28205***	.05128	5.50	.0000	.18155	.38256
A2_STA	−.04117	.02763	−1.49	.1361	−.09532	.01297
A2_ETA	−.05425***	.01822	−2.98	.0029	−.08997	−.01853
D_CON1	.08968***	.02275	3.94	.0001	.04509	.13426
D_T1A	.02997***	.00559	5.36	.0000	.01902	.04092
D_T2A	−.04543***	.00572	−7.95	.0000	−.05663	−.03423
D_FA	.02269***	.00299	7.59	.0000	.01683	.02856
D_STA	−.00447***	.00170	−2.64	.0084	−.00779	−.00115
D_ETA	.00390***	.00114	3.43	.0006	.00167	.00614
G_CON1	−.43793***	.08629	−5.08	.0000	−.60705	−.26881
G_T1A	.05304**	.02318	2.29	.0221	.00761	.09846
G_T2A	−.05573**	.02226	−2.50	.0123	−.09935	−.01210
G_FA	−.02336**	.01179	−1.98	.0475	−.04646	−.00026
G_STA	−.01708***	.00634	−2.69	.0071	−.02951	−.00466
G_ETA	−.01426***	.00427	−3.34	.0008	−.02263	−.00590
A_CON1	.78568***	.15862	4.95	.0000	.47479	1.09657
A_T1A	.02047	.04258	.48	.6306	−.06298	.10393
A_T2A	.00998	.04084	.24	.8070	−.07006	.09001
A_FA	.03427	.02176	1.57	.1153	−.00838	.07692
A_STA	.01222	.01155	1.06	.2901	−.01042	.03486
A_ETA	.03781***	.00781	4.84	.0000	.02251	.05311
E_CON1	−1.22192***	.13105	−9.32	.0000	−1.47876	−.96507
E_T1A	.02977	.03930	.76	.4488	−.04726	.10680
E_T2A	.03079	.03797	.81	.4174	−.04362	.10520
E_FA	−.10348***	.01924	−5.38	.0000	−.14119	−.06576
E_STA	−.04325***	.01066	−4.06	.0000	−.06414	−.02237
E_ETA	−.03816***	.00708	−5.39	.0000	−.05204	−.02427
CON2	−.83714***	.04473	−18.71	.0000	−.92481	−.74947
T1B	.22147***	.06316	3.51	.0005	.09768	.34526
T2B	−.20251***	.05973	−3.39	.0007	−.31958	−.08545
FB	−.32149***	.06916	−4.65	.0000	−.45703	−.18594
STB	−.13459***	.03037	−4.43	.0000	−.19412	−.07506
ETB	−.09108***	.02250	−4.05	.0001	−.13517	−.04699
XTTC	−.03527**	.01771	−1.99	.0464	−.06997	−.00056
A1_CON2	−.04371	.03096	−1.41	.1580	−.10438	.01696
A1_T1B	.05260	.04472	1.18	.2395	−.03505	.14025
A1_T2B	−.02960	.04428	−.67	.5038	−.11639	.05718
A1_FB	.01205	.06981	.17	.8630	−.12479	.14888
A1_STB	−.05982**	.02922	−2.05	.0406	−.11709	−.00255
A1_ETB	.03234	.02150	1.50	.1325	−.00980	.07448
A1_XTTC	−.00802	.01241	−.65	.5181	−.03233	.01630
A2_CON2	−.01688	.03060	−.55	.5812	−.07685	.04310
A2_T1B	−.06482	.04347	−1.49	.1360	−.15002	.02039
A2_T2B	.00146	.04425	.03	.9737	−.08526	.08818
A2_FB	.12558	.11957	1.05	.2936	−.10878	.35994

A2_STB	−.04161	.05095	−.82	.4141	−.14147	.05826
A2_ETB	.06047	.03757	1.61	.1075	−.01317	.13411
A2_XTTC	.01218	.01215	1.00	.3161	−.01163	.03599
D_CON2	.04171***	.00549	7.60	.0000	.03095	.05246
D_T1B	−.04023***	.00777	−5.18	.0000	−.05545	−.02501
D_T2B	.03885***	.00783	4.96	.0000	.02350	.05420
D_FB	−.00080	.00670	−.12	.9050	−.01393	.01233
D_STB	.01129***	.00315	3.59	.0003	.00512	.01746
D_ETB	.00384*	.00225	1.71	.0873	−.00056	.00824
D_XTTC	−.01173***	.00226	−5.19	.0000	−.01616	−.00730
G_CON2	−.02448	.02152	−1.14	.2554	−.06667	.01771
G_T1B	.00841	.03041	.28	.7823	−.05120	.06801
G_T2B	−.00143	.03051	−.05	.9626	−.06123	.05837
G_FB	−.04304	.02654	−1.62	.1048	−.09505	.00897
G_STB	−.00188	.01171	−.16	.8721	−.02483	.02106
G_ETB	−.00498	.00872	−.57	.5675	−.02207	.01210
G_XTTC	.00773	.00841	.92	.3579	−.00875	.02421
A_CON2	−.03117	.03948	−.79	.4297	−.10854	.04620
A_T1B	−.07351	.05581	−1.32	.1878	−.18290	.03589
A_T2B	−.01865	.05598	−.33	.7390	−.12838	.09107
A_FB	.09431*	.04834	1.95	.0511	−.00044	.18907
A_STB	.04741**	.02140	2.22	.0267	.00547	.08935
A_ETB	.04878***	.01592	3.06	.0022	.01758	.07999
A_XTTC	.08821***	.01555	5.67	.0000	.05774	.11868
E_CON2	.05879	.03779	1.56	.1198	−.01528	.13286
E_T1B	−.00817	.05267	−.16	.8767	−.11141	.09507
E_T2B	−.04560	.05312	−.86	.3907	−.14971	.05852
E_FB	−.17246***	.04365	−3.95	.0001	−.25800	−.08692
E_STB	−.01216	.02007	−.61	.5445	−.05150	.02717
E_ETB	−.00726	.01476	−.49	.6226	−.03618	.02166
E_XTTC	−.05109***	.01510	−3.38	.0007	−.08067	−.02150

***, **, * ==> Significance at 1%, *5%, 10% level*.
Model was estimated on May 30, 2023 at 00:14:58 PM

D Estimations Latent Class Models

Listing D1: 2 class LCM (Tables 21 & 22)

```
|-> Reset $
|-> Read; File=XXX\results-survey169147 df7.csv$
|-> Reject ; trustw = 0$
|-> Create ; p1 = 0 ; p2 = 0$
|-> Namelist ; cp = p1,p2$
|-> Nlogit
    ; lhs = choice, numalt, count
    ; rhs = con1, t1A, t2A, fA, stA, etA, a1_con1, a1_t1A, a1_t2A, a1_fA, a1_stA,
        a1_etA, a2_con1, a2_t1A, a2_t2A, a2_fA, a2_stA, a2_etA, d_con1, d_t1A, d_
        t2A, d_fA, d_stA, d_etA, con2, t1B, t2B, fB, stB, etB, xttc, a1_con2, a
        1_t1B, a1_t2B, a1_fB, a1_stB, a1_etB,a1_xttc, a2_con2, a2_t1B, a2_t2B, a2_
        fB, a2_stB, a2_etB,a2_xttc, d_con2, d_t1B, d_t2B, d_fB, d_stB, d_etB,
         d_xttc
    ; Choices = 1,2,3
    ; lcm
    ; classp = cp
    ; pds = nument
    ; pts = 2
    ; maxit = 250
    $
Error    352: Model with Panel. Sum of T(i) not equal to full sample size
Constructed name A1_CON|1 was not unique. Changed to A1_CO1|1
Constructed name A2_CON|1 was not unique. Changed to A2_CO1|1
Constructed name A1_CON|2 was not unique. Changed to A1_CO1|2
Constructed name A2_CON|2 was not unique. Changed to A2_CO1|2
Iterative procedure has converged
Normal exit:   7 iterations. Status=0, F=    .1642550D+05

---------------------------------------------------------------------------------
Discrete choice (multinomial logit) model
Dependent variable                Choice
Log likelihood function     -16425.50163
Estimation based on N =  29418, K =  52
Inf.Cr.AIC  =  32955.0 AIC/N =    1.120
-----------------------------------------
            Log likelihood R-sqrd R2Adj
ASCs  only  model must be fit separately
               Use NLOGIT ;...;RHS=ONE$
Note: R-sqrd = 1 - logL/Logl(constants)
Warning:  Model does not contain a full
set of ASCs. R-sqrd is problematic. Use
model setup with ;RHS=one to get LogL0.
-----------------------------------------
Response data are given as ind. choices
Number of obs.= 29418, skipped    0 obs
---------+-----------------------------------------------------------------------
         |                Standard            Prob.      95% Confidence
  CHOICE|  Coefficient       Error       z    |z|>Z*         Interval
---------+-----------------------------------------------------------------------
 CON1|1|   -6.96243***      .15957   -43.63  .0000    -7.27518  -6.64968
  T1A|1|    -.11897***      .03639    -3.27  .0011     -.19029   -.04765
  T2A|1|     .35921***      .03495    10.28  .0000      .29071    .42770
   FA|1|    -.92668***      .02839   -32.65  .0000     -.98231   -.87104
  STA|1|    -.11770***      .01414    -8.33  .0000     -.14541   -.09000
  ETA|1|    -.18743***      .00980   -19.13  .0000     -.20664   -.16822
A1_CON|1|     .16006         .12392     1.29  .1965     -.08282    .40294
```

A1_T1A|1|	−.00324	.03401	−.10	.9242	−.06989	.06342
A1_T2A|1|	−.00027	.03174	−.01	.9932	−.06248	.06194
A1_FA|1|	.09106***	.02967	3.07	.0021	.03291	.14920
A1_STA|1|	.00576	.01541	.37	.7085	−.02444	.03597
A1_ETA|1|	.00661	.01032	.64	.5220	−.01363	.02685
A2_CON|1|	−.06375	.11946	−.53	.5936	−.29788	.17038
A2_T1A|1|	.02600	.03255	.80	.4243	−.03779	.08980
A2_T2A|1|	.05612*	.03190	1.76	.0785	−.00639	.11864
A2_FA|1|	.28324***	.05107	5.55	.0000	.18314	.38334
A2_STA|1|	−.04208	.02745	−1.53	.1253	−.09589	.01172
A2_ETA|1|	−.05310***	.01815	−2.93	.0034	−.08867	−.01752
D_CON1|1|	.09350***	.02282	4.10	.0000	.04878	.13822
D_T1A|1|	.02944***	.00555	5.30	.0000	.01856	.04033
D_T2A|1|	−.04500***	.00569	−7.91	.0000	−.05615	−.03386
D_FA|1|	.02278***	.00299	7.62	.0000	.01692	.02864
D_STA|1|	−.00429**	.00169	−2.53	.0113	−.00761	−.00097
D_ETA|1|	.00409***	.00114	3.60	.0003	.00186	.00632
CON2|1|	−.78505***	.03653	−21.49	.0000	−.85664	−.71346
T1B|1|	.11416***	.03727	3.06	.0022	.04112	.18721
T2B|1|	.12705***	.03236	3.93	.0001	.06363	.19047
FB|1|	−1.36965***	.05699	−24.03	.0000	−1.48136	−1.25795
STB|1|	−.26662***	.02306	−11.56	.0000	−.31182	−.22143
ETB|1|	−.28362***	.01748	−16.23	.0000	−.31788	−.24937
XTTC|1|	−.07967***	.01390	−5.73	.0000	−.10692	−.05242
A1_CO1|1|	−.04251	.03075	−1.38	.1668	−.10278	.01776
A1_T1B|1|	.04871*	.02853	1.71	.0878	−.00721	.10463
A1_T2B|1|	−.03022	.03055	−.99	.3225	−.09009	.02965
A1_FB|1|	.09905	.06285	1.58	.1150	−.02413	.22224
A1_STB|1|	−.05079**	.02461	−2.06	.0390	−.09901	−.00256
A1_ETB|1|	.03689**	.01872	1.97	.0487	.00021	.07358
A1_XTT|1|	−.00613	.01230	−.50	.6179	−.03023	.01797
A2_CO1|1|	−.01775	.03034	−.59	.5584	−.07722	.04171
A2_T1B|1|	−.03015	.02827	−1.07	.2862	−.08555	.02525
A2_T2B|1|	.05039*	.03025	1.67	.0958	−.00891	.10968
A2_FB|1|	.39565***	.10742	3.68	.0002	.18511	.60620
A2_STB|1|	−.07803*	.04251	−1.84	.0664	−.16134	.00528
A2_ETB|1|	.00774	.03264	.24	.8126	−.05623	.07171
A2_XTT|1|	.01209	.01202	1.01	.3144	−.01146	.03565
D_CON2|1|	.04171***	.00544	7.66	.0000	.03104	.05238
D_T1B|1|	−.01152**	.00535	−2.15	.0313	−.02200	−.00103
D_T2B|1|	−.00632	.00532	−1.19	.2354	−.01675	.00412
D_FB|1|	.02344***	.00597	3.92	.0001	.01173	.03515
D_STB|1|	.00683***	.00264	2.59	.0096	.00166	.01199
D_ETB|1|	.00770***	.00192	4.00	.0001	.00393	.01148
D_XTTC|1|	−.01144***	.00223	−5.12	.0000	−.01582	−.00706

***, **, * ==> Significance at *1%, 5%, 10% level*.
Model was estimated on Apr 25, 2023 at 11:02:23 PM

Line search at iteration 176 does not improve the function
Exiting optimization

Latent Class Logit Model
Dependent variable CHOICE
Log likelihood function −18338.52879
Restricted log likelihood −32318.97631
Chi squared [105](P= .000) 27960.89504
Significance level .00000
McFadden Pseudo R−squared .4325771
Estimation based on N = 29418, K = 105

```
Inf.Cr.AIC  =  36887.1 AIC/N =     1.254
-----------------------------------------
           Log likelihood R-sqrd R2Adj
No coefficients **********  .4326 .4312
Constants only can be computed directly
             Use NLOGIT ;...;RHS=ONE$
At start values **********  .2754 .2737
Note: R-sqrd = 1 - logL/Logl(constants)
Warning:  Model does not contain a full
set of ASCs. R-sqrd is problematic. Use
model setup with ;RHS=one to get LogL0.
-----------------------------------------
Response data are given as ind. choices
Number of latent classes =             2
Average Class Probabilities
     .528  .472
LCM model with panel has    1546 groups
Variable number of obs./group =NUMENT
Number of obs.= 29418, skipped    0 obs
```

CHOICE	Coefficient	Standard Error	z	Prob. |z|>Z*	95% *Confidence* Interval	
	Random utility parameters in latent class -->> 1..................					
CON1|1|	-3.67084***	.18565	-19.77	.0000	-4.03471	-3.30696
T1A|1|	.03883	.05360	.72	.4688	-.06622	.14389
T2A|1|	.38243***	.05252	7.28	.0000	.27949	.48537
FA|1|	-.50832***	.03749	-13.56	.0000	-.58179	-.43485
STA|1|	-.08608***	.02103	-4.09	.0000	-.12729	-.04487
ETA|1|	-.08176***	.01498	-5.46	.0000	-.11112	-.05241
A1_CON|1|	.18449	.13269	1.39	.1644	-.07558	.44456
A1_T1A|1|	.06631	.04841	1.37	.1708	-.02858	.16119
A1_T2A|1|	-.02556	.04749	-.54	.5904	-.11864	.06752
A1_FA|1|	.12285***	.03884	3.16	.0016	.04672	.19899
A1_STA|1|	-.01688	.02309	-.73	.4648	-.06213	.02837
A1_ETA|1|	-.00766	.01516	-.51	.6134	-.03737	.02205
A2_CON|1|	.13424	.13459	1.00	.3186	-.12955	.39804
A2_T1A|1|	.03161	.04766	.66	.5073	-.06181	.12502
A2_T2A|1|	.14382***	.04788	3.00	.0027	.04998	.23766
A2_FA|1|	.23435***	.06873	3.41	.0007	.09963	.36907
A2_STA|1|	-.07970*	.04149	-1.92	.0547	-.16102	.00162
A2_ETA|1|	-.06246**	.02725	-2.29	.0219	-.11586	-.00906
D_CON1|1|	.02793	.02532	1.10	.2699	-.02169	.07755
D_T1A|1|	.01051	.00824	1.28	.2019	-.00563	.02666
D_T2A|1|	-.03614***	.00844	-4.28	.0000	-.05267	-.01960
D_FA|1|	.00116	.00400	.29	.7716	-.00667	.00899
D_STA|1|	.00017	.00250	.07	.9454	-.00474	.00508
D_ETA|1|	.00166	.00159	1.04	.2979	-.00147	.00479
CON2|1|	-.74998***	.06444	-11.64	.0000	-.87629	-.62368
T1B|1|	.18036***	.06240	2.89	.0038	.05807	.30266
T2B|1|	.15075**	.05876	2.57	.0103	.03557	.26592
FB|1|	-.12520**	.05911	-2.12	.0342	-.24104	-.00936
STB|1|	.06092*	.03123	1.95	.0511	-.00029	.12213
ETB|1|	.00818	.02250	.36	.7164	-.03593	.05228
XTTC|1|	-.09411***	.02421	-3.89	.0001	-.14157	-.04665
A1_CO1|1|	-.02675	.05167	-.52	.6046	-.12801	.07451
A1_T1B|1|	.00711	.05120	.14	.8896	-.09324	.10745
A1_T2B|1|	.10648**	.05222	2.04	.0414	.00413	.20883
A1_FB|1|	-.01703	.06351	-.27	.7886	-.14151	.10745
A1_STB|1|	-.00653	.03529	-.19	.8531	-.07570	.06264
A1_ETB|1|	.00234	.02394	.10	.9221	-.04458	.04926
A1_XTT|1|	.03006	.02043	1.47	.1412	-.00998	.07010

A2_CO1|1	.01763	.05273	.33	.7380	-.08571	.12098
A2_T1B|1	.10589**	.04971	2.13	.0332	.00846	.20331
A2_T2B|1	-.07710	.05266	-1.46	.1432	-.18030	.02611
A2_FB|1	-.02392	.11053	-.22	.8286	-.24055	.19270
A2_STB|1	.01532	.05984	.26	.7979	-.10196	.13261
A2_ETB|1	-.01567	.04149	-.38	.7057	-.09698	.06564
A2_XTT|1	-.00462	.02000	-.23	.8173	-.04382	.03458
D_CON2|1	.02525***	.00917	2.75	.0059	.00727	.04323
D_T1B|1	-.00959	.00910	-1.05	.2920	-.02743	.00825
D_T2B|1	-.00199	.00902	-.22	.8250	-.01967	.01568
D_FB|1	-.00144	.00593	-.24	.8084	-.01306	.01018
D_STB|1	-.00706**	.00348	-2.03	.0421	-.01387	-.00025
D_ETB|1	.00036	.00245	.15	.8840	-.00444	.00516
D_XTTC|1	.00579	.00372	1.56	.1192	-.00149	.01307
|Random utility parameters in latent class —>> 2..................						
CON1|2	-16.7739***	.85285	-19.67	.0000	-18.4454	-15.1023
T1A|2	-.17914**	.07384	-2.43	.0153	-.32387	-.03441
T2A|2	.40470***	.06958	5.82	.0000	.26832	.54107
FA|2	-1.90285***	.09299	-20.46	.0000	-2.08512	-1.72059
STA|2	-.32220***	.03580	-9.00	.0000	-.39238	-.25203
ETA|2	-.42664***	.02920	-14.61	.0000	-.48387	-.36941
A1_CON|2	-2.12018**	.89803	-2.36	.0182	-3.88028	-.36008
A1_T1A|2	-.05646	.07292	-.77	.4387	-.19938	.08645
A1_T2A|2	.10056	.06536	1.54	.1239	-.02755	.22867
A1_FA|2	-.12747	.09750	-1.31	.1911	-.31857	.06364
A1_STA|2	-.09159**	.03766	-2.43	.0150	-.16542	-.01777
A1_ETA|2	-.05637*	.03106	-1.82	.0695	-.11724	.00449
A2_CON|2	.48008	.65978	.73	.4668	-.81307	1.77323
A2_T1A|2	.00274	.06866	.04	.9682	-.13184	.13731
A2_T2A|2	.00257	.06275	.04	.9674	-.12042	.12555
A2_FA|2	.34376**	.15595	2.20	.0275	.03811	.64942
A2_STA|2	-.12848**	.06217	-2.07	.0388	-.25034	-.00663
A2_ETA|2	-.09515*	.05182	-1.84	.0663	-.19672	.00642
D_CON1|2	.26589*	.15273	1.74	.0817	-.03345	.56523
D_T1A|2	.05379***	.01129	4.77	.0000	.03167	.07591
D_T2A|2	-.06248***	.01139	-5.49	.0000	-.08480	-.04015
D_FA|2	.07573***	.00905	8.37	.0000	.05799	.09347
D_STA|2	.00714*	.00413	1.73	.0839	-.00096	.01524
D_ETA|2	.01441***	.00334	4.32	.0000	.00787	.02096
CON2|2	-.28289***	.03989	-7.09	.0000	-.36108	-.20470
T1B|2	.37095***	.04187	8.86	.0000	.28888	.45302
T2B|2	.15224***	.03815	3.99	.0001	.07747	.22700
FB|2	-.29550***	.04183	-7.06	.0000	-.37749	-.21352
STB|2	.09464***	.01956	4.84	.0000	.05630	.13298
ETB|2	.05164***	.01463	3.53	.0004	.02296	.08032
XTTC|2	-.09652***	.01524	-6.33	.0000	-.12639	-.06665
A1_CO1|2	-.10696***	.03330	-3.21	.0013	-.17223	-.04169
A1_T1B|2	.07409**	.03418	2.17	.0302	.00710	.14107
A1_T2B|2	.04099	.03484	1.18	.2394	-.02730	.10928
A1_FB|2	.02321	.04619	.50	.6152	-.06731	.11374
A1_STB|2	-.05763***	.02226	-2.59	.0096	-.10126	-.01400
A1_ETB|2	-.01316	.01573	-.84	.4028	-.04399	.01767
A1_XTT|2	.02440*	.01323	1.84	.0652	-.00153	.05033
A2_CO1|2	.05549*	.03366	1.65	.0992	-.01047	.12146
A2_T1B|2	.08842***	.03282	2.69	.0071	.02409	.15275
A2_T2B|2	-.03506	.03456	-1.01	.3103	-.10279	.03267
A2_FB|2	.06234	.07812	.80	.4249	-.09077	.21545
A2_STB|2	-.05797	.03863	-1.50	.1335	-.13369	.01775
A2_ETB|2	-.07095***	.02747	-2.58	.0098	-.12479	-.01711
A2_XTT|2	.00338	.01297	.26	.7945	-.02204	.02880
D_CON2|2	.02548***	.00590	4.32	.0000	.01392	.03704
D_T1B|2	-.04629***	.00608	-7.61	.0000	-.05821	-.03437

```
 D_T2B|2|     -.00962          .00597     -1.61  .1073      -.02133     .00209
  D_FB|2|     -.00331          .00414      -.80  .4248      -.01143     .00481
 D_STB|2|     -.00747***       .00217     -3.45  .0006      -.01172    -.00322
 D_ETB|2|     -.00192          .00161     -1.19  .2331      -.00508     .00124
D_XTTC|2|     -.00094          .00238      -.40  .6917      -.00561     .00372
         |Estimated latent class probabilities...............................
 PrbCls1|     1.00000***    .2572D-07 ********  .0000      1.00000    1.00000
 PrbCls2|         0.0       .2568D-07      .00 1.0000 -.50336D-07  .50336D-07
---------+--------------------------------------------------------------------
nnnnn.D-xx or D+xx => multiply by 10 to -xx or +xx.
***, **, * ==>  Significance at 1%, 5%, 10% level.
Model was estimated on Apr 25, 2023 at 11:04:57 PM
-----------------------------------------------------------------------------
```

Listing D2: 3 class LCM (Tables 23 & 24)

```
|-> Reset $
|-> Read; File=XXX\results-survey169147 df7.csv$
|-> Reject ; trustw = 0$
|-> Create ; p1 = 0 ; p2 = 0; p3 = 0$
|-> Namelist ; cp = p1,p2,p3$
|-> Nlogit
    ; lhs = choice, numalt, count
    ; rhs = con1, t1A, t2A, fA, stA, etA, a1_con1, a1_t1A, a1_t2A, a1_fA, a1_stA,
       a1_etA, a2_con1, a2_t1A, a2_t2A, a2_fA, a2_stA, a2_etA, d_con1, d_t1A,  d_
       t2A,  d_fA,  d_stA,  d_etA, con2, t1B, t2B, fB, stB, etB, xttc, a1_con2, a
       1_t1B, a1_t2B, a1_fB, a1_stB, a1_etB, a1_xttc, a2_con2, a2_t1B, a2_t2B, a
       2_fB, a2_stB, a2_etB, a2_xttc, d_con2, d_t1B,  d_t2B,  d_fB,  d_stB,  d_
       etB,  d_xttc
    ; Choices = 1,2,3
    ; lcm
    ; classp = cp
    ; pds = nument
    ; pts = 3
    ; maxit = 250
    ; keep =p1,p2,p3
    $
Error    352: Model with Panel. Sum of T(i) not equal to full sample size
Constructed name A1_CON|1 was not unique. Changed to A1_CO1|1
Constructed name A2_CON|1 was not unique. Changed to A2_CO1|1
Constructed name A1_CON|2 was not unique. Changed to A1_CO1|2
Constructed name A2_CON|2 was not unique. Changed to A2_CO1|2
Constructed name A1_CON|3 was not unique. Changed to A1_CO1|3
Constructed name A2_CON|3 was not unique. Changed to A2_CO1|3
Iterative procedure has converged
Normal exit:   7 iterations. Status=0, F=    .1642550D+05

-----------------------------------------------------------------------------
Discrete choice (multinomial logit) model
Dependent variable               Choice
Log likelihood function     -16425.50163
Estimation based on N =  29418, K =  52
Inf.Cr.AIC  =  32955.0 AIC/N =    1.120
---------------------------------------
              Log likelihood R-sqrd R2Adj
ASCs  only  model must be fit separately
                 Use NLOGIT ;...;RHS=ONE$
Note: R-sqrd = 1 - logL/Logl(constants)
Warning:  Model does not contain a full
set of ASCs. R-sqrd is problematic. Use
model setup with ;RHS=one to get LogL0.
---------------------------------------
```

Response data are given as ind. choices
Number of obs.= 29418, skipped 0 obs

CHOICE	Coefficient	Standard Error	z	Prob. |z|>Z*	95% *Confidence* Interval	
CON1|1|	−6.96243***	.15957	−43.63	.0000	−7.27518	−6.64968
T1A|1|	−.11897***	.03639	−3.27	.0011	−.19029	−.04765
T2A|1|	.35921***	.03495	10.28	.0000	.29071	.42770
FA|1|	−.92668***	.02839	−32.65	.0000	−.98231	−.87104
STA|1|	−.11770***	.01414	−8.33	.0000	−.14541	−.09000
ETA|1|	−.18743***	.00980	−19.13	.0000	−.20664	−.16822
A1_CON|1|	.16006	.12392	1.29	.1965	−.08282	.40294
A1_T1A|1|	−.00324	.03401	−.10	.9242	−.06989	.06342
A1_T2A|1|	−.00027	.03174	−.01	.9932	−.06248	.06194
A1_FA|1|	.09106***	.02967	3.07	.0021	.03291	.14920
A1_STA|1|	.00576	.01541	.37	.7085	−.02444	.03597
A1_ETA|1|	.00661	.01032	.64	.5220	−.01363	.02685
A2_CON|1|	−.06375	.11946	−.53	.5936	−.29788	.17038
A2_T1A|1|	.02600	.03255	.80	.4243	−.03779	.08980
A2_T2A|1|	.05612*	.03190	1.76	.0785	−.00639	.11864
A2_FA|1|	.28324***	.05107	5.55	.0000	.18314	.38334
A2_STA|1|	−.04208	.02745	−1.53	.1253	−.09589	.01172
A2_ETA|1|	−.05310***	.01815	−2.93	.0034	−.08867	−.01752
D_CON1|1|	.09350***	.02282	4.10	.0000	.04878	.13822
D_T1A|1|	.02944***	.00555	5.30	.0000	.01856	.04033
D_T2A|1|	−.04500***	.00569	−7.91	.0000	−.05615	−.03386
D_FA|1|	.02278***	.00299	7.62	.0000	.01692	.02864
D_STA|1|	−.00429**	.00169	−2.53	.0113	−.00761	−.00097
D_ETA|1|	.00409***	.00114	3.60	.0003	.00186	.00632
CON2|1|	−.78505***	.03653	−21.49	.0000	−.85664	−.71346
T1B|1|	.11416***	.03727	3.06	.0022	.04112	.18721
T2B|1|	.12705***	.03236	3.93	.0001	.06363	.19047
FB|1|	−1.36965***	.05699	−24.03	.0000	−1.48136	−1.25795
STB|1|	−.26662***	.02306	−11.56	.0000	−.31182	−.22143
ETB|1|	−.28362***	.01748	−16.23	.0000	−.31788	−.24937
XTTC|1|	−.07967***	.01390	−5.73	.0000	−.10692	−.05242
A1_CO1|1|	−.04251	.03075	−1.38	.1668	−.10278	.01776
A1_T1B|1|	.04871*	.02853	1.71	.0878	−.00721	.10463
A1_T2B|1|	−.03022	.03055	−.99	.3225	−.09009	.02965
A1_FB|1|	.09905	.06285	1.58	.1150	−.02413	.22224
A1_STB|1|	−.05079**	.02461	−2.06	.0390	−.09901	−.00256
A1_ETB|1|	.03689**	.01872	1.97	.0487	.00021	.07358
A1_XTT|1|	−.00613	.01230	−.50	.6179	−.03023	.01797
A2_CO1|1|	−.01775	.03034	−.59	.5584	−.07722	.04171
A2_T1B|1|	−.03015	.02827	−1.07	.2862	−.08555	.02525
A2_T2B|1|	.05039*	.03025	1.67	.0958	−.00891	.10968
A2_FB|1|	.39565***	.10742	3.68	.0002	.18511	.60620
A2_STB|1|	−.07803*	.04251	−1.84	.0664	−.16134	.00528
A2_ETB|1|	.00774	.03264	.24	.8126	−.05623	.07171
A2_XTT|1|	.01209	.01202	1.01	.3144	−.01146	.03565
D_CON2|1|	.04171***	.00544	7.66	.0000	.03104	.05238
D_T1B|1|	−.01152**	.00535	−2.15	.0313	−.02200	−.00103
D_T2B|1|	−.00632	.00532	−1.19	.2354	−.01675	.00412
D_FB|1|	.02344***	.00597	3.92	.0001	.01173	.03515
D_STB|1|	.00683***	.00264	2.59	.0096	.00166	.01199
D_ETB|1|	.00770***	.00192	4.00	.0001	.00393	.01148
D_XTTC|1|	−.01144***	.00223	−5.12	.0000	−.01582	−.00706

***, **, * ==> Significance at 1%, 5%, 10% *level*.
Model was estimated on Apr 25, 2023 at 11:10:40 PM

```
Line search at iteration 234 does not improve the function
Exiting optimization
```

```
Latent Class Logit Model
Dependent variable                 CHOICE
Log likelihood function      -17804.81138
Restricted log likelihood    -32318.97631
Chi squared [158](P= .000)    29028.32985
Significance level                 .00000
McFadden Pseudo R-squared        .4490911
Estimation based on N =  29418, K = 158
Inf.Cr.AIC  =  35925.6 AIC/N =     1.221
-----------------------------------------
          Log likelihood R-sqrd R2Adj
No coefficients **********  .4491 .4471
Constants only can be computed directly
              Use NLOGIT ;...;RHS=ONE$
At start values **********  .2956 .2931
Note: R-sqrd = 1 - logL/Logl(constants)
Warning:  Model does not contain a full
set of ASCs. R-sqrd is problematic. Use
model setup with ;RHS=one to get LogL0.
-----------------------------------------
Response data are given as ind. choices
Number of latent classes =            3
Average Class Probabilities
    .316  .314  .369
LCM model with panel has   1546 groups
Variable number of obs./group =NUMENT
Number of obs.= 29418, skipped    0 obs
```

CHOICE	Coefficient	Standard Error	z	Prob. |z|>Z*	95% *Confidence* Interval	
	Random utility parameters in latent class -->> 1..................					
CON1|1	−13.7688***	.99201	−13.88	.0000	−15.7131	−11.8245
T1A|1	−.05282	.11741	−.45	.6528	−.28294	.17729
T2A|1	.23344**	.11103	2.10	.0355	.01583	.45105
FA|1	−1.57614***	.11736	−13.43	.0000	−1.80616	−1.34611
STA|1	−.33348***	.05073	−6.57	.0000	−.43292	−.23405
ETA|1	−.39393***	.03899	−10.10	.0000	−.47035	−.31751
A1_CON|1	−1.59577*	.95584	−1.67	.0950	−3.46917	.27764
A1_T1A|1	.06283	.11102	.57	.5715	−.15476	.28042
A1_T2A|1	.02756	.09953	.28	.7819	−.16751	.22262
A1_FA|1	−.03982	.13721	−.29	.7717	−.30875	.22911
A1_STA|1	−.04352	.05469	−.80	.4262	−.15072	.06368
A1_ETA|1	−.04756	.04372	−1.09	.2767	−.13325	.03813
A2_CON|1	.87122	.63534	1.37	.1703	−.37402	2.11647
A2_T1A|1	−.05860	.09785	−.60	.5493	−.25038	.13319
A2_T2A|1	.12079	.09330	1.29	.1954	−.06207	.30365
A2_FA|1	.18358	.20113	.91	.3614	−.21063	.57779
A2_STA|1	−.12851	.09078	−1.42	.1569	−.30643	.04942
A2_ETA|1	−.11761*	.06600	−1.78	.0747	−.24697	.01174
D_CON1|1	.52911***	.10692	4.95	.0000	.31955	.73867
D_T1A|1	.02397	.01656	1.45	.1477	−.00848	.05643
D_T2A|1	−.04259***	.01635	−2.61	.0092	−.07463	−.01055
D_FA|1	.06723***	.01246	5.39	.0000	.04280	.09166
D_STA|1	.01411**	.00579	2.44	.0148	.00276	.02547
D_ETA|1	.02203***	.00456	4.83	.0000	.01309	.03097
CON2|1	−1.24387***	.18218	−6.83	.0000	−1.60093	−.88681

T1B|1|	-.55326***	.16591	-3.33	.0009	-.87843	-.22808
T2B|1|	.12928	.11058	1.17	.2423	-.08744	.34600
FB|1|	-3.92685***	.38789	-10.12	.0000	-4.68709	-3.16661
STB|1|	-1.06414***	.12191	-8.73	.0000	-1.30308	-.82520
ETB|1|	-.91642***	.10954	-8.37	.0000	-1.13112	-.70171
XTTC|1|	-.21110***	.05021	-4.20	.0000	-.30950	-.11270
A1_CO1|1|	.19463*	.11537	1.69	.0916	-.03148	.42075
A1_T1B|1|	.21273**	.10276	2.07	.0384	.01132	.41413
A1_T2B|1|	-.14481	.09678	-1.50	.1346	-.33449	.04487
A1_FB|1|	-.05039	.48987	-.10	.9181	-1.01051	.90973
A1_STB|1|	-.04755	.13170	-.36	.7180	-.30567	.21057
A1_ETB|1|	-.02332	.09970	-.23	.8151	-.21872	.17208
A1_XTT|1|	.01291	.04571	.28	.7777	-.07669	.10251
A2_CO1|1|	-.27813**	.12137	-2.29	.0219	-.51601	-.04024
A2_T1B|1|	-.26938***	.10321	-2.61	.0091	-.47168	-.06709
A2_T2B|1|	.14631	.10193	1.44	.1512	-.05347	.34610
A2_FB|1|	1.06502	.79034	1.35	.1778	-.48401	2.61406
A2_STB|1|	-.09438	.21824	-.43	.6654	-.52211	.33336
A2_ETB|1|	-.10678	.18310	-.58	.5598	-.46564	.25208
A2_XTT|1|	.10727**	.04659	2.30	.0213	.01596	.19858
D_CON2|1|	.08598***	.02271	3.79	.0002	.04146	.13049
D_T1B|1|	.07054***	.02171	3.25	.0012	.02798	.11309
D_T2B|1|	-.00255	.01788	-.14	.8867	-.03759	.03250
D_FB|1|	.08772*	.05011	1.75	.0800	-.01050	.18594
D_STB|1|	.07236***	.01489	4.86	.0000	.04318	.10153
D_ETB|1|	.04057***	.01124	3.61	.0003	.01855	.06260
D_XTTC|1|	-.01809**	.00838	-2.16	.0307	-.03451	-.00168
|	Random utility parameters in latent class -->> 2..................					
CON1|2|	-15.1647***	.79351	-19.11	.0000	-16.7199	-13.6094
T1A|2|	-.19136**	.07898	-2.42	.0154	-.34615	-.03657
T2A|2|	.44675***	.07442	6.00	.0000	.30090	.59261
FA|2|	-1.76467***	.09454	-18.67	.0000	-1.94996	-1.57937
STA|2|	-.26720***	.03658	-7.31	.0000	-.33889	-.19552
ETA|2|	-.36604***	.02956	-12.38	.0000	-.42397	-.30811
A1_CON|2|	-1.37183**	.65507	-2.09	.0362	-2.65574	-.08792
A1_T1A|2|	-.04521	.07728	-.59	.5585	-.19667	.10625
A1_T2A|2|	.05688	.07009	.81	.4171	-.08050	.19426
A1_FA|2|	-.11068	.10165	-1.09	.2762	-.30991	.08855
A1_STA|2|	-.09172**	.03962	-2.32	.0206	-.16938	-.01407
A1_ETA|2|	-.04994	.03206	-1.56	.1193	-.11277	.01289
A2_CON|2|	-.32649	.62078	-.53	.5989	-1.54319	.89020
A2_T1A|2|	.00329	.07255	.05	.9638	-.13890	.14549
A2_T2A|2|	.00625	.06550	.10	.9240	-.12213	.13463
A2_FA|2|	.35006**	.16016	2.19	.0288	.03616	.66397
A2_STA|2|	-.12800**	.06438	-1.99	.0468	-.25418	-.00182
A2_ETA|2|	-.09837*	.05244	-1.88	.0607	-.20115	.00442
D_CON1|2|	.20053*	.11974	1.67	.0940	-.03415	.43521
D_T1A|2|	.05258***	.01190	4.42	.0000	.02925	.07591
D_T2A|2|	-.05848***	.01200	-4.88	.0000	-.08200	-.03497
D_FA|2|	.06959***	.00945	7.36	.0000	.05106	.08811
D_STA|2|	.00305	.00437	.70	.4851	-.00551	.01161
D_ETA|2|	.01110***	.00343	3.23	.0012	.00437	.01783
CON2|2|	-.30697***	.04409	-6.96	.0000	-.39338	-.22057
T1B|2|	.36969***	.04565	8.10	.0000	.28022	.45916
T2B|2|	.17312***	.04176	4.15	.0000	.09128	.25497
FB|2|	-.19158***	.04078	-4.70	.0000	-.27151	-.11166
STB|2|	.10056***	.02133	4.71	.0000	.05875	.14238
ETB|2|	.06903***	.01554	4.44	.0000	.03858	.09949
XTTC|2|	-.09590***	.01669	-5.75	.0000	-.12862	-.06319
A1_CO1|2|	-.12648***	.03710	-3.41	.0007	-.19920	-.05375
A1_T1B|2|	.02843	.03748	.76	.4481	-.04503	.10189
A1_T2B|2|	.07961**	.03841	2.07	.0382	.00432	.15489

A1_FB|2|	.01464	.04576	.32	.7491	−.07506	.10433
A1_STB|2|	−.04005*	.02407	−1.66	.0961	−.08722	.00713
A1_ETB|2|	−.01837	.01668	−1.10	.2709	−.05107	.01433
A1_XTT|2|	.01222	.01451	.84	.3996	−.01622	.04066
A2_CO1|2|	.06716*	.03724	1.80	.0713	−.00584	.14015
A2_T1B|2|	.12242***	.03622	3.38	.0007	.05143	.19340
A2_T2B|2|	−.07887**	.03814	−2.07	.0386	−.15362	−.00412
A2_FB|2|	.03254	.07637	.43	.6700	−.11714	.18223
A2_STB|2|	−.02864	.04165	−.69	.4917	−.11027	.05300
A2_ETB|2|	−.07099**	.02913	−2.44	.0148	−.12808	−.01390
A2_XTT|2|	.00890	.01433	.62	.5348	−.01920	.03699
D_CON2|2|	.02631***	.00657	4.01	.0001	.01344	.03919
D_T1B|2|	−.04515***	.00665	−6.79	.0000	−.05818	−.03213
D_T2B|2|	−.01144*	.00655	−1.75	.0807	−.02427	.00140
D_FB|2|	−.00229	.00421	−.54	.5861	−.01055	.00596
D_STB|2|	−.00721***	.00232	−3.10	.0019	−.01176	−.00265
D_ETB|2|	−.00112	.00170	−.66	.5079	−.00445	.00220
D_XTTC|2|	.00146	.00257	.57	.5697	−.00358	.00651
|Random utility parameters in latent class —>> 3..................						
CON1|3|	−2.89839***	.19537	−14.84	.0000	−3.28132	−2.51546
T1A|3|	.06140	.05983	1.03	.3048	−.05586	.17867
T2A|3|	.38967***	.06010	6.48	.0000	.27189	.50746
FA|3|	−.41547***	.04066	−10.22	.0000	−.49516	−.33577
STA|3|	−.07055***	.02373	−2.97	.0029	−.11706	−.02405
ETA|3|	−.06609***	.01619	−4.08	.0000	−.09783	−.03435
A1_CON|3|	.20291	.14435	1.41	.1598	−.08001	.48582
A1_T1A|3|	.06211	.05432	1.14	.2528	−.04435	.16857
A1_T2A|3|	−.00320	.05431	−.06	.9530	−.10965	.10325
A1_FA|3|	.12211***	.04244	2.88	.0040	.03893	.20529
A1_STA|3|	−.01999	.02620	−.76	.4456	−.07134	.03137
A1_ETA|3|	−.00653	.01708	−.38	.7024	−.04001	.02696
A2_CON|3|	.10451	.14534	.72	.4721	−.18036	.38937
A2_T1A|3|	.05744	.05380	1.07	.2856	−.04799	.16288
A2_T2A|3|	.13681**	.05380	2.54	.0110	.03135	.24226
A2_FA|3|	.23072***	.07518	3.07	.0021	.08336	.37807
A2_STA|3|	−.07867*	.04675	−1.68	.0924	−.17030	.01297
A2_ETA|3|	−.05275*	.03035	−1.74	.0822	−.11223	.00673
D_CON1|3|	.00206	.02727	.08	.9397	−.05138	.05551
D_T1A|3|	.00881	.00922	.96	.3393	−.00926	.02687
D_T2A|3|	−.03865***	.00952	−4.06	.0000	−.05732	−.01998
D_FA|3|	−.00414	.00443	−.93	.3508	−.01283	.00455
D_STA|3|	.00163	.00284	.58	.5645	−.00392	.00719
D_ETA|3|	−.10210D−04	.00177	−.01	.9954	−.34703D−02	.34499D−02
CON2|3|	−.82665***	.07644	−10.81	.0000	−.97646	−.67683
T1B|3|	.14503**	.07335	1.98	.0480	.00128	.28879
T2B|3|	.15412**	.06853	2.25	.0245	.01980	.28844
FB|3|	−.10603	.06655	−1.59	.1111	−.23646	.02441
STB|3|	.08740**	.03703	2.36	.0183	.01482	.15998
ETB|3|	.02169	.02652	.82	.4135	−.03029	.07367
XTTC|3|	−.08690***	.02837	−3.06	.0022	−.14251	−.03129
A1_CO1|3|	−.02190	.06177	−.35	.7229	−.14297	.09916
A1_T1B|3|	−.00561	.06008	−.09	.9256	−.12336	.11214
A1_T2B|3|	.13951**	.06077	2.30	.0217	.02041	.25862
A1_FB|3|	.01346	.07229	.19	.8523	−.12823	.15516
A1_STB|3|	.00338	.04170	.08	.9354	−.07835	.08512
A1_ETB|3|	−.00042	.02821	−.01	.9882	−.05570	.05487
A1_XTT|3|	.02418	.02440	.99	.3217	−.02365	.07201
A2_CO1|3|	.01528	.06168	.25	.8044	−.10561	.13616
A2_T1B|3|	.08936	.05785	1.54	.1224	−.02403	.20275
A2_T2B|3|	−.03335	.06160	−.54	.5883	−.15409	.08739
A2_FB|3|	.02652	.12651	.21	.8339	−.22143	.27447
A2_STB|3|	.03543	.06984	.51	.6119	−.10145	.17232

A2_ETB|3	−.00850	.04869	−.17	.8615	−.10393	.08694
A2_XTT|3	−.00297	.02371	−.13	.9004	−.04944	.04350
D_CON2|3	.02533**	.01106	2.29	.0220	.00366	.04700
D_T1B|3	−.00161	.01071	−.15	.8803	−.02261	.01938
D_T2B|3	−.00482	.01058	−.46	.6484	−.02556	.01591
D_FB|3	.00121	.00686	.18	.8597	−.01223	.01465
D_STB|3	−.00924**	.00409	−2.26	.0239	−.01725	−.00122
D_ETB|3	.00119	.00288	.41	.6796	−.00446	.00684
D_XTTC|3	.00544	.00432	1.26	.2082	−.00303	.01391
	Estimated latent class probabilities					
PrbCls1	.03129	.02636	1.19	.2353	−.02038	.08296
PrbCls2	0.0	.4067D−07	.00	1.0000	−.79711D−07	.79711D−07
PrbCls3	.96871***	.02636	36.74	.0000	.91704	1.02038

nnnnn.D−xx or D+xx => multiply by 10 to −xx or +xx.
***, **, * ==> Significance at 1%, 5%, 10% level.
Model was estimated on Apr 25, 2023 at 11:14:26 PM