PRE-TRIP INFORMATION SYSTEMS
AND MODE CHOICE MODELLING
IN THE ERA OF ON-DEMAND MOBILITY SERVICES

by

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Zusammenfassung

Kontext und Motivation. Großstädte leiden heutzutage unter extremem Verkehr und Staus. Sowohl das Pendeln als auch Freizeitfahrten in Großstädten sind für viele Reisende zu einer Herausforderung hinsichtlich Zeit und Stress geworden. Beispielsweise verlieren Münchner im Durchschnitt mehr als zwei Tage Freizeit pro Jahr durch Staus. Neben notwendigen Änderungen auf der Ebene der Verkehrssysteme und der Verkehrsstrategie könnte dieses Verkehrsproblem teilweise durch individuelle Verhaltensänderungen der Reisenden selbst reduziert werden. Beispielsweise können Reisende ihr privates Auto effizienter nutzen, indem sie in einem gegenwärtigen Szenario Fahrgemeinschaften im Sinne von Carpooling bilden oder in einem zukünftigen Szenario Fahrgemeinschaften in Robo-Taxis bilden (d.h. Ridepooling). Darüber hinaus steht es den Reisenden frei, sich vor der Reise über ihre Mobilitätsmöglichkeiten zu informieren und überlastete Strecken zu vermeiden, ihr multimodales Mobilitätsverhalten zu verbessern und modale Entscheidungen effizienter zu treffen. Trotz dieser Möglichkeiten wird das private Auto von vielen Reisenden immer noch als das bequemste Verkehrsmittel angesehen.

Zielsetzungen. Diese Arbeit befasst sich mit der allgemeinen Herausforderung, Reisende mit Hilfe von Pre-Trip-Informationssystemen zu motivieren, ihre monomodalen Mobilitätsgewohnheiten und modalen Entscheidungen zu überdenken. Dabei werden Pre-Trip-Informationssysteme als eine Möglichkeit angesehen, dem zunehmenden Verkehrskollaps entgegenzuwirken, indem Veränderungen auf der Ebene des individuellen Verhaltens der Reisenden erreicht werden. Dieses Gesamtziel wird in drei Hauptschritten angegangen. Zunächst werden die pragmatischen und hedonischen Bedürfnisse der Reisenden in Bezug auf Pre-Trip-Informationssysteme in Anforderungen an diese Systeme zusammengefasst und in einen Pre-Trip Prototyp implementiert. Als nächstes wird dieser Pre-Trip Prototyp evaluiert. Das Kernstück der nutzerzentrierten Evaluierung ist ein Technologie-Akzeptanzmodell für Pre-Trip-Informationssysteme. Das dritte Ziel dieser Arbeit ist es, ein tieferes Verständnis für die modalen Entscheidungen der Reisenden in einem gegenwärtigen und zukünftigen Szenario zu erlangen. Dabei soll festgestellt werden, was die modalen Entscheidungen in einem gegenwärtigen und zukünftigen Szenario beeinflusst und welche pre-trip Informationen für den Entscheidungsträger, d.h. den einzelnen Reisenden, wichtig sind. Daher ist es notwendig zu klären, welche Präferenzen diesen modalen Entscheidungen zugrunde liegen, wie sich diese Präferenzen zwischen einzelnen Reisenden unterscheiden und welche Einflüsse kontextuelle Faktoren haben (d.h. Reisezweck und Zeitdruck). Insbesondere bei modalen Entscheidungen kann es sinnvoll sein, einzelne Reisende in ihren Entscheidungen zu beeinflussen, um sie zu motivieren, ihre Mobilitätsgewohnheiten zu überdenken, alternative Verkehrsmittel zu nutzen oder Fahrgemeinschaften in Form von Carpooling oder Ridepooling zu bilden. Daher werden die Ergebnisse des dritten Teils der Arbeit in zwei Artefakten zusammengefasst, nämlich (1) eine Zusammenfassung Individuen-spezifischer Merkmale, die die Wahrscheinlichkeit für Carpooling und Ridepooling erhöhen (2) und ein Sensitivitäts-Barometer Alternativen-spezifischer Attribute für Carpooling und Ridepooling.

Forschungsdesign und Methodik. Es wurde eine Online-Vorstudie durchgeführt, um festzustellen, welche Informationen sich Reisende in Pre-Trip-Informationssystemen wünschen. Die Erkenntnisse aus der Vorstudie wurden in einen Adobe Experience Design

Klick-Prototypen umgesetzt. Der Prototyp wurde in die bereits vorhandene Hardware des BMW Connected Mirror integriert, der als interaktiver Spiegel ein beispielhafter Pre-Trip Prototyp ist. Anschließend wurde die Technologieakzeptanz dieses Pre-Trip Prototypen in einer Nutzerstudie in der BMW Welt in München untersucht. Darauf folgend wurden in der BMW Welt in München zwei wahlbasierte Conjoint-Studien durchgeführt, um das Verständnis für modale Entscheidungen in einem gegenwärtigen und zukünftigen Szenario zu vertiefen. Hier wurden acht verschiedene diskrete Wahlmodelle entwickelt. Die diskreten Wahlmodelle unterscheiden sich hinsichtlich des Kontextes, auf den sie sich beziehen, nämlich ein gegenwärtiges und ein zukünftiges Szenario, die beide zwei Routenzwecke (d.h. Pendeln und Freizeit) und zwei Ebenen des Zeitdrucks (d.h. gering vs. hoch) unterscheiden.

Ergebnisse. Die Vorstudie und die Auswertung des Pre-Trip Prototypen haben gezeigt, dass Reisende eine Ausgewogenheit zwischen pragmatischen und hedonischen Produktqualitäten in Pre-Trip-Informationssystemen schätzen. Dazu gehört die Kombination von informationsbasierten Fakten und anregenden Funktionen, die den Kundennutzen durch Stimulation und eine positiven Benutzererfahrung maximieren. Insbesondere die nutzerzentrierte Evaluation hat gezeigt, dass die Leistungserwartung der Reisenden und ihre hedonische Motivation in Bezug auf ein Pre-Trip-Informationssystem die beiden wichtigsten Prädiktoren für ihre Intention sind, ein Pre-Trip-Informationssystem zu akzeptieren und zu nutzen. Darüber hinaus hat sich durch die beiden wahlbasierten Conjoint-Studien herausgestellt, dass die meisten Reisenden klare Präferenzen für modale Entscheidungen haben. In den diskreten Wahlmodellen wurde herausgestellt, dass die Bereitschaft zum Ridepooling besonders von der individuellen Einstellung des Reisenden zum autonomen Fahren und zu Robo-Taxen beeinflusst wird. Das wahrgenommene Vertrauen der Reisenden in öffentliche Verkehrsmittel und autonome Fahrzeuge, ihr Interesse an neuen Technologien und ihre wahrgenommene hedonische Motivation in Bezug auf Fahrten mit Robo-Taxen, haben ihre Bereitschaft, Robo-Taxen überhaupt zu nutzen, und auch ihre Bereitschaft, ihre Fahrt zu teilen, stark beeinflusst. Diese Ergebnisse belegen empirisch die Notwendigkeit, bestehende Verkehrsmittelwahlmodelle durch die Persönlichkeit und Psychologie des Reisenden zu modifizieren und zu erweitern. Was die Alternativen-spezifischen Attribute betrifft, so sind die meisten Reisenden sehr preis- und zeitorientiert. Diese Präferenzen wurden signifikant durch die beiden Kontextfaktoren Reisezweck (d.h. Pendeln und Freizeit) und Zeitdruck (d.h. niedrig vs. hoch) beeinflusst. So zeigten beispielsweise optionale Ausstattungen wie Massagesitze oder weitere Luxusausstattungen in Autos oder Robo-Taxen nur in den Szenarien mit geringem Zeitdruck signifikante Auswirkungen.

Implikationen. Die identifizierten Faktoren für die Technologieakzeptanz sowie die identifizierten diskreten Wahlmodelle ermöglichen eine nutzerzentrierte Entwicklung von Pre-Trip-Informationssystemen. Pre-Trip-Informationssysteme sollten die Präferenzen des Reisenden kennen. Auf der Grundlage der zuvor getroffenen modalen Entscheidungen des Reisenden und der kontextabhängigen Einflüsse, wie z.B. Reisezweck und Zeitdruck, sollten Pre-Trip-Informationssysteme proaktiv modale Alternativen präsentieren. Dabei ist es wichtig, den gewünschten Grad an Autonomie des Reisenden in Bezug auf Informationssystem zu berücksichtigen, der z.B. in einer individuellen Kalibrierung vor dem ersten Gebrauch eingestellt werden kann. Im Falle eines geringen Autonomiebedarfs können Pre-Trip-Informationssysteme den eigenen Entscheidungsprozess des Reisenden ersetzen, indem sie proaktiv eine modale Entscheidung vorschlagen, ohne zwei oder mehr modale Alternativen vorzuschlagen und die endgültige Entscheidung dem Nutzer zu überlassen. Im Falle eines höheren Autonomiebedarfs sollte die endgültige Entscheidung dem Reisenden überlassen werden. Um Reisende zu motivieren, ihre modalen Entscheidungen auf der Grundlage von Pre-Trip-Informationssystemen zu überdenken, müssen die in Pre-Trip-Informationssystemen integrierten Algorithmen daher auf den individuellen Mustern des Entscheidungsprozesses der Reisenden basieren. Eine solche nutzerzentrierte Entwicklung von Pre-Trip-Informationssystemen kann Reisende dazu motivieren, Pre-Trip-Informationssysteme tatsächlich zu nutzen und ihre monomodalen Mobilitätsgewohnheiten und ihre modalen Entscheidungen auf der Grundlage der proaktiv präsentierten Informationen zu überdenken. Darüber hinaus schafft die Kombination aus der Erfüllung der Bedürfnisse nach funktionalen Informationen und hedonischer Stimulation eine positive Benutzererfahrung und erhöht die Loyalität der Reisenden gegenüber Pre-Trip-Informationssystemen.

Ausblick. Basierend auf den Ergebnissen der vorliegenden Arbeit sollen weitere Simulationen im Kontext von On-Demand-Mobilität erforscht und Algorithmen entwickelt werden. Die in den diskreten Wahlmodellen identifizierten Präferenzen und Kontextfaktoren können zur Optimierung von Car-Passenger-Matching Algorithmen im Rahmen von Ridehailing, Carpooling und Ridepooling genutzt werden. Darüber hinaus sollten die Parameter der diskreten Wahlmodelle zur Optimierung der Preisgestaltung zukünftiger Ridehailing- und Ridepooling-Dienste genutzt werden. Außerdem sollte die zukünftige Forschung Experimente durchführen, um die Effekte der proaktiven Informationspräsentation mit Pre-Trip-Informationssystemen auf die modalen Entscheidungen des Reisenden empirisch zu analysieren. Hier wäre es interessant, zu quantifizieren, in welchem Ausmaß die auf der Grundlage der in dieser Arbeit vorgestellten Modelle optimierten Pre-Trip-Informationssysteme tatsächlich modale Entscheidungen beeinflussen können.

BUNDESWEHR UNIVERSITY MUNICH

DOCTORAL THESIS

Pre-trip Information Systems and Mode Choice Modelling in the Era of On-demand Mobility Services

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by

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A thesis submitted to the Bundeswehr University Munich for the degree of Doktor der Ingenieurwissenschaften (Dr.-Ing.)

in the

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Executive Summary

Context and Motivation. Today's urban cities suffer from extreme traffic and traffic jams. Commuting as well as leisure time trips in large cities have become challenging for lots of travelers regarding time and stress. For example, on average Munich inhabitants lose more than two days of leisure time in traffic jams each year. Besides necessary changes on the traffic system and strategy level, this traffic problem could partly be reduced by individual behavior changes by the travelers themselves. For example, travelers are free to use their private car more efficiently by carpooling in a present scenario or ridepooling in a future scenario. Moreover, travelers are free to inform themselves about their mobility options pre-trip and avoid congested routes, enhance their multi-modal mobility behavior, and make modal decisions more efficiently. In spite of these possibilities, private cars are still perceived as the most convenient mode of transport by lots of travelers.

Objectives. This thesis addresses the overall challenge to motivate travelers to rethink their mono-modal mobility habits and modal decisions with the help of pre-trip information systems (IS). Thereby, pre-trip ISs are regarded as an opportunity to counteract the rising traffic collapse by achieving changes on the individual behavior level of travelers. This overall goal is addressed in three main steps. First, the pragmatic and hedonic needs of travelers concerning pre-trip ISs will be summarized into requirements for pre-trip ISs and implemented into a pre-trip prototype. Next, the pre-trip prototype will be evaluated. The core artefact of the user-centered evaluation is a technology acceptance model for pre-trip ISs. The third objective of this thesis is to provide a deeper understanding of travelers' modal decisions in a present and future scenario. Thereby, this thesis aims to identify what influences modal decisions in a present and future scenario and which pre-trip information is important for the decision maker, i.e., the individual traveler. Therefore, it is necessary to clarify which preferences underlie these modal decisions, how these preferences differ between individual travelers and what are the influences contextual factors have (i.e., trip purpose and level of time pressure). Especially in modal decisions, it may be useful to influence individual travelers in their decisions in order to motivate them to rethink their mobility habits, use alternative means of transport or use carpooling or ridepooling. Therefore, the results of the third part of the thesis are summarized in two main artefacts, namely (1) a summary of individual-specific characteristics that enhance the probability for carpooling and ridepooling (2) and a sensitivity-barometer of alternative-specific attributes for carpooling and ridepooling.

Design and Methodology. An online pre-study was carried out to determine which information travelers desire in pre-trip ISs. The insights of the pre-study were implemented into an Adobe Experience Design prototype. The prototype was integrated into the already existing hardware of the BMW Connected Mirror, which is an exemplary pre-trip prototype in the form of an interactive mirror. Afterwards, the technology acceptance of this pre-trip prototype was examined in a user study in the BMW World in Munich. Finally, two choice-based conjoint studies were conducted in the BMW World in Munich in order to deepen the understanding of modal decisions in a present and future scenario. Here, eight different discrete choice models were developed. The discrete choice models differ with regard to the context they focus on, namely a present and future scenario both distinguishing two route purposes (i.e., commuting and leisure time) and two levels of time pressure (i.e., low vs. high).

Results. The pre-study and the evaluation of the pre-trip prototype have highlighted that travelers appreciate a balance of pragmatic and hedonic product qualities in pre-trip ISs. This includes the combination of information-based hard facts and more stimulating functions that maximize customer benefit through creating perceived enjoyment and a positive user experience. Especially the user-centered evaluation has shown that the travelers' performance expectancy and their hedonic motivation regarding a pre-trip IS are the two most important predictors for their intention to accept and use a pre-trip IS. Furthermore, through the two choice-based conjoint analyses, it turned out that most travelers have clear preferences for modal decisions. The discrete choice models stressed that the willingness for ridepooling is especially influenced by the traveler's individual attitudes on autonomous driving and robo-taxis. The traveler's perceived trust in public transport and autonomous vehicles, their interest in new technologies and their perceived hedonic motivation towards travelling by robo-taxis highly influenced their willingness to use robo-taxis at all and also their willingness to share their ride. These findings empirically prove the necessity of modifying and expanding existing mode choice models by the personality and psychology of the traveler. Regarding alternative-specific attributes, most travelers are highly price-focused and time-focused. These preferences were significantly influenced by the two contextual factors trip purpose (i.e., commuting and leisure time) and time pressure (i.e., low vs. high). For example, optional equipment such as massage seats or further luxury equipment in cars or robo-taxis only showed significant effects in the scenarios with low time pressure.

Implications. The identified factors for technology acceptance as well as the identified discrete choice models enable the user-centered development of pre-trip ISs. These pre-trip ISs should learn the traveler's preferences. Based on the traveler's previously made modal decisions and contextual influences, such as trip purpose and time pressure, the pre-trip ISs should present modal alternatives proactively. Here, it is important to consider the traveler's desired level of autonomy regarding ISs which can for example be assessed in an individual device calibration before the first operation. In case of a low need for autonomy, the pre-trip ISs may even replace the traveler's own decision-making process by simply suggesting a modal decision proactively without suggesting two or more modal alternatives and leaving the final decision to the user. In case of a higher need for autonomy, the final decision should be left to the traveler. Hence, in order to motivate travelers to rethink their modal decisions based on pre-trip ISs, the algorithms integrated in pre-trip ISs have to be based on the patterns of the decision-making process of the individual. Such a user-centered development of pre-trip ISs can motivate travelers to actually use pre-trip ISs and rethink their mono-modal mobility habits and their modal decisions based on the proactively presented information. Additionally, the combination of fulfilling the need for functional information and hedonic stimulation creates a satisfying user experience and increases the travelers' loyalty towards the pre-trip IS.

Outlook. Based on the results of the present thesis further simulations in the context of on-demand mobility should be researched and algorithms should be developed. More precisely, the preferences and contextual factors identified in the discrete choice models should be used to optimize algorithms for car-passenger matching in the context of ridehailing, carpooling and ridepooling services. Additionally, the parameters of the discrete choice models should be used to optimize the pricing of future ridehailing and ridepooling services. Furthermore, future research should conduct experiments in order to analyze the effect of proactive information presentation with pre-trip ISs on the traveler's modal decisions empirically. Here, it would be interesting to quantify to which extent pre-trip ISs, that are optimized based on the models presented in this thesis, can actually influence modal decisions.

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1 Introduction

The rising scope of urban traffic and traffic jams has a new name: “Carmageddon” [16]. In 2017, 723,000 traffic jams with a total length of 1,448,000 kilometers were reported on German highways [2]. In sum, the progressing traffic collapse burdens the economy, the environment and each individual traveler.

From the monetary perspective, Europe currently suffers from immense costs caused by traffic jams. In concrete terms, market research predicts an increase in annual costs up to 293,1 billion US Dollars in Europe and the United States by the year 2030 [16]. Congestion costs include direct and indirect cost components for national economies. For example, direct congestion costs contain the costs for infrastructure as well as the value of the consumed fuel and the time lost in traffic jams that could have been used for productive work. Examples of indirect congestion costs are rising costs for freight services and company cars.

From the environmental perspective, gas emissions caused by passenger cars make up a high percentage of the total greenhouse gas emissions in Europe and thereby enhance global warming [99]. For example, in Germany traffic produces 20% of the total carbon dioxide emissions [100]. Although Europe tried to establish regulations to reduce passenger car gas emissions, some car manufacturers found a detour around the regulations [30]. Hence, carbon dioxide emissions caused by passenger cars remain high and damage our environment.

Furthermore, from the individual perspective, European travelers lose hundreds of hours during traffic jams each year [183]. For example, Munich inhabitants are the German “Carmageddon” leaders. On average Munich inhabitants spend 51 hours in traffic jams each year [191]. In other words, optimizing the Munich traffic situation could enrich Munich inhabitants with more than two days of leisure time each year. Another time-consuming traffic related pain point is the search for a parking slot in urban areas. Moreover, fine particles which are byproducts of combustion engines can damage our health and cause lung diseases [100]. Another byproduct of urban traffic is noise which provokes stress and also contributes to various diseases.

In conclusion, reducing urban traffic and traffic jams would relieve our national economies, protect our environment sustainably and enrich travelers with time, health and relaxation. Despite all the disadvantages of urban traffic explained above, private cars are still the most convenient mode of transport for many travelers. Consequently, in order to reduce traffic jams, modern cities need attractive alternatives to private car usage that can motivate travelers to use their private car more efficiently, use alternative means of transport or even give up their private car-ownership.

Therefore, this thesis focuses on multi-modal mobility and pre-trip information systems (ISs) that can motivate travelers to rethink their mobility decisions and use alternative means of transport. Without multi-modal pre-trip IS, planning individual mobility and selecting mobility options is still a pain point for many travelers. For example, travelers have to analyze different sources of information and combine many decision-relevant aspects [176]. Hence, many travelers stick to habitual mobility behavior without weighing up different alternatives [124]. Innovative multi-modal pre-trip ISs will, however, facilitate individual mobility planning by presenting alternatives proactively and thus reducing the cognitive load of modal and temporal choices. Since the integration of multi-modal mobility services in the everyday life of the end-user is still in its infancy stages [20,176] this thesis focuses on the customer-centered development of multi-modal pre-trip ISs.

1.1 Research Context

In this chapter, the research context and the three research questions to be answered in this thesis are motivated and formulated based on the previous introductory considerations. This concretizes the objectives to be achieved in the present thesis (see Chapter 1.2) and subdivides these objectives into independent work packages including the design and methodology applied in the present work (see Chapter 1.3). Based on the research context, the research questions, objectives, and methodology, the overall structure of the present work will be derived in Chapter 1.4.

Current transportation research mainly distinguishes three kinds of mobility behaviors, namely mono-modality, multi-modality, and inter-modality. While mono-modality refers to the exclusive use of one particular mode of transport (e.g., bike, car or public transport) on any route within a certain period of time, multi-modality refers to the alternating use of different means of transport within a certain period of time. In contrast, inter-modality refers to the use and thus the combination of different means of transport in the course of one particular route without any temporal reference unit [43]. More details on the definition of multi-modal mobility behavior and the means of transport that will be considered in this thesis will be presented in detail in Chapter 2.1 and Chapter 2.2.

This thesis focuses on multi-modal mobility. As described above, reinforcing multi-modal mobility is a core solution possibility to reduce urban traffic and traffic jams. Offering attractive multi-modal alternatives to private car usage can motivate travelers to rethink their habitual mobility behavior and use alternative means of transport or simply use their private car more efficiently by sharing cars (i.e., carsharing) or rides (i.e., carpooling or ridepooling).

Multi-modal mobility behavior requires a modal and temporal decision-making process of the traveler. The traveler has to analyze different mobility options regarding decision-relevant aspects like trip duration, price of the mobility option and departure time. Finally, and ideally after weighting up the different means of transport, travelers make their modal and temporal mobility decision. However, the variety of offers and the huge number of digital services for urban transportation [176] overwhelm travelers. Hence, for many travelers it is more convenient to stick to their habitual mobility behavior without weighing up different means of transport [124]. Consequently, there is a need to reduce the excessive demand of the traveler and facilitate the pre-trip decision-making process. A core solution for this problem is the optimization and innovation of multi-modal pre-trip ISs.

In order to facilitate individual mobility planning and reduce the cognitive load of pre-trip decision-making and thereby contribute to the reduction of urban traffic and traffic jams, this thesis concentrates on the user-centered development and evaluation of pre-trip ISs. Thereby, this thesis analyzes the following main research questions (RQs):

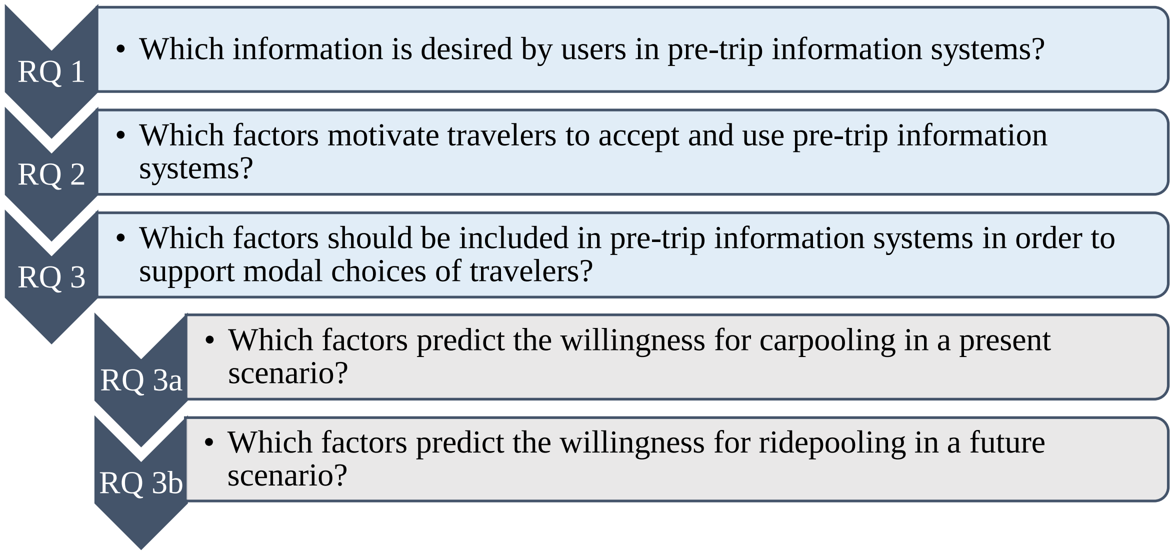


Figure 1.1 Summary of Research Questions (RQs) (own illustration).

1.2 Research Objectives

This thesis aims to answer the research questions defined above (see Figure 1.1). The analysis of the research questions goes along with the following research objectives:

Literature review and market analysis. Innovating pre-trip ISs requires a wide review of existing literature. Therefore, the first objective of this thesis is to understand past research on multi-modal mobility behavior. This includes general means of transport such as public transport and private car usage as well as current and future on-demand mobility services (see Chapter 2.1 and Chapter 2.2). Moreover, pre-trip decision-making and the parameters included in discrete choice models for modal choices will be reviewed (see Chapter 2.1.2 and Chapter 2.2.2). Furthermore, the current offer of digital services for urban transportation and in particular the current offer of pre-trip ISs will be analyzed (see Chapter 2.3). The derived knowledge will be included in the requirements of the pre-trip prototype (see Chapter 3 and Chapter 4) and the defined pre-trip choice models (see Chapter 6).

Empirical data analysis. Moreover, this thesis focuses on a user-centered development approach. Hence, the objective of this thesis is to generate and analyze empirical user-centered data in multiple steps, namely to identify pre-trip traveler needs (see Chapter 3), to develop and evaluate a pre-trip prototype (see Chapter 4 and Chapter 5) and to define pre-trip choice models (see Chapter 6). The derived knowledge will be included in the requirements of the prototype (see Chapter 4 and Chapter 5) and the defined choice models (see Chapter 6).

Identification of pre-trip traveler needs. The third objective of this thesis is to better understand the situation in which travelers inform themselves about their mobility options at home in order to plan upcoming trips to work or to leisure time activities (see Chapter 3). The deductively and inductively identified traveler needs will be included in a pre-trip prototype in a next step (see Chapter 4). Additionally, the derived knowledge will further help to model modal pre-trip decisions later on (see Chapter 6).

Development and evaluation of a pre-trip prototype. The fourth objective of this thesis is the user-centered development and evaluation of a pre-trip prototype. Here, the beforehand identified traveler needs will be implemented in a pre-trip prototype (see Chapter 4). Next, the pre-trip prototype will be evaluated regarding its technology acceptance and traveler satisfaction (see Chapter 5).

Development of discrete choice models. Finally, the core objective of this thesis is to support pre-trip decision-making with the help of proactive pre-trip recommendations on modal choices. Therefore, discrete choice models in a present and future scenario will be defined (see Chapter 6).

1.3 Research Design and Methodology

The main research questions and objectives defined above build the basis for the whole research agenda of this thesis. In the following, the overall research agenda with the applied research design and methodology will be described (see Figure 1.2). Since this thesis was worked out in cooperation with the German car manufacturer and mobility provider Bayerische Motorenwerke (BMW Group), the research design includes studies that took place in a showroom of the BMW Group in Munich (Germany), i.e., the BMW World.

First of all, this thesis will start with an analysis of the corresponding state of the art. Answering the research questions requires a literature review of past research on multi-modal mobility behavior, different means of transport (i.e., general means of transport and current and future on-demand mobility services), pre-trip decision-making, and the parameters included in discrete choice models for modal choices. Furthermore, answering the research questions requires a market analysis of the current offer of digital services for urban transportation and in particular the current offer of pre-trip ISs. The state-of-the-art analysis provides the basis for the following research design.

Research Question 1. In RQ 1 an online survey (n = 158) was used to learn about the situation in which travelers use digital services at home in order to inform themselves about their mobility options. The survey focuses on mobility habits as well as the usage of pre-trip ISs. The survey included five main aspects, namely (1) the pain points and the stress level regarding mobility-centered information search at home, (2) the time and type of mobility-centered information search at home, (3) the interest in vehicle-centered information at home, (4) the current and future use of different smart home features and (5) additional non-mobility centered needs that are also relevant in this situation for the traveler. Since the survey contained a mixed-method design with open and closed questions, the data analysis included descriptive statistics, inferential statistics (i.e., paired t-tests and chi-square-tests) and qualitative clustering. Main parts of the results of RQ 1 were already published in a journal article [160] and a conference proceeding [161].

Research Question 2. RQ 2 addresses the development and evaluation of a pre-trip prototype. Based on the insights of RQ 1, features and product qualities were selected (e.g., the traveler's calendar, weather report and mobility-centered information) and implemented into a pre-trip prototype. Next, the instrumental and experiential value of the prototype were evaluated in a quantitative user study (n = 548) in the BMW World. The evaluation of the prototype contained two main parts, namely (1) the evaluation of its technology acceptance and (2) the analysis of the traveler's experienced satisfaction and loyalty concerning the usage of pre-trip ISs. The first part of the evaluation relies on a well-established model from the field of information systems, i.e., the Unified Theory of Acceptance and Use of Technology (i.e., UTAUT2: [203]). The UTAUT2 focuses on the influence of the traveler's performance expectancy, their effort expectancy, the expected social influence and facilitating conditions on their behavioral intention and their actual usage of a new technology. Moreover, the influences of habit, price value and hedonic motivation on the intention to use a technology are integrated in the model. These influences are moderated by the user's age, gender and experience with the technology. The second part of the evaluation extends the UTAUT2 by more outcome variables of technology acceptance, namely satisfaction and loyalty. The data from the user study was analyzed with the help of structured equation modelling (SEM). Main parts of the results of RQ 2 were already presented at a scientific conference [159] and published in three conference proceedings [158,161,214].

Research Question 3. RQ 3 focuses on modelling travelers' modal choices. RQ 3 contains two main studies. RQ 3a elaborates attitudes towards carpooling as a driver or passenger in contrast to more traditional means of transport such as private car usage without pooling and using public transport. RQ 3b is dedicated to attitudes and choice behaviors in a future scenario in order to investigate the potential as well as remaining challenges of more flexible modes of transportation such as shareable robo-taxis. In addition, both studies accommodated a manipulation varying between commuting and leisure time trips in the context of high or low time pressure. This way the results can predict mode choice decisions in a wide variety of situations. In sum, eight different discrete choice models will be presented: (1) commuting in the context of high and (2) low time pressure and (3) leisure time trips in the context of high and (4) low time pressure, each for the present and future scenario.

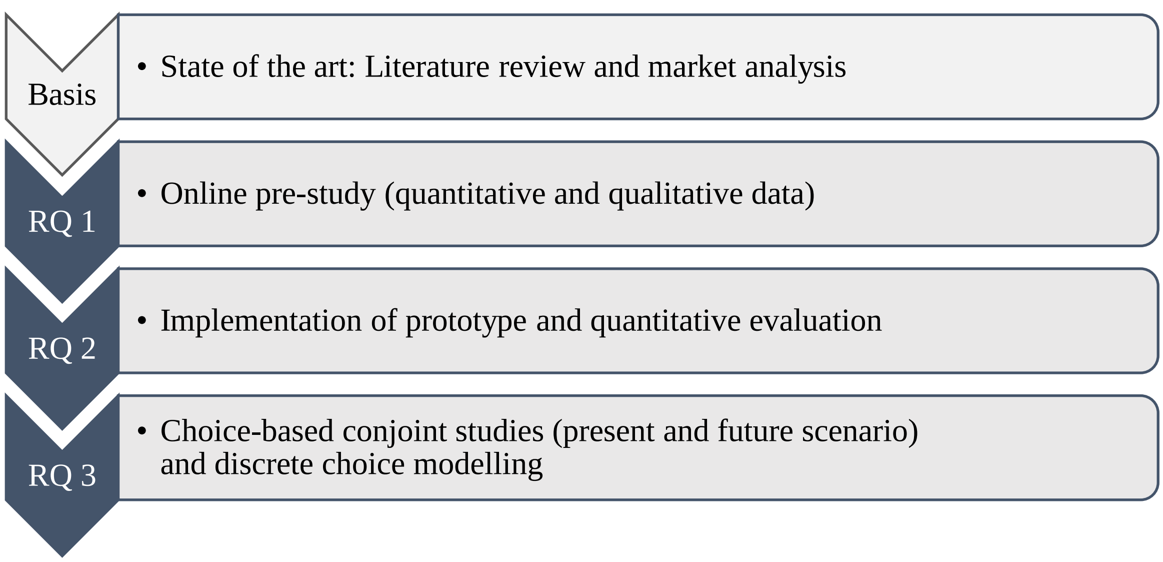


Figure 1.2 Summary of Research Design and Methodology (own illustration).

1.4 Outline of the Dissertation

This paragraph combines the main research questions (see Figure 1.1) and objectives as well as the research design and methodology (see Figure 1.2) described above into the overall outline of this dissertation. Figure 1.3 illustrates the detailed outline of this dissertation. This dissertation is structured as follows:

Chapter 2 gives an overview of recent research on multi-modal mobility behavior with general means of transport (i.e., private car, bike, and public transport) as well as current and future on-demand mobility services (e.g., carsharing and ridepooling). Furthermore, pre-trip decision-making and the parameters included in discrete choice models for modal decisions will be reviewed (see Chapter 2.1.2 and Chapter 2.2.2). Moreover, Chapter 2.3 provides an overview of the current offer of digital services for urban transportation. The market analysis focuses in particular on the current offer of pre-trip ISs.

Chapters 3 to 6 contain the analysis of the research questions defined above. First of all, Chapter 3 describes the analysis of mobility habits and the situation in which travelers inform themselves about their mobility options at home before their upcoming trip. The results of the mixed-method pre-study will subsequently be summarized in a functional design of a pre-trip ISs and implemented in a pre-trip prototype. Next, Chapter 4 describes the pre-trip prototype considered in this thesis.

Chapter 5 addresses research question 2, i.e., the evaluation of the pre-trip prototype. This chapter contains the description of a user study and the modelling of the empirical results regarding the prototype's technology acceptance and the traveler's motivation to actually use pre-trip ISs.

Chapter 6 contains the core objective of this dissertation, namely the analysis of how pre-trip ISs can support modal choices of travelers. This chapter elaborates two user studies of modal choices in a present scenario with currently available means of transport (i.e., private car, public transport, and carpooling) and a future scenario with future means of transport (i.e., robo-taxis and ridepooling).

Finally, Chapter 7 concludes the dissertation by summarizing the theoretical and practical implications of the insights described in Chapters 3 to 6. Additionally, Chapter 7 summarizes the limitations of this work and gives an outlook on future research questions in the field of multi-modal mobility and pre-trip ISs.

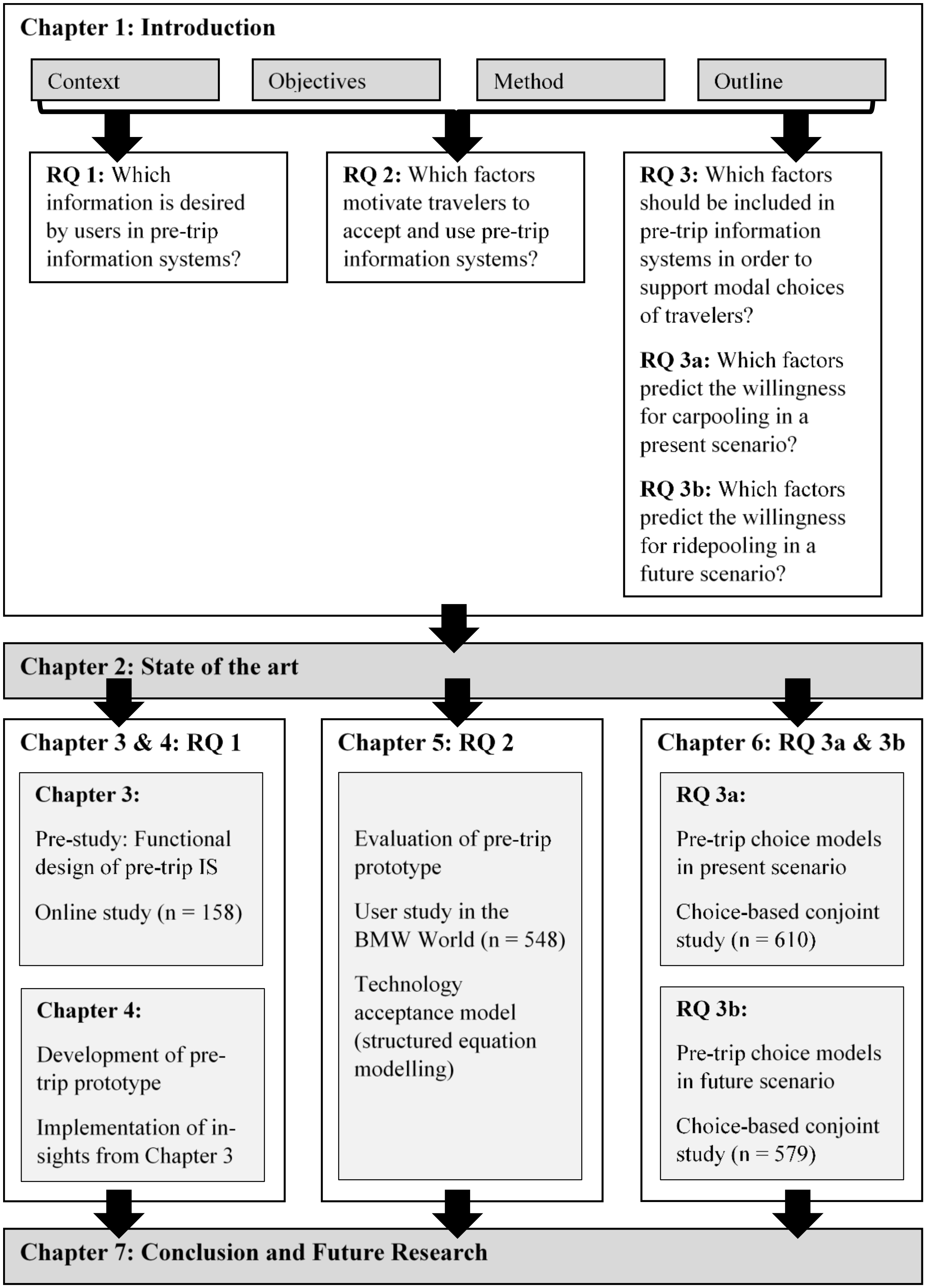


Figure 1.3 Outline of the Dissertation (own illustration).

2 State of the art

Answering the research questions described in the introduction demands an informed theoretical background. Therefore, this chapter explains the development of multi-modal mobility behavior. Thereby, multi-modal mobility will be defined and distinguished clearly from other types of mobility behavior (i.e., mono-modality and inter-modality). Moreover, the following paragraphs will describe and distinguish the different current (e.g., private car) and future means of transport (e.g., robo-taxis) as well as on-demand mobility services that can be included in multi-modal mobility planning. Furthermore, this chapter contains a literature review on past research on modal choices and existing choice models in multi-modal mobility settings. The analysis of the existing discrete choice models and the methodology used to calculate them provides the basis for the core objective of this thesis, i.e., the discrete choice modelling presented in Chapter 6.

Besides multi-modal mobility and on-demand mobility services, the third major topic in the theoretical background is pre-trip ISs for travelers. Chapter 2.3 contains an extensive literature review and market analysis on existing pre-trip ISs. The chapter provides an overview of different kinds of services and their modules. The literature review and market analysis provide the basis for the studies presented in Chapter 3 to 6.

2.1 Multi-modal Mobility

The following sections concentrate on multi-modal mobility behavior. This includes a definition and delineation of multi-modal mobility to other types of mobility behavior (i.e., mono-modality and inter-modality). Moreover, studies on multi-modal mobility will be reviewed. The literature review concentrates on multi-modal mobility hubs, the segmentation of mono- and multi-modal groups and discrete choice modelling in the context of modal decisions of travelers.

2.1.1 Definition and Overview

In order to understand and explore multi-modal mobility behavior, it is important to define and distinguish different kinds of mobility behavior. Therefore, this section provides an overview of the three main kinds of mobility behaviors, namely (1) mono-modality, (2) multi-modality, and (3) inter-modality, their respective definition and their distinction from each other. Afterwards, the meaning and goals of multi-modality and inter-modality with regard to traffic systems and political strategies will be elaborated.

Current transportation research mainly distinguishes three kinds of mobility behaviors, namely (1) mono-modality, (2) multi-modality, and (3) inter-modality (see Table 2.1). Mono-modality refers to the exclusive use of one particular mode of transport (e.g., only private car) on any route within a certain period of time. In contrast, multi-modality refers to the alternating use of different means of transport (e.g., private car and public transport) within a certain period of time. Inter-modality is a special kind of multi-modal behavior. The difference between multi-modality and inter-modality is that inter-modality refers to the combination of different means of transport in the course of one particular route while multi-modality only refers to the use of different means of transport in the course of a certain period of time including different routes

[43]. Table 2.1 summarizes the three definitions for (1) mono-modality, (2) multi-modality, and (3) inter-modality.

Table 2.1 Definition, Delineation, Examples and Reference Units of Mono-, Multi- and Inter-modality (own illustration).

	Definition	Example	Reference unit
Mono-modality	Exclusive use of one particular mode of transport on any route within a certain period of time	Exclusive use of a private car for any route within one week	Period of time (at least one week)
Multi-modality	(Alternating) Use of different means of transport on any route within a certain period of time	Using a private car for commuting and using public transport for reaching leisure time activities within one week	Period of time (at least one week)
Inter-modality	Use and thus combination of different means of transport in the course of one particular route	Going to work by riding a bike to a public transport station and then taking the subway to the office	One particular route

Depending on the concrete research context, the definitions of multi-modality and inter-modality vary in their details [140]. For example, this dissertation distinguishes between three different kinds of car usage, i.e., (1) driving in a private car, (2) sharing rides in a private car and (3) using cars from a carsharing provider. In the following chapters, combining two or more of these three alternatives of car usage is regarded as multi-modality. Hence, although in this example the mode of transport is always the car, this dissertation distinguished different kinds of car usage and therefore defines the combination of different kinds of car usage as multi-modality. Furthermore, in this dissertation, a route is only regarded as inter-modal if different means of transport are combined on one route (e.g., bike and public transport). A route is not regarded as inter-modal if two means of transport of the same kind are combined (e.g., two different subway lines).

Another detail about the definition of multi-modality is the concrete length of the considered period of time. One stream of research came to the conclusion that multi-modality can be defined as the exclusive use of one particular mode of transport on any route within one week [140]. This conclusion is based on the finding that intrapersonal variation of the use of different means of transport can be described based on the mobility behavior of one week. However, other studies concluded that multi-modality has to be defined based on the mobility behavior of at least two weeks [173]. This conclusion is based on the insight that even habitual trips may only be repeated less often than once a week. Hence, these trips would not be detected in a time period of one week and travelers might be falsely identified as mono-modal. Therefore, the studies described in Chapters 3 to 6 always refer to a time period of more than two weeks with regard to mobility habits.

For a further delineation between multi-modality and inter-modality it is important to explain the meaning of multi- and inter-modality with regard to traffic systems and political strategies

[140]. Table 2.2 summarizes the overall goals of multi- and inter-modality on two levels, i.e., (1) the traffic system level and (2) the level of political strategies.

Table 2.2 Meaning and Goals of Multi-modality and Inter-modality with regard to Traffic Systems and Political Strategies (Adapted from [140, p. 24]).

<table>
<tr><th></th><th colspan="2">Goals</th></tr>
<tr><th></th><th>Traffic system level</th><th>Political strategy level</th></tr>
<tr><td>Multi-modality</td><td>Facilitating access to different means of transport and increasing its offer

Reducing the spatial distance between important places (e.g., residential areas, offices, and shopping centers) and alternative means of transport (e.g., bus stops)

Expanding the competitiveness of alternative means of transport (e.g., bike or public transport) compared to private car usage</td><td><u>Transport system level:</u>
Promotion of a wide range of alternative traffic carriers
Strengthening alternative means of transport
<u>Level of traffic behavior:</u>
Promoting the acceptance and usage of different means of transport in everyday life</td></tr>
<tr><td>Inter-modality</td><td>Optimizing interfaces and facilitating the transition from one mode of transport to another

Improving the accessibility by combining the specific strengths of the single means of transport</td><td><u>Transport system level:</u>
Promotion of interface optimization of the different traffic carriers
Promotion of the specific strengths of single traffic carriers
<u>Level of traffic behavior:</u>
Promoting the acceptance of intermodal routes in specific areas</td></tr>
</table>

In conclusion, this dissertation concentrates on multi-modal mobility because the present work aims to support the overall goal of reducing urban traffic and traffic jams. This high-level goal is targeted by facilitating the access to alternative means of transport and enhancing the competitiveness of alternative means of transport compared to private car usage by optimizing and innovating pre-trip ISs. On the transport system level optimizing and innovating pre-trip ISs supports the goal of promoting and strengthening alternative traffic carriers and alternative means of transport. On the level of traffic behavior, this dissertation also analyzes the acceptance and use of pre-trip ISs and thus the willingness to accept and use different means of transport. Summarizing, since this dissertation focuses on traffic behavior and traffic strategies, the following chapters concentrate on multi-modality instead of inter-modality. For the general acceptance and use of a certain mode of transport, it is irrelevant whether the modality is used with or without the combination with other modes. Here, it is just important that the travelers are in general willing to include different means of transport in their modal choice and to decide between them [150].

2.1.2 Studies on Multi-modal Mobility

After defining and differentiating between mono-, multi-, and inter-modality in the previous paragraphs, the following paragraphs now focus on multi-modal mobility in particular. Since the core focus of this thesis is multi-modal mobility behavior, the following paragraphs review recent studies on multi-modal mobility behavior. After providing a short introduction to the overall field of investigating multi-modal mobility behavior, studies on (1) multi-modal mobility hubs, (2) the analysis of modal groups and (3) the modelling of modal choices will be elaborated successively.

Generally, multi-modal mobility behavior is a quite young research topic in the field of transportation and traffic planning. Due to missing longitudinal studies and data, multi-modal mobility behavior has only been studied for the last 10 to 15 years [140]. A good example of long-term multi-modal mobility research is the German Mobility Panel (MOP: [35]). The MOP continuously analyzes the mobility behavior in Germany since 1994. The core focus of this long-term study is the everyday mobility of German people, including parameters like the time and miles travelled with different means of transport and the fuel consumption of cars in private households. In sum, the MOP provides a detailed long-term overview of multi-modal mobility behavior in Germany. Figure 2.1 illustrates the development of multi-modal mobility behavior in Germany from 1997 to 2011. In this example, multi-modality is defined as the usage of a bike, a car, and public transport within one week. The figure highlights that multi-modal mobility behavior has increased significantly in all age groups in Germany. Nevertheless, the total percentage of multi-modal travelers is still astonishingly low, i.e., ranging from 4% to 9% depending on the age group.

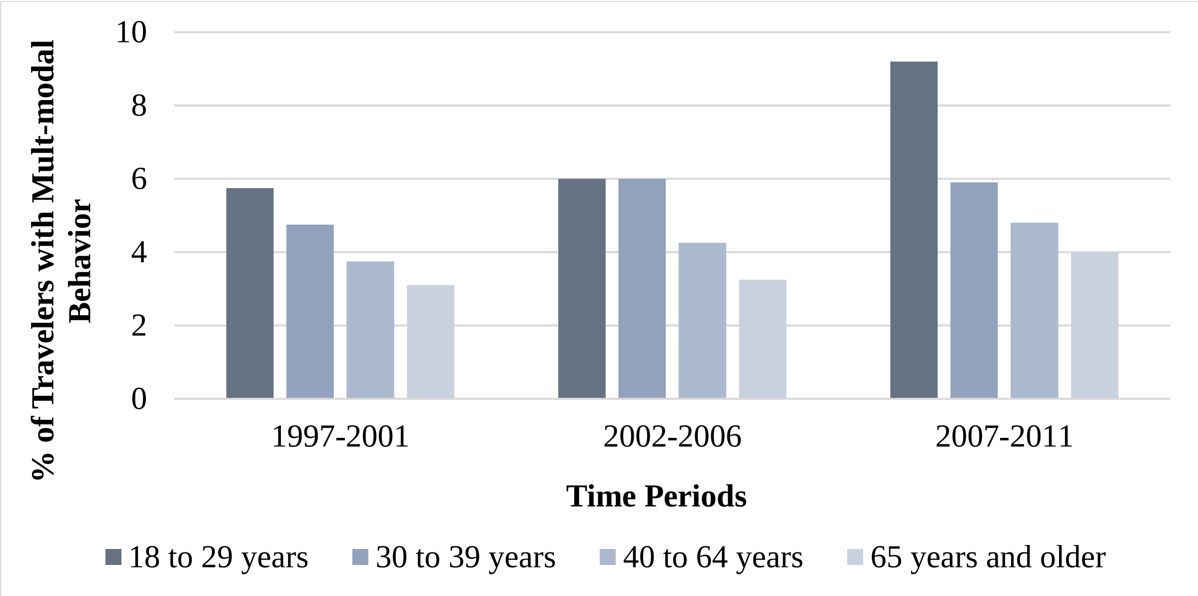


Figure 2.1 Development of Multi-modal Mobility Behavior (Adapted from [105, p. 4]. Here multi-modality is defined as the usage of a bike, a car and public transport within one week.).

Summarizing, recent longitudinal studies illustrate that multi-modal mobility behavior has increased significantly within the last decade. Since the overall percentages of multi-modal travelers are still low, we still need strategies for the broader dissemination of multi-modal mobility behavior. One possible strategy to promote multi-modality is the construction of multi-modal mobility hubs, which will be elaborated in the following.

Multi-modal Hubs. Another interesting stream of research within the field of multi-modal mobility contains the analysis of multi-modal passenger transport hubs. Multi-modal hubs are a core element on the traffic system level that reduces the spatial distance between the accesses to different means of transport and thus facilitate the access to different means of transport. Thereby, multi-modal hubs are an enabler for individual multi-modal behavior. For example, a research project in the German city Cologne identified potential multi-modal hubs for Cologne [196]. The multi-modal hubs were identified based on a location and utility analysis including reachability, availability of public transport services and presence of parking spaces for carsharing vehicles. Most of the identified potential multi-modal mobility hubs were identified within or very close to the city center. Figure 2.2 illustrates the location of the identified multi-modal mobility hubs in Cologne.

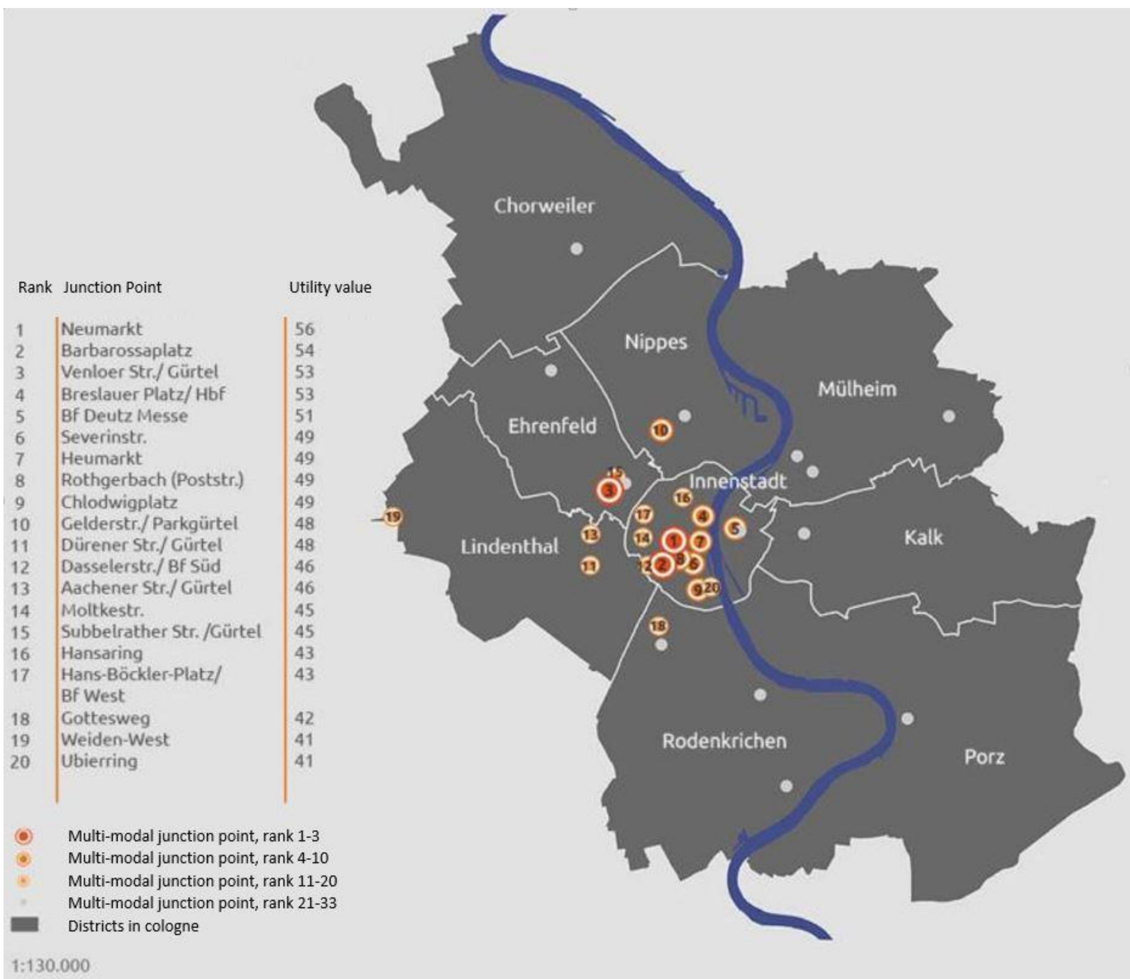
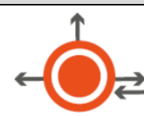
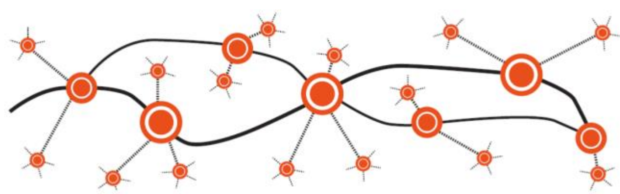


Figure 2.2 Multi-modal Mobility Hubs in Cologne (Adapted from [196, p. 47]).

Furthermore, the identified multi-modal mobility hubs were clustered regarding their size, i.e., small, medium or large (see Table 2.3). The conclusion of the study was that multi-modal mobility stations have to be integrated at multi-modal hubs in order to enable travelers to combine different means of transport efficiently. These multi-modal stations should be complemented by comprehensible mobility services such as smartphone apps. Making multi-modal trips as convenient and seamless as possible will motivate travelers to use alternative means of transport and reduce their mono-modal private car usage [196]. Chapter 2.3 will describe in detail how intelligent traveler information systems (ITIS) such as pre-trip ISs are related to multi-modal mobility behavior.

Table 2.3 Clustering of Multi-modal Mobility Hubs in Cologne (Adapted from [196, p. 48]).

	Small		Medium		Large	
Spatial arrangement						
Modes & characteristics	Public Transport	1	Public Transport	2	Public Transport	2-3
	Carsharing	2	Carsharing	5	Carsharing	8
	E-Carsharing	1	E-Carsharing	2	E-Carsharing	4
	Bike-Sharing	2	Bike-Sharing	15	Bike-Sharing	30
	E-Bike-Sharing	10	E-Bike-Sharing	4	E-Bike-Sharing	6
	Bike Boxes	5	Bike Boxes	10	Bike Boxes	20
	Bike & Ride	42	Bike & Ride	60	Bike & Ride	100
Spatial pattern						

While the example of Cologne [196] concentrates on a current mobility scenario, other examples already concentrate on future scenarios of multi-modal mobility hubs. An exemplary future scenario is illustrated in Figure 2.3. Here, the vision of multi-mobility hubs with bike sharing and Segway sharing (i.e., a scooter with two parallel wheels and a handlebar) is visualized. Chapter 2.2 will elaborate more insights into future multi-modal mobility.

Summarizing, multi-modal hubs are one possible strategy to promote and enable multi-modal mobility on an individual level. The example of Cologne illustrates that some German cities have already integrated multi-modal hubs with a combination of public transport, bike boxes, bike and ride stations, (e-)carsharing and (e-)bike sharing in order to facilitate multi-modality and inter-modality in the traveler’s everyday life. Future ideas for the extension of multi-modal hubs include the integration of more modalities such as Segways or future on-demand mobility services (e.g., robo-taxis). In order to identify fitting and demanded combinations of modalities for multi-modal hubs, it is necessary to identify different modal groups. Therefore, the segmentation of modal groups will be described in the following.

Figure 2.3 Future Scenario of Multi-modal Mobility Hubs (Source: [23, p. 26]).

Analyzing Modal Groups. A further fundamental characteristic of studies on multi-modal mobility behavior is the definition of modal groups. As mentioned in Chapter 2.1.1, from the temporal perspective, most studies consider a time period of one week [e.g., 110]. Moreover, modal groups can either be formed on a traveler level (see Figure 2.4) or on a route purpose level (e.g., commuting, shopping, going for a drive or reaching leisure time activities) [e.g., 110,206]. Depending on the number of means of transport considered for the classification of mono- and multi-modality, the possible number of mono- and multi-modal groups might become really high [140]. For example, the integration of only four different means of transport already results in 15 different mono- and multi-modal groups. This relationship is illustrated in Table 2.4. Therefore, most studies focus on a rather small number of different means of transport when analyzing modal groups [e.g., 110]. Three main differences between modal groups are: (1) the inclusion or exclusion of walking as a mode of transport, (2) the differentiation between the driver and fellow passenger in cars and (3) the differentiation between different means of public transport such as bus and subway [140].

Table 2.4 Possible Numbers of Modal Groups Depending on the Number of Means of Transport Considered for the Classification of Mono- and Multi-modality (Adapted from: [140]).

	Number of means of transport considered for the classification of mono- and multi-modality						
	2	**3**	**4**	**5**	**6**	**7**	**8**
Possible number of multi-modal groups	1	4	11	26	57	120	247
Possible number of mono- and multi-modal groups	3	7	15	31	63	127	255

Figure 2.4 illustrates an example of modal group analysis of German travelers based on the MOP. The different modal groups were identified based on five different means of transport, namely (1) walking, (2) being a fellow passenger, (3) using a bike, (4) a car or (5) public transport. In sum, the results from 1996 to 2010 highlight that “car only” is still the biggest modal group compared to “bike only”, “public transport only” and the possible multi-modal combinations of the five means of transport listed above (e.g., the combination of bike and public transport).

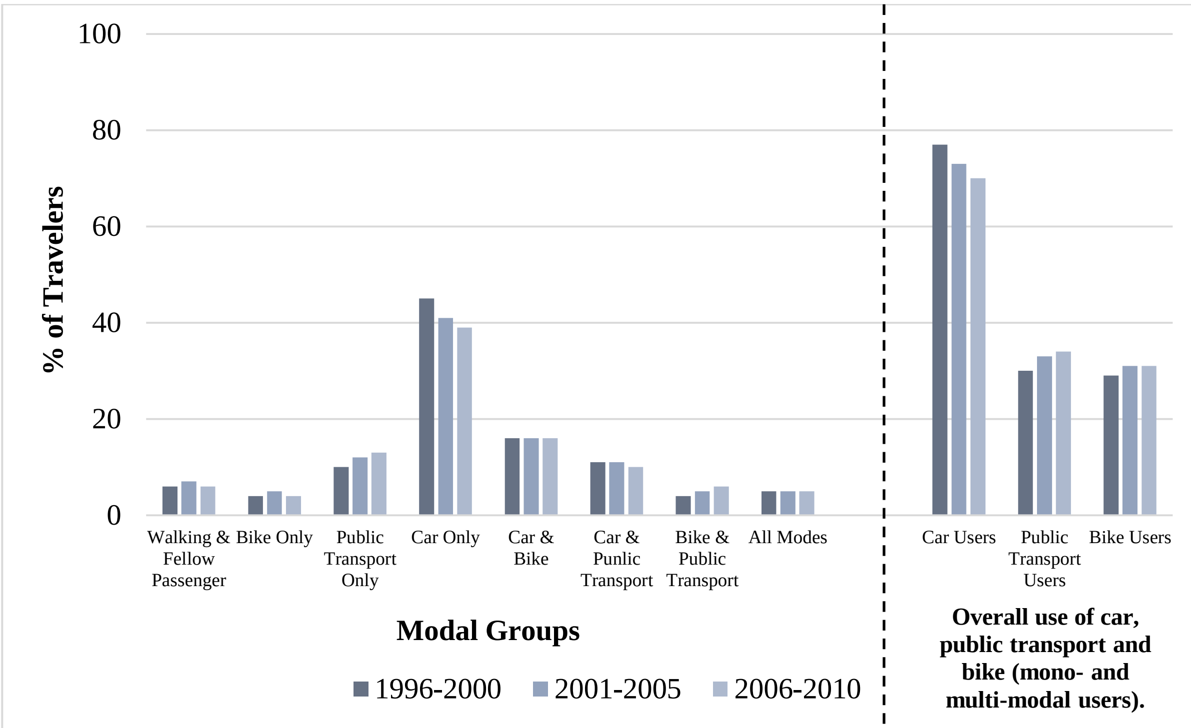


Figure 2.4 Clustering of German Travelers (18 years and older) Regarding Modal Groups (Adapted from [110, p. 57]).

Summarizing, the segmentation of modal groups shows again that multi-modal mobility behavior has increased within the last decade. Nevertheless, the mono-modality and especially car usage is still the most dominant mobility habit of German travelers. For promoting alternative means of transport, it is necessary to understand the traveler’s reasons for choosing a specific mode of transport. Knowing the parameters included in the decision-process is the starting point for developing strategies to promote changes in mobility habits. Therefore, the next paragraph concentrates on understanding the reasons for modal choices.

Analyzing Modal Choices. Next, scientific studies on the criteria influencing the traveler’s decisions on transport modes will be reviewed. Generally, studies on transport mode choice can be divided in two main streams, namely (1) studies dealing with stated preferences and (2) studies dealing with revealed preferences of travelers [58]. Stated preference studies assess hypothetical mode choices of travelers. Obviously, the practical limitation of this method is the lack of actually observed modal choices and travel behavior. Nevertheless, the great advantage of stated preference methods is that a wide range of different conditions and scenarios can be tested, including future scenarios with means of transport that are not available on the transportation market right now (e.g., robo-taxis). Table 2.5 provides an overview of recent research on stated preference studies on transport mode choice.

In contrast, revealed preference studies include observed choices and decisions from the traveler's actual mobility behavior. However, observing real modal choices also underlies some practical limitations such as high survey costs and the difficulty to assess the importance of latent variables (e.g., quality and convenience of different modes). Moreover, future scenarios with currently unavailable means of transport such as shared autonomous vehicles (SAVs) or rather robo-taxis cannot be tested using revealed preference designs [58]. Table 2.6 provides an overview of recent research on revealed preference studies on transport mode choice.

For example, Vrtic and Fröhlich [207] conducted a stated preference study in order to analyze mode choices between the three modes (1) own car, (2) public transport and (3) walking. In this study, travel time was the most important predictor for mode choices. Moreover, travel comfort, access time, reliability, price, private car ownership and season ticket ownership of public transports were significant predictors for modal decisions.

Walker [208] came to a similar conclusion. Analyzing modal decisions, the author identified time costs and monetary costs as the core predictors of mode choices. Nevertheless, factors such as comfort, convenience, reliability, and safety also influenced the traveler's final modal decision. Moreover, Walker [208] integrated traveler attitudes regarding environmental sustainability and the effects of social influences into the discrete choice model and found significant effects of both groups of parameters.

The different groups of parameters mentioned above and listed in Table 2.5 and Table 2.6 were summarized into a motivational model by Steg [189,190]. The author distinguishes three sets of motives influencing car usage, namely (1) instrumental motives such as speed, flexibility, safety, and environmental sustainability, (2) social motives such as the meaning of cars as status symbols and (3) affective motives such as experiencing driving pleasure.

Table 2.5 Literature Review on Stated Preference Studies on Transport Mode Choice (own illustration in chronological order).

Authors (year)	**Research question**	**Compared modes**	**Model parameters**	**Method**	**SP/RP**	**n**
Motoaki & Daziano (2015) [134]	Latent-class model for the analysis of the effects of weather on cycling demand	Bike (comparing routes)	Bike route option, demographics, attitudes, weather	Latent-class model	SP/RP	599
Baidoo & Nyarko (2015) [14]	Transport mode choice in Ghana	Car, bus	Price, comfort, noise level, time, habit	Binary logit model	SP	181
Shen, Sakata & Hashimoto (2008) [182]	Influence of environmental consciousness on travel mode choice	Car, train	In vehicle time, access time, frequency, fare or cost, impact on environment, education, age, income	Binominal logistic regression	SP	637
Vrtic & Fröhlich (2006) [207]	Investigation of mode choice and route choice	Car, public transport, walking	Duration of trip, cost, in-vehicle time, access time, interval of public transport, transfers, reliability of mode of transport,	Multinomial logit model	SP	2 studies: 828/806
Ewing, Schroeer & Green (2004) [67]	Influencing factors on mode choice of travel to school	Car, school bus, bike, walking	Household income, household car ownership, license ownership, walk time per trip, bike time per trip, average sidewalk coverage, home-based other accessibilities	Multinomial logistic regression, nested logit model	SP/RP	3815

Authors (year)	Research question	Compared modes	Model parameters	Method	SP/RP	n
Brownstone, Bunch & Train (2000) [32]	Preference for fuel types in cars	Car (comparing attributes)	Fuel type, vehicle range, price, home refueling type/ cost, service station refueling time/ cost/ availability, acceleration, speed, emissions, vehicle size, body type of vehicle, luggage space	Multinomial and mixed logit models	SP	2857-4747 (depending on assessment wave)
Abdel-Aty. Kitamaura & Jovanis (1997) [1]	Effect on advanced traffic information on driver's route choice	car (comparing routes)	Road type, average travel time, traffic information, expected travel time on this day, information on the cause of the delay, attitude towards shorter distance, difference between average and expected travel time, receiving pre trip information, age	Binary logit models	SP	564
Wardman, Bonsall & Shires (1997) [209]	Driver's response to variable message signs	Car (comparing traffic situations)	Delay, length of delay, accident/ congestion/ roadworks/ no information on route, age, gender, street options in the area, time	Multinomial logit model	SP	289
Polak & Jones (1993) [151]	Introduction to travel information systems, stated preference experiment of transport information acquisition	Car, bus	Gender, age, socio economic group, trip purpose (work vs. personal), frequency of journey to city center, free parking in center, journey time to avoid congestion, country, current travel time, current parking search	Multinomial logit model	SP	666

Table 2.6 Literature Review on Revealed Preference Studies on Transport Mode Choice (own illustration in chronological order).

Authors (Year)	**Research question**	**Compared modes**	**Model parameters**	**Method**	**SP/RP**	**n**
Rayaprolu, Llorca & Moeckel (2018) [154]	Effects of bicycle highways on commute mode choice	Car, public transport, bike, walking	Age, gender, driver's license, number of cars in household, distance to transit, travel time	Multinomial logit model and nested logit model	RP	25000 (German household travel survey)
Ashrafi & Neumann (2017) [12]	Travel mode choice of commuters in Vorarlberg	Bike, walk, car, public transport	Population density, distance to closest public transport station, living space, age, gender, number of car owners in the family, reason of travel (business vs. shopping), income	Bivariate and multinomial logit models	RP	6214
Moeckel, Fussell & Donnelly (2015) [132]	Development of a new nested multinomial logit model for long distance travel	Drive alone, shared ride 2 people, shared ride 3 p., shared ride 4+ p., bus, train, plane	Travel costs, distance, transit station accessibility, service frequency, number of transfers, parking costs	Nested logit model (R^3 Logit)	RP	45165 trips (National Household Travel Survey)
Ashalatha, Manju & Zacharia (2013) [11]	Travel mode choice of commuters in an Indian city	Car, two-wheeler, bus	Age group, gender, income, vehicle ownership, distance in km, time/distance, cost/distance	Multinomial logistic regression	RP	739

Authors (Year)	Research question	Compared modes	Model parameters	Method	SP/RP	n
Buehler (2010) [33]	Comparison of transport mode choice in Germany and the USA	Car, walk, bike, public transport	Distance to public transport stop, population density, mix of population and density, income, car access, children, gender, household lifecycle and employment, trip purpose, nationality	Multinomial logistic regression	RP	122611
Limtanakool, Dijst & Schwanen (2006) [120]	Influence of the spatial configuration of land use and transport systems on mode choice for medium and longer distance travel	Car, train	Age, gender, income, education, household status (couple vs. family), number of workers per household, car availability index, land attributes (suburban, more urbanized, inner city), population density, travel time (car vs. rail)	Binary logit models	RP	6330
Asensio (2002) [10]	Travel mode choice for suburbanized commuters in Barcelona	Car, bus, public transport	Cost, travel time, waiting time, distance, access, egress, frequency, sex, head of household, density, inclusive value	Two-stage multinomial nested logit model	RP	1381

Summarizing, modal choices are analyzed using stated and revealed preference data. In both streams of research, modal choices are mainly analyzed using logistic regression and logit models (e.g., mixed logit models and nested logit models). The theory of the applied data analysis of this stream of research will be elaborated in detail in Chapter 6. The studies listed in Table 2.5 and Table 2.6 illustrate that discrete choice models in the context of modal decisions include the following groups of parameters (see Figure 2.5):

- Sociodemographic parameters of the traveler (e.g., age, gender, socio-economic group, and license ownership)
- Mobility habits of the traveler (e.g., car ownership, frequency of journeys to the city center)
- Mobility-centered attitudes of the traveler (e.g., environmental attitudes)
- Infrastructure-related parameters (e.g., access to public transport, distance to next bus stop and availability of parking spaces)
- Quantitative characteristics of the mode of transport (e.g., price, duration of the trip, noise level and space for luggage)
- Qualitative characteristics of the mode of transport (e.g., comfort and convenience)
- Characteristics of the trip (e.g., time pressure, time of day and reason for travelling)
- Other side conditions (e.g., weather)

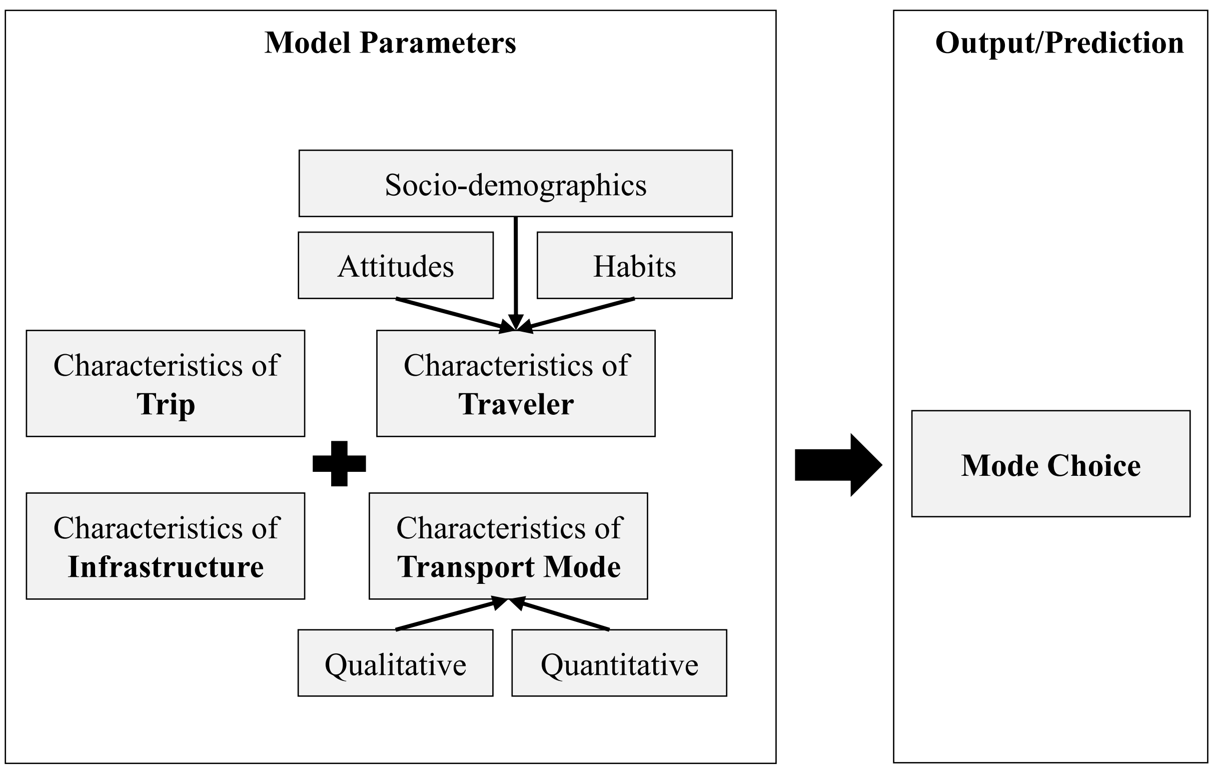


Figure 2.5 Overview of Model Parameters in Discrete Choice Models for Mode Choice Prediction (own illustration).

2.2 On-demand Mobility Services

The following paragraphs concentrate on on-demand mobility services. This includes a definition and delineation of on-demand mobility services to other means of transport (i.e., general means of transport such as private car usage or public transport). Moreover, studies on on-demand mobility services will be reviewed. The literature review concentrates on discrete choice modelling in the context of current and future on-demand mobility decisions of individual travelers. Moreover, the differences between choice modelling in the context of general means of transport, current and future ODM services will be discussed.

2.2.1 Definition and Overview

In order to understand and explore multi-modal mobility behavior, it is important to define and distinguish different kinds of ODM services. Therefore, this section provides an overview of the different kinds of current and future ODM services, their respective definition and their distinction from each other.

On-demand mobility (ODM) services comprise services that enable travelers to use shared means of transport exactly as needed and on a short-term basis. Typically, ODM services contain services such as carsharing (e.g., Drive Now and Car2Go), ridesharing or rather carpooling (e.g., BlaBlaCar), ridehailing or rather ridesourcing and e-hailing services (e.g., Uber and Mytaxi). Future ODM services will contain shared autonomous vehicles or rather robo-taxis [79]. Table 2.7 provides an overview of the different kinds of current and future ODM services, including their definitions and exemplary services from the German and American urban mobility market.

Having a closer look at the German ODM market in 2018, Car2Go represents the leading carsharing operator in Germany with 916,000 registered travelers. Car2Go is followed by DriveNow with 730,000 registered travelers and Flinkster with 315,000 registered travelers [187]. Regarding the number of vehicles operating, Flinkster has the largest vehicle fleet with 4,000 vehicles and is followed by Car2Go (3,910 vehicles) and DriveNow (3,370 vehicles). Compared internationally, Europe is the leading carsharing nation with 2.1 million registered travelers and a total fleet of 31,000 vehicles. In contrast, North America only counts 1.5 registered travelers and a fleet of 22,000 vehicles [22]. North America is, however, the leading ridehailing nation compared to Europe and in particular Germany [76]. Uber and Lyft are the two leading ridehailing providers in the USA [184] whereas in Germany Uber has to fight against the leading ridehailing provider Mytaxi and local taxi providers such as Taxi Berlin [93,177]. Future developments on the international ODM services market concentrate on higher levels of vehicle automation (see Table 2.8) and the offer of carsharing with autonomous vehicles. Recent trend analyzes predict that shared ODM services possibly increase their market share up to 10% of all trips in Germany by 2035 [197].

Besides carsharing, carpooling is also integrated into the German ODM services market by several operators such as BlaBlaCar (see Table 2.7). The leading carpooling operator in Germany is BlaBlaCar which was founded in 2006 and entered the German market in 2013. BlaBlaCar counts 65 million registered travelers worldwide. However, only 20 million travelers use the platform every 3 months [27]. Despite the diverse carpooling offer, in Germany, the average car occupancy has barely changed within the last 15 years. More specifically, as measured in 2002 and 2008, the average car occupancy in Germany is still about 1,5 travelers

[34]. Thus, in order to reduce urban traffic and traffic jams, we need to deepen our understanding of how to motivate travelers to share cars and rides. These motivators will be focused in the next paragraphs.

Table 2.7 Overview, Definitions and Examples of the Different Kinds of ODM Services (own illustration based on [79]).

ODM Service	**Definition**	**Examples from Germany and USA**
Carsharing	Carsharing comprises the short-term access of travelers to shared vehicles. Individual travelers benefit from private vehicle use without the costs and responsibilities of private car ownership. Individual travelers usually pay a monthly fee and/or a per-use fee. For accessing vehicles, individual travelers join an organization that manages a vehicle fleet. Possible carsharing service models include: • roundtrip carsharing (i.e., the car is returned to origin after trip) • one-way station-based carsharing (i.e., the car is returned to a designated carsharing location after a trip) • one-way free-floating (i.e., the car can be returned anywhere within a geo-fenced area after a trip)	**Germany**: Drive Now, Car2Go, Flinkster, Cambio, Stadtmobil **USA**: Reach Now, Car2Go, ZipCar
Ridesharing/ Carpooling	Ridesharing or rather carpooling comprises the sharing of a vehicle for a particular trip, including several travelers who have more or less the same origin and destination (e.g., commuting with colleagues). Here, the shared vehicle can be owned by one of the travelers.	**Germany** [212]: BlaBlaCar.de, Fahrgemeinschaft.de, Flinc, BesserMitfahren.de, Twogo, MiFaZ, Mitfahrportal.de, mitfahren.de, drive2day.de, Pendlerportal.de, Karzoo.de, Fahrfahraway.com, Bringhand.de **USA** [75]: Carma, BlaBlaCar, Ridejoy
Ridehailing/ Ridesourcing and e-hailing services	Ridehailing comprises transportation network companies that connect professional drivers with a private vehicle with passengers. If the booking of the ride, the evaluation of the driver and the payment is handled completely electronically, ridehailing services are categorized as e-hailing services.	**Germany**: Uber, Mytaxi **USA**: Uber, Lyft, Sidecar, Via, Gett, Mytaxi
Robo-taxis and ridepooling	Robo-taxis comprise future ridehailing services in a fully self-driving car without any human control (i.e., level 5 of vehicle automation levels; see Table 2.8). Robo-taxis may be used by one passenger only or shared by different passengers (i.e., ridepooling).	Future scenario

Table 2.8 Overview of Different Levels of Vehicle Automation (Adapted from: [79]).

Automation	Definition
Level 0	No automation
Level 1	Autonomy of one primary control function, e.g., adaptive cruise control, self-parking, lane-keep assist, or autonomous braking
Level 2	Autonomy of two or more primary control functions “designed to work in unison to relieve the driver of control of those functions”
Level 3	Limited self-driving; driver may “cede full control of all safety-critical functions under certain traffic or environmental conditions,” but it is “expected to be available for occasional control” with adequate warning
Level 4	Full self-driving; driver “is not expected to be available for control at any time during the trip” (includes unoccupied vehicles)
Level 5	Full self-driving without human controls

In sum, ODM services are independent marketable mobility services that support individual travelers in reaching their destination. European and American travelers already profit from a rowing carsharing, ridesharing and ridehailing market. The rise and further development of the different ODM services listed in Table 2.7 were boosted by wireless connectivity and new aspiring technologies (e.g., spreading of smartphones and vehicle automation). The main advantages of ODM services are the high flexibility, efficiency, and convenience experienced by the traveler [184]. Future developments in the field of ODM services concentrate on higher levels of vehicle automation and the access to (shared) robo-taxis with automation level 5.

2.2.2 Studies on On-demand Mobility Services

This paragraph concentrates on the criteria influencing the traveler’s decisions on using current and future ODM services such as carsharing, carpooling, ridehailing and robo-taxis. As described above, studies on transport mode choice can generally be divided in two main streams of research (see Chapter 2.1.2), namely (1) studies dealing with stated preferences and (2) studies dealing with revealed preferences of travelers [21]. Since carsharing, carpooling and ridehailing are already available on the market, the literature review on these means of transport contains stated as well as revealed preference studies. Table 2.9 provides an overview of recent research on stated and revealed preference studies on currently available ODM services. As explained in the market analysis above, ridehailing is less popular in the German market than carsharing and carpooling. Therefore, the literature review mainly concentrates on carsharing and carpooling. Since (shared) autonomous vehicles are not available on the transportation market right now, the literature review on robo-taxis and ridepooling will solely focus on stated preference studies. Table 2.10 provides an overview of discrete choice modelling in the context of future ODM services.

Current ODM Services. As explained in the ODM services market analysis above, the use of ridehailing is more common on the North American than on the German market. Since this dissertation mostly analyzes the German market, the subsequent literature review focuses on carsharing and carpooling.

For example, Schmöller, Weikl, Müller and Bogenberger [175] analyzed booking data from a German free-floating carsharing service in Munich and Berlin. The authors found temporal factors, spatial factors and weather to be important predictors for booking frequencies. However, sociodemographic characteristics of the travelers only had small influences in the model.

In contrast, Efthymiou and Antoniou [63], Efthymiou, Antoniou and Waddell [62] and Kim, Ko and Park [109] investigated the criteria for using different carsharing services and identified sociodemographic characteristics of the traveler such as age, gender, and income as important predictors for carsharing usage. More specifically, travelers with a medium or low income and high environmental consciousness tend to adopt carsharing services more frequently [63]. The relevance of environmental attitudes or motives was highlighted in multiple studies on carsharing usage. For example, Schaefers [172] applied a hierarchical means-end chain analysis and explored four main carsharing usage motives, namely (1) value-seeking, (2) convenience, (3) lifestyle, and (4) environmental motives.

Furthermore, Seign and Bogenberger [178] focused on a specific kind of carsharing, namely carsharing with electric vehicles. After analyzing $n = 34$ interviews with different stakeholders, the authors identified the following top six success factors for electronic carsharing: (1) absolute population of a city, (2) existing charging infrastructure, (3) quality of public transport, (4) education level of potential travelers, (5) regulatory or possibility to park on-street, and (6) vehicle availability.

Besides carsharing recent studies have also focused on investigating the factors for carpooling. Regarding carpooling, Tahmasseby, Kattan and Barbour [193] investigated the influence of socio-economic, psychological and trip-related factors on the propensity to participate in a hypothetical peer-to-peer social-network-based carpooling program called “FacePorter”. The results of the modelling showed significant effects of socio-economic factors such as occupation, income, and marital status. Moreover, working schedule flexibility, trip characteristics (i.e., distance, travel time, and number of transfers), weather and carpooling fees are important predictors. Additionally, pooling-specific factors, namely the perceived rider and driver profiles derived from the social network, also influence the market demand of a carpooling system significantly.

Table 2.9 Literature Review on Transport Mode Choice including existing ODM services (own illustration in chronological order).

Authors (Year)	**Research question**	**Compared modes**	**Model parameters**	**Method**	**SP/RP**	**n**
Hyland, Frei, Frei & Mahmassani (2018) [97]	Demand of flexible transit and weather/ seasonality effects on commute mode choice in Chicago	Fixed route transit (i.e., public transport), car (driving alone), flexible transit (i.e., pooling, hailing, sharing)	Cost, waiting time, headway, transfers, in-vehicle travel time, walk time, parking cost at work, commute trip distance, Google estimated walk time to nearest transit stop from home, frequency walking to work, frequency biking to work, frequency driving to work, frequency carrying a gym bag to work, bike sharing membership, gender, age (categorial), annual income (categorial), employer provides cost reimbursement, weather, season, employment, education, weather	Mixed logit models with interactions	SP	153
Frei, Hyland, & Mahmassani (2017) [72]	Assessment of the demand of flexible transit in Chicago	See above	See above	Mixed logit models	SP	153
Efthymiou & Antoniou (2016) [63]	Factors influencing the propensity to join a carsharing scheme	Carsharing	Taking taxis/buses for social activities, environmental consciousness, satisfaction with current travel pattern, time travelling to work/school per day, age, marital status, household income, car ownership	Ordered logit models and SEM	SP	351
Malodia & Singla (2016) [130]	Factors influencing the propensity of carpooling at morning commute	Car (driving alone), carpool	Extra travel time, walking time to reach meeting point, waiting time, cost saved per month, income, occupation, marital status, work flexibility, environmental concerns, transfer time, time of the day, activities on the way, importance of time savings, existing carpool arrangement	Type of model not mentioned	SP/RP	106
Schmid, Schmutz & Axhausen (2016) [174]	Mode choice in a future scenario without private car ownership	Carpooling, carsharing, taxi, bike, walking	Car ownership, environmental concerns, public transport affinity, walk affinity, bike affinity, hypothetical transport modes	Multinomial logit model	SP	54

Authors (Year)	Research question	Compared modes	Model parameters	Method	SP/RP	n
Tahmasseby, Kattan & Barbour (2016) [193]	Examination of the potential of peer to peer carpooling in Calgary (Canada)	Two Groups: car (drive alone) vs. carpooling as a driver; public transport vs. carpooling as a passenger	Driving alone, offering ride, drive time, cost, weather, rider profile, commute via pool, required postpone/prepone departure time	Binominal logit models and ordinal logit models	SP	210
de Luca & Di Pace (2015) [128]	Mode choice and switching behavior of short trip inter-city morning commuting	Car (driving alone), carsharing, carpooling, public transport	Travel time, cost, access time to carsharing/ public transport, age, gender, driving frequency, frequency of trips, stops on way home, city, car availability	(Mixed) Multinomial logit model	SP	500
Kim, Ko & Park (2015) [109]	3 Models: Willingness to (1) dispose current vehicle, (2) purchase an electronic vehicle, and (3) continue participating in an electric vehicle sharing program	Own car, electric vehicle, electric vehicle sharing	Booking, fee and payment; renting, charging and driving; social and economic perspectives; gender, age, income, car ownership, single, occupation, trip purpose (commuting vs. leisure time)	Ordered probit models	SP/RP	533
Efthymiou, Antoniou & Waddell (2013) [62]	Propensity to join carsharing and bike sharing in a given time	Bike sharing, carsharing	Environmental consciousness, household income, distance travel per week, taxi for social activities, walk to school, household sizes, >60min to work/school, education, mode for work/school trips	Ordered logit models	SP/RP	233

Authors (Year)	Research question	Compared modes	Model parameters	Method	SP/RP	n
Ciari & Axhausen (2012) [44]	Investigation of carsharing and carpooling in Switzerland	Car (driving alone), public transport, carpooling as a driver, carpooling as a passenger	Costs, distance, walking time, travel time, transfer time, number of transfers, season ticket, parking cost, availability of car, previous experience with carpooling, opinion on carpooling, no show risk, trip mate (colleague vs. acquaintance), work trip, household dimension, age, gender, income, language, education,	Multinomial logit models with interactions	SP	876
Correia & Viegas (2011) [50]	Investigation of carpooling and carpool clubs in Lisbon	Car (driving alone), carpooling	Children on the way to work, driving time, walking to meeting point, walking to workplace, cost, number of friends in group, number of colleagues in the group, household member in the group, guaranteed ride home, flexible car usage, reduction of toll, age, marital status, student, white collar job, children under 16, employed, usually luxury vehicle, number of licenses per vehicle at home, difference between cost of car and carpool, parking difficulties, time of leaving home, needing car after work, extra activity	Binary logit model	SP	996
Catalano, Lo Casto & Migliore (2008) [37]	Choice experiment to develop demand model parameters for innovative transport modes in Palermo	Car (driving alone), carsharing, carpooling, public transport	Travel time, cost, parking, number of cars, parking time, access time,	Multinomial logit model	SP	495
Washbrook, Haider & Jaccard (2006) [211]	Investigation of the impact of road pricing and parking charges on commuter's mode choice	Car (driving alone), carpooling, express bus	In-vehicle time, road charge, parking cost, pickup time, wait time, walk time	Conditional logit model	SP	529

Authors (Year)	Research question	Compared modes	Model parameters	Method	SP/RP	n
Horne, Jaccard & Tiedemann (2005) [94]	Choice of vehicle and commuting decisions in Canada	Car (driving alone), carpooling, transit, park and ride, walking, bike	Cost, driving time, pick up/ drop off time, Walking/ waiting time, transfers, cycling path, fuel type Nested: Gasoline, other fuels, alternative fuels	Multinomial logit model	1150	SP
O'Fallon, Sulliva & Hensher (2004) [141]	Investigation of reasons why morning commuters choose the car instead of alternative means of transport	Car (driving alone), passenger in a car, carpooling, park and ride, public transport, bike	Parking cost, parking availability, registration charge, toll, company vehicle, family vehicle, own vehicle, car use today, parking habits, trip distance, trips before work, student, children in household, household status, employment status, age, gender, access to public transport within 400m	Multinomial logit model, nested logit model	SP	732
Bhat & Castelar (2002) [25]	Reactions of San Francisco Bay Bridge users to changes in travel conditions	Car (driving alone), carpooling, Alameda County Transit, Bay Area Rapid Transit	Drive alone off-peak, carpool peak, carpool off-peak, Alameda County Transit, Bay Area Rapid Transit, vehicles per worker in household, gender, employment, income, travel time, cost	Mixed logit models	SP/RP	136
Washbrook (2002) [210]	Investigation of the potential of road and parking charges to reduce drive alone commuting	Car (driving alone), carpooling, transit	In-vehicle time, road charge, parking cost, pickup time, wait time, walk time	Conditional logit model	SP	548

Authors (Year)	Research question	Compared modes	Model parameters	Method	SP/RP	n
De Palma & Rochat (1999) [146]	Impacting factors of commuter's mode choice in Geneva	Car (alone, carsharing), bus, motorbike, train	Age, education, gender, flexible working hours, occupation, days going to work in a week, ownership of driver's license, household income, number of household members working, household size, household composition, children drive to work, number of cars owned, usual travel mode, evaluation of comfort, evaluation of availability, evaluation of safety, average travel time, average time of daily congestion, frequency of congestion during a week, frequency of late arrival due to congestion, weather	Descriptive weighting of attributes	SP	800
Bhat (1997) [24]	Impact of number of non-work stops on commute mode choice	Car (driving alone), shared ride (use of a car by more than one traveler) and transit (bus, commuter rail, or local rail)	Mode, income, vehicles per household, travel time, out of vehicle travel time, cost, work duration, employment density at work zone, age, household status, stops on the way	Multinomial logit model	SP	618
Hunt & McMillan (1997) [96]	Influences on the decision to carpool to work in Canada	Car (driving alone), carpooling as a driver, carpooling as a passenger	Driver of car, carpool, number of added people, friends in car, coworker in car, parking cost, ride time, time spent picking up people, walking before transit, walk after transit, guaranteed ride home, waiting time for guaranteed ride home	Binary logit model	SP	678
Srinivasan, Dajani & Flachsbart (1981) [185]	Impacting factors of commuter's mode choice	Car (driving alone), carpooling, transit	Price, parking, occupants in pool, excess ride time compared to car, walk, wait, fare	Conditional logit model	SP	106

Future ODM Services. Next, scientific studies on criteria influencing the traveler's modal decisions in a future scenario with (shared) autonomous will be reviewed. Contrary to the studies on current ODM services described above, studying future ODM services is a quite young field of research. Published choice models considering (shared) autonomous vehicles can be found in the academic literature approximately since the last four years. Hence, the number of published models is still small. However, several papers concentrate on demand and discrete choice modelling in the context of autonomous vehicles from a theoretical perspective and the technology acceptance of (shared) autonomous vehicles.

Cyganski [53] regarded choice and demand modelling in the context of autonomous vehicles from a theoretical perspective. The author highlighted that choice and demand modelling from the field of current means of transport cannot just be transferred to the use of future autonomous vehicles. Instead, traditional choice and demand models have to be modified and expanded by changing characteristics of the trip such as the less obvious transition between driving and being driven, usefulness of travel time, higher safety and flexibility, less effort at the beginning and end of a trip, shorter overall travel time and characteristics of the vehicles such as powertrain type and vehicle size.

Zmud, Sener and Wagner [223] supported the necessity to expand traditional mode choice models empirically with qualitative interviews and a quantitative survey on consumer acceptance and adoption of autonomous vehicles in Texas (USA). The empirical results highlighted the importance of the following variables:

- Having physical conditions that prohibit driving
- Thinking autonomous vehicles decrease crash risks
- Using smartphones, text messaging, social media, and transportation apps
- Not being concerned with data privacy in the context of smart technologies
- Thinking using autonomous vehicles is fun
- Being informed about vehicle automation
- Trusting new technologies

Based on their results, the authors concluded that "[a]t this early stage in market development for self-driving vehicles, the personality and psychology of the consumers are much more important than their demographic profile" (p. 19).

In contrast to Zmud, Sener and Wagner [223], other studies still emphasize the importance of socio-demographic traveler profiles for the usage and willingness to pay for (shared) autonomous vehicles. For example, Bansal, Kockelman and Singh [18] conducted an online survey in Texas (USA) and found that tech affine male travelers with higher income and a residence in metropolitan areas and more crash experiences have a higher willingness to pay for vehicle automation.

Another example is provided by Krueger, Rashidi and Rose [112]. Analyzing potential profiles of shared autonomous vehicle users in Australia, the authors found that young travelers who already use carsharing services and thus show multi-modal mobility habits are more likely to use shared autonomous vehicles with dynamic ridesharing. Moreover, the authors also replicated travel costs, waiting time, and travel time as important predictors for accepting shared autonomous vehicles and dynamic ridesharing services.

One of the first empirical choice models concerning future ODM services was published in March 2017 by Haboucha, Ishaq and Shiftan [81]. In their literature review, the authors even stated that “[they] haven’t found any discrete choice models estimating the choice between regular cars, private autonomous vehicles, and shared autonomous vehicles, but a few publications have used discrete choice theory to model various aspects of autonomous vehicles” (p. 38). Haboucha, Ishaq and Shiftan [81] used stated preference data (n = 721) to calculate a mixed multinomial logit model regarding the motivations for choosing to own and use autonomous vehicles and the long-term decisions regarding autonomous vehicles. The authors considered the North American and Israeli market and compared three different modes, namely (1) continuing regular private car usage, (2) shifting to use privately owned autonomous vehicles, and (3) shifting to use shared autonomous vehicles. Similar to the current choice models described in the last paragraphs the authors identified criteria such as travel time, purchase price, subscription cost, trip cost, increase in parking price, number of days to commute, frequency of errands as part of the commute, and the possibility to store items in a car. Moreover, environmental concerns and socio-demographic factors such as gender, age, education, and number of young children were significant predictors for modal decisions. Additionally, the authors expanded regular choice models by driving pleasure and a positive attitude towards vehicle automation. More concrete examples of discrete choice models in the context of future ODM services are listed in Table 2.10.

Table 2.10 Literature Review on Transport Mode Choice in future scenarios (own illustration in chronological order).

Authors (Year)	**Research question**	**Compared modes**	**Model parameters**	**Method**	**SP/RP**	**n**
Correia, Looff, Van Cranenburgh, Snelder & Van Arem (2019) [49]	Impact of vehicle automation on the value of travel time while performing work and leisure activities in a car or an autonomous vehicle (AV)	1. Car, AV with office interior, AV with leisure interior 2. Car, chauffeur driven car with office interior, chauffeur driven car with leisure interior	Travel time, travel cost, walking time, travel companions, AV activity, age > 60, retired, part time work, daily use of bus/ tram/ metro, use of carpooling, willing to work in AV, ability to work in a car, attitude towards convenience of AV	Multinomial logit model, hybrid choice model	SP	Study 1: 178 Study 2: 146
Bansal & Daziano (2018) [17]	Welfare measures associated with the use of autonomous taxis in New York	Low emission Uber, low emission UberPool (ridesharing), car	Walk and wait time, in-vehicle travel time, trip cost, parking cost, CO2 emissions, automation level	Multinomial logit model	SP	298
Jiang, Zhang, Wang & Wang (2018) [103]	Investigation of the propensity of ownership of autonomous vehicles (AVs) in Japan	AV (different automation levels: conditional, high, full), conventional vehicle	Additional purchase cost, insurance reduction rate, penetration rate, parking cost reduction rate, insurance reduction rate, release timing of autonomous vehicles, driving safety improvement, expected income improvement, long/short driving experience, time per trip, driving frequency, driving purpose (shopping/commuting), age, gender, education, elderlies in household, students in household	Mixed multinomial logit model	SP	1728

Authors (Year)	Research question	Compared modes	Model parameters	Method	SP/RP	n
Shabanpour, Golshani, Shamshiripour & Mohammadian (2018) [179]	Investigation of preferred attributes leading to AV adoption	Different features of AVs	Fuel cost, driving range, overall safety, emission rate, driver is liable for crashes, exclusive lane is provided, purchase price, work parking cost, shared ride to work, home location downtown, accident experience, not safe interactions with pedestrians/cyclists, age, gender, income, household size	Binary logit model	SP	1013
Steck, Kolarova, Bahamonde-Birke, Trommer, Lenz (2018) [188]	Impact of autonomous driving on value of travel time savings, and mode choices for commuting trips	Walking, bike, AV, SAV, public transport	Travel time, travel cost, shared ride for driverless taxi, preference to drive privately owned autonomous vehicle manually/autonomously, license ownership, ownership of public transport pass, access and egress, waiting time, age, income class	Mixed multinomial logit model	SP	172
Dong, DiScenna & Guerra (2017) [60]	Exploration of transit users' choice to use driverless busses	Willing, uncertain and unwilling to drive a driverless bus	Gender, age, bus usage, employee monitoring operations, employee delivering customer service, having heard of AV's, concern about vehicle safety, concern about lack of assistance for disabled passengers, concern about access to information	Mixed logit model	SP	891
Haboucha, Ishaq & Shiftan (2017) [81]	Motivations for choosing to own and use AVs and development of a model of long-term decisions regarding AVs	Car, privately owned AV (PAV), SAV	Travel time, purchase price, subscription cost, trip cost, increase in parking price, frequency of errands as part of the commute, store items in car, gender, age, education, number of days to commute, number of young children, enjoy driving, environmental concern, pro AV attitude	Mixed multinomial logit model	SP	721

Authors (Year)	Research question	Compared modes	Model parameters	Method	SP/RP	n
Bansal, Kockelman & Singh (2016) [18]	Impact of demographics and other variables on willingness to pay for an automated module in a car	SAVs with three different price scenarios	Number of past crash experience, familiar with carsharing, familiar with UberX or Lyft, dive alone for work trips, drive alone for social trips, annual vehicle miles traveled, distance from workplace, gender, driver license, number of children, age, employment density, income	Bivariate ordered probit model	SP	347
Krueger, Rashidi & Rose (2016) [112]	Characteristics of users who are likely to adopt SAVs and dynamic ride sharing (DRS)	SAV with DRS, SAV without DRS	Age, gender, income, presence of children, car availability, means of transportation, trip purpose (work, shopping, leisure, medical), carsharing user, modality (clustered users)	Mixed logit model	SP	435
Yap, Correia & van Arem (2016) [219]	Exploration of the choice of AVs for the last mile trips between a train station and the traveler's final destination	Car, train and bus/ tram/ metro, train and bicycle, train and AV (driver drives), train and AV (autonomous driving)	Travel time, waiting time, walking time, fuel cost, travel cost, train class, sharing, purpose, age, income, gender, trust, service reliability, sustainability, productivity, enjoyment of car driving	Mixed logit model	SP	761
Payre, Cestac & Delhomme (2014) [148]	Predictors of the intention to use an automated car	Automated car	Gender, age, driving-related sensation-seeking scale score, interest in using FAV, impaired acceptability, contextual acceptability, attitudes towards FAV	Hierarchical linear regression	SP	421

In conclusion, discrete choice modelling in the context of current ODM services is based on stated and revealed preference data whereas discrete choice modelling in the context of future ODM services can only be based on stated preference data. In both streams of research, mainly logit models (e.g., multinomial logit models and mixed logit models) are used to estimate the influence of different parameters on mode choices. The studies listed in Table 2.9 and Table 2.10 illustrate that modal decisions in the context of ODM services are based on similar predictors as modal decisions in the context of general means of transport (see Figure 2.5). However, the shaping of the predictors has to be transferred from general means of transport to ODM services. More specifically, the choice models include sociodemographic parameters of the traveler (e.g., age and license ownership), mobility habits of the traveler (e.g., frequency of driving to work), mobility-centered attitudes of the traveler (e.g., environmental attitudes), infrastructure-related parameters (e.g., availability of carsharing parking spaces), quantitative and qualitative characteristics of the mode of transport (costs, access time to carsharing), characteristics of the trip (e.g., extra walking or driving time for reaching carpooling meeting point), and side conditions such as weather and season.

Despite these similarities between the choice models from the three different fields analyzed above, the factors influencing the use of general means of transport, current ODM services and future ODM services differ. Thus, discrete choice models from the field of current means of transport cannot just be transferred to the field of (shared) autonomous vehicles. This is due to changing side conditions of travelling in (shared) autonomous vehicles compared to currently available means of transport such as the less obvious transition between driving and being driven, higher safety and flexibility, less effort at the beginning and end of a trip, and shorter overall travel time. In particular, the discrete choice models regarding (shared) autonomous vehicles need to include additional factors such as powertrain type, vehicle size, and usefulness of travel time.

Moreover, the literature review revealed several open questions concerning modal choices in the context of current and future ODM services, which are summarized in the following research gaps:

- **German Carpooling**. There is no up-to-date stated preference analysis and discrete choice modelling concerning carpooling in large German cities (e.g., Munich). Since German cities differ from Canadian or American cities with regard to multiple aspects such as infrastructure and costs for mobility, it is necessary to transfer and validate discrete choice models from a Canadian or American sample to a German sample. Analyzing German carpooling scenarios and the criteria influencing a traveler's decision for or against pooling can help us to reduce urban traffic by making carpooling more attractive for the travelers and strengthening the traveler's motivation to pool.

- **Carpooling as a Driver vs. Carpooling as a Passenger.** Regarding carpooling, most studies only distinguish between carpooling and other means of transport. However, we need to distinguish between carpooling as a driver and carpooling as a passenger in order to understand the traveler's motivation in more detail. This detailed differentiation is only regarded in few empirical choice models.

- **Carpooling during Commuting vs. Carpooling during Leisure Time Travelling.** Another aspect concerning carpooling is that most studies focus on carpooling during commuting and not on carpooling to reach leisure time activities. Here, it would be interesting to compare different choice models of carpooling during commuting and carpooling during leisure time travelling. This aspect is strongly related to the influence of time pressure on carpooling which is also still under-researched.

- **Ridepooling vs. Carpooling.** Moreover, the literature review highlights that previous research on robo-taxis has only marginally focused on traveler preferences for service attributes of shared autonomous vehicles. While the feasibility, operations, and costs of autonomous vehicles are well studied, only few studies concentrate on individual preferences for service attributes of shared autonomous vehicles and the traveler's willing to choose and pay for these ODM services. Here, it would be interesting to compare the traveler's willingness to pool in a current and future scenario in order to understand the different motivators for carpooling and ridepooling in more detail.

2.3 Pre-trip Information Systems

This chapter concentrates on pre-trip information systems (IS). Reaching the research objectives described in the introduction requires a solid theoretical background on pre-trip ISs. This includes defining pre-trip ISs and differentiating them from other kinds of mobility-centered information systems. Additionally, an overview of existing pre-trip ISs, their modules and services will be provided. Main parts of the literature review presented below were already published in a journal paper [160] and two conference proceedings [161,214].

2.3.1 Definition and Overview

In order to investigate and innovate pre-trip ISs, it is important to define and distinguish different kinds of transport information and control systems. Therefore, the following paragraphs define different service categories with regard to their content, information type, retrieval format, and the media through which the service can be displayed. After defining and differentiating different service categories, this section will elaborate on the potential influence of different ISs on travel behavior.

A good basis for defining and classifying pre-trip ISs provides the International Organization for Standardization (ISO). ISO has built a taxonomy of transport information and control systems services. The taxonomy differentiates eight different categories of services, namely (1) traffic and travel information, (2) traffic management, (3) vehicle-related, (4) commercial vehicle, (5) public transport, (6) emergency management, (7) electronic payment and (8) safety services. According to the ISO taxonomy of transport information and control systems services pre-trip services belong to the category of traffic and travel information [98] (see Table 2.11). Traffic and travel information can be grouped by when or where in the trip chain the traveler seeks the information (i.e., pre-trip, wayside, in-vehicle, and mobile), what kind of information is retrieved (i.e., static and real-time information) and how the information is retrieved (i.e., proactive and interactive). Table 2.12 illustrates that pre-trip traffic and travel information contains static as well as real-time information that can be retrieved proactively and interactively from a variety of media ranging from printed media to smartphones. In sum, pre-trip ISs present static and real-time traffic and travel information through different media channels proactively and interactively.

Table 2.11 Taxonomy of Transport Information and Control System Services Categories (Adapted from [145, p. 47-48]).

Category	Service
Traffic and travel information	• Pre-trip information • On-trip driver information • On-trip public transport information • Personal information services • Route guidance and navigation
Traffic management	• Transportation planning support • Traffic control • Incident management • Demand management • Policing/enforcing traffic regulations • Infrastructure maintenance management
Vehicle-related	• Vision enhancement • Automated vehicle operation • Longitudinal collision avoidance • Lateral collision avoidance • Safety readiness • Pre-crash restraint deployment
Commercial vehicles	• Commercial vehicle pre-clearance • Commercial vehicle administrative processes • Automated roadside safety inspection • Commercial vehicle on-board safety monitoring • Commercial vehicle fleet management
Public transport	• Public transport management • Shared transport management
Emergency management	• Emergency notification and personal security • Emergency vehicle management • Hazardous materials and incident notification
Electronic payment	• Electronic financial transactions
Safety	• Public travel security • Safety enhancement for vulnerable road users • Intelligent junctions

Table 2.12 Media, Content, Information Type, and Retrieval Format of Pre-trip Information (Adapted from: [198]).

	When/Where				What		How	
	Pre-trip	**Wayside**	**In-vehicle**	**Mobile**	**Static**	**Real-time**	**Proactive**	**Interactive**
Printed material	x	x	x		x		x	
Telephone	x				x	x		x
Mobile phone	x	x	x	x	x	x	x	x
Smartphone	x	x	x	x	x	x	x	x
E-mail	x	x	x	x	x	x	x	
SMS	x	x	x	x		x	x	
Other mobile devices (e.g., tablet)	x	x	x	x	x	x	x	x
Internet/Website	x				x	x		x
Kiosk	x	x			x			x
Television	x				x	x	x	
Dynamic message sign		x	x		x	x	x	
Annunciator		x	x			x	x	
Social media	x			x		x	x	
Interactive voice response	x			x	x	x		x

The provision of pre-trip information affects travelers as well as the managers of transport systems. From the operators' perspective, the ongoing development of data gathering and tracking [222] in the context of pre-trip ISs represents new means for monitoring and controlling transport systems. Furthermore, the provision of traffic and travel information by pre-trip ISs affects individual travel behavior [151]. The extent to which individual travel behavior is affected by the provided information differs. The influence depends on the content (i.e., what information?), the time and place of the provision (i.e., where and when?), and the retrieval format (i.e., how?). Finally, travelers also differ individually in their extent to which they actually use the provided pre-trip information.

This dissertation focuses on pre-trip ISs because pre-trip information generally have a higher influence on travel behavior than roadside or in-vehicle information [151]. This is due to the fact that pre-trip ISs reach more dimensions of potential behavioral responses than roadside or in-vehicle information provision (see Table 2.13). More specifically, roadside or in-vehicle ISs primarily affect route choices. Moreover, sub-mode choices can also be affected during the trip. For example, sub-mode choices in the context of public transport would include decisions about taking the bus or taking the subway. Another example of sub-mode decision are parking decisions between city center parking and park and ride parking. Overall mode choices about trip suppression are very unlikely to happen during a trip apart from decisions made in the context of extreme traffic jams. Besides route choices and sub-mode choices, pre-trip information retrieved at intermediate destinations has the potential to provoke changes in destinations and re-timing. In contrast, pre-trip ISs in-home has the highest impact on travel behavior, including trip generation and suppression, mode choices and changes in timing [151].

Table 2.13 The Potential Influence of Different Information Systems on Travel Behavior (Adapted from [151, p.181]).

Behavioral response	**Pre-trip in-Home**	**Pre-trip non-Home**	**In-vehicle/ roadside**
Trip/tour generation/suppression	✓		
Public/private mode choice	✓		
Change in trip timing	✓		
Change in destination/trip/sequences	✓	✓	
Change in sub-mode choice	✓	✓	✓
Change in route	✓	✓	✓

Summarizing, traffic and travel information can be retrieved by travelers pre-trip, wayside, in-vehicle, and mobile. Depending on the concrete services, the information is provided static or real-time and proactive or interactive. Within the category of pre-trip ISs, transportation research distinguishes between pre-trip in-home and non-home. Since pre-trip ISs in-home have the widest impact on travel behavior, this dissertation concentrates on the investigation of pre-trip ISs in the traveler's home. Pre-trip ISs have the potential to influence travel behavior significantly because the provision of traffic and travel information expands the traveler's possible choice sets while the quality of the information is improved contemporaneously by ongoing developments in telecommunications and information processing technologies. Due to the limited potential of in-vehicle and roadside ISs to change travel behavior substantially, we need to optimize pre-trip ISs in order to resolve our current problems regarding urban traffic, transport network capacity, and transport demand as described in the introduction. Pre-trip ISs have a great potential to motivate travelers to use public instead of private means of transport, re-time trips away from peak times and even suppress trips.

2.3.2 Modularization of Digital Mobility Services

Facing the variety of offers on the market of intelligent transportation systems (ITS) and intelligent traveler information systems (ITIS) demands a clear structure of available digital mobility services. Therefore, after deducing the reasons for the rapid development of the service market, this section divides available digital mobility services into different categories concerning their service focus, their modules, and underlying data sources.

The development of technologies for locating and tracking mobile phones in the early 2000s has revolutionized the market of ITS and ITIS [222]. Based on these technological developments, innovative digital mobility and especially location-based services have entered the ITS market. Consequently, digital mobility and especially location-based services have expanded the field of ITS by appearing in cars and on smartphones and became a strong influencer of travel behavior [71].

Integrating digital mobility services on smartphones has an ongoing multiplier effect on the development of digital mobility services. For example, the introduction of Google Maps in 2005 helped Google to collect even more data regarding traffic flow, congestion and points of interest (POI) from travelers, which in turn helps Google to continuously innovate and improve their services. Further examples of crowdsourcing-based improvement of digital mobility services are the monitoring of pavement conditions [220] and the prediction of parking spaces [36]. Hence, travelers use services like Google Maps in order to optimize their individual mobility and service providers such as Google are able to improve their services by collecting more and more data, which in turn improves their predictions.

Since the landscape of digital mobility services is wide, it is important to structure the services according to different service categories, service modules, and their underlying data sources. An extensive overview and categorization were provided by Schreieck, Wiesche and Krcmar [176]. Through a structured search within app stores and articles from blogs, the authors provided an overview of currently existing urban mobility services. This overview includes 59 digital mobility services (see Appendix A and Appendix B) that can be grouped in six different categories, namely (1) trip planners (e.g., Moovel), (2) car or ride sharing services (e.g., DriveNow), (3) navigation (e.g., Google Maps), (4) smart logistics (e.g., Uber cargo), (5) location-based information (e.g., ChargeNow) and (6) parking services (e.g., ParkNow) (listed in order of decreasing category size; see Figure 2.6). The examples illustrate that each of the six categories contains services that can be classified as pre-trip ISs.

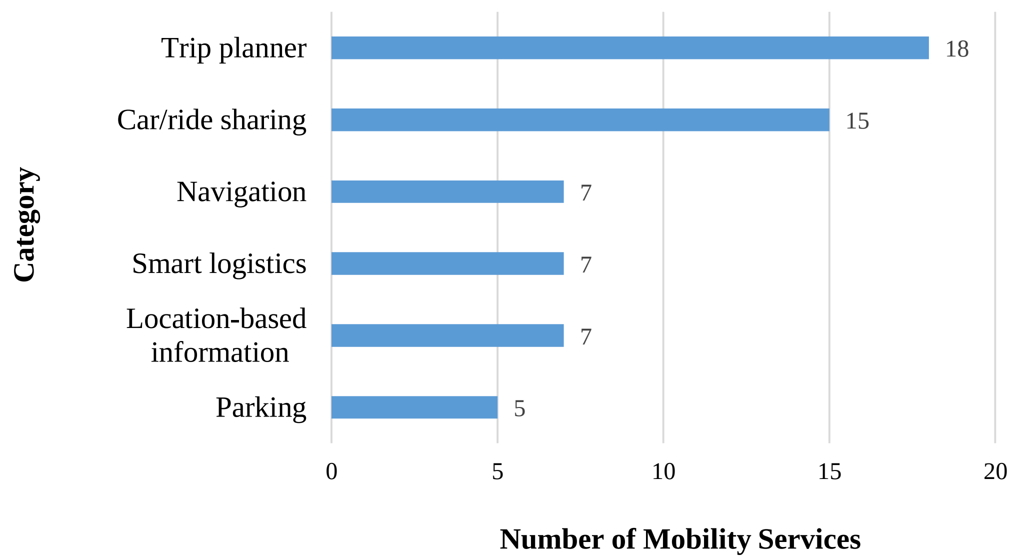


Figure 2.6 Categories of Digital Mobility Services (Source: [176, p. 5]).

In a deeper analysis, the authors examined, which data sources and service modules are integrated in which of the six service categories listed above (see Figure 2.7). Data sources of digital mobility services are Google, device sensors, other private providers, public transportation providers, and public administration. Service modules of digital mobility services comprise map view, routing, points of interest, location sharing, traffic information, parking information and matching of demand and supply. Interestingly, the results show a very heterogeneous combination of service modules in digital mobility services. For example, traffic information services are only included in 40% of the digital mobility services that focus on navigation, in 60% of the location-based information services and in none of the other four service categories. Moreover, parking information is only included in 60% of the parking services and in none of the other service categories. The only two service modules that can be found in all of the six categories of digital mobility services are map view and routing. Within the categories, however, these two service modules are not part of every single digital mobility service.

	Service modules							Data sources					
Category	**Map view**	**Routing**	**POIs**	**Location sharing**	**Traffic information**	**Parking information**	**Matching**	**Google**	**Device sensors**	**Crowdsourced**	**Other private providers**	**Public transport provider**	**Public administration**
Navigation	●	●	●	◔	◍	○	○	◑	●	◑	◔	◍	◑
Trip planner	◕	●	◑	○	○	○	○	◕	●	◔	◕	●	◔
Smart logistics	◕	◔	○	◍	○	○	◍	◕	●	◑	◍	○	○
Parking service	●	●	●	○	○	◕	◔	◕	●	●	●	○	●
Car/ride sharing	●	◍	◍	◔	○	○	◍	●	●	◍	◍	○	○
Location-based information	●	◍	◑	○	◕	○	○	●	●	◕	◔	○	◍

Used in more than ● 80%, ◕ 60%, ◑ 40%, ◔ 20% of the services.

Figure 2.7 Service Modules and Data Sources of Digital Mobility Services (POI = Point of Interest; Source: [176, p. 7]).

In conclusion, the findings described above highlight that some features are rarely integrated in digital mobility services, although they might provide a comfort service for the travelers (e.g., parking information). Therefore, while planning their mobility travelers have to fall back upon multiple mobility services in order to satisfy their individual need for information sufficiently. The ideal situation, however, would include a smart and multi-modal all-in-one pre-trip IS. Instead of searching for mobility-centered information using different services and putting effort into evaluating and combining the information from different sources, the traveler's workload should be reduced through providing individually tailored pre-trip information at the right time proactively. Therefore, the development and design of pre-trip ISs come along with the following questions for traffic and transportation researchers and engineers:

- “What are the pre-trip information needs of travelers?
- In what detail and form should the information be presented?
- What use are travelers likely to make of different types and sources of information?
- And how will the provision of pre-trip information affect travel behavior?” [151, p. 180]

In order to optimize pre-trip ISs, we need to develop a well-structured service system that provides useful and integrated services to the travelers. Developing a service system with multiple interoperable modular digital mobility services enables value co-creation [28]. Therefore, we need to understand the current pain points the traveler faces while using digital mobility services. Moreover, we need to assess the traveler’s mobility-centered pragmatic needs (e.g., time and type of information) and the traveler’s non-mobility-centered additional needs (e.g., news, preparing grocery shopping), which are associated to the situation in which travelers inform themselves about their mobility options. The user-centered development of pre-trip ISs will be elaborated in detail in Chapter 3.

3 Pre-study: Functional Design of Pre-trip Information Systems

Smart environments change our daily life and our daily mobility. Especially in growing smart cities, we need innovative solutions of smart multi-modal transport services for travelers. In the near future, most travelers will start their multi-modal journey through a seamlessly connected smart city with intelligent mobility services at home. Nevertheless, there is a lack of well-founded requirements for smart in-house pre-trip IS. Therefore, this chapter aims to answer the first of the three research questions introduced at the beginning of this thesis (see Chapter 1.1):

- Research Question 1: Which information is desired by users in pre-trip information systems?

Thereby, this chapter presents a first step towards a better understanding of the situation in which travelers use digital services at home in order to inform themselves about their multi-modal mobility options. As an initial step, an online survey was used to question participants (n = 158) about their current mobility-centered needs at home.

This chapter proceeds as follows: In order to analyze the first research question, an online survey was conducted. The next section describes the overall approach and the goals of the pre-study. Then, in the method and design section, it will be explained in detail, which material and variables were used in the online study. This also includes a description of the sample of participants who answered the online survey. Moreover, the theory of the applied data analysis will be explained. Afterwards, the results on mobility habits, mobility-centered needs at home and additional digital user needs will be presented. Finally, the results will be discussed and ideas for future research will be elaborated. Main parts of this chapter were already published in a journal article [160] and a conference proceeding [161].

3.1 Overall Approach and Goals of the Pre-Study

Within the last few years, the interest in smart environments has grown intensely in scientific research (e.g., [199,205]). With regard to various target groups, smart environments can be seen as a wide field of research addressing any potential location, ranging from public institutions such as hospitals or nursing centers (e.g., [205]) to private smart homes [6]. One topic that is connected to all of these aspects is smart mobility. Every day a growing amount of travelers need to find their way through rapidly growing smart cities [137]. In order to face this challenge, travelers need to inform themselves about their multi-modal mobility options. This information search includes a complex decision-making process which includes multiple decision-relevant aspects [20], for example: choosing the right mode of transportation (e.g., going by car or using public transport) and calculating travel durations. Since in the morning, most travelers start their daily journey at home, the present research focuses on easing daily life in smart environments by providing smart pre-trip ISs for the traveler's home. Pre-trip ISs are an interesting field of application because instead of providing one smart and individually tailored service, the market provides a huge list of digital mobility services with different features [135,167,176]. Facing this variety of offers and the constantly changing environment [20,137] in which these services are used, raises the question about the traveler's requirements for in-house pre-trip IS. Therefore, this chapter focuses on providing an initial step towards formulating requirements for smart in-house pre-trip ISs for smart homes as private living spaces. Hence, this chapter aims to answer the first of the three research questions introduced at the beginning of this thesis (see Chapter 1.1): Which information is desired by users in pre-trip information systems? This overall research question is addressed with the help of the following three sub-questions:

- Which are currently the most pressing pain points for travelers at home when they inform themselves about their mobility options and which stress level do they cause?
- Which mobility-centered pragmatic needs (e.g., time and type of information) do travelers have when they inform themselves about their mobility options at home?
- Which non-mobility-centered additional needs (e.g., news, listening to music, preparing grocery shopping) are associated with the situation in which travelers inform themselves about their mobility options at home?

These research questions were answered with the help of an online survey. The method and design of the survey will be explained in detail in the next section. Through answering the three research questions listed above, this thesis will provide theoretical and practical contributions. First, this thesis will contribute to the field of smart environments and transportation research through identifying user needs deductively and inductively and providing insights into the situation in which the traveler accesses mobility-centered information at home. The main benefit of these insights is that the better we know how the travelers actually behave in this situation, the better we can design digital services that can support them in this situation. Thereby, this thesis will make a first step towards formulating user-centered requirements for smart in-house mobility services that can serve as guidelines in future development processes of pre-trip IS. In sum, the identified requirements will help to provide sustainable customer value in the context of pre-trip ISs (e.g., providing comfort for the traveler, saving the traveler's time and effort).

3.2 Method and Design of the Pre-Study

For the present study, an online survey was conducted. This section describes the method and design of this survey. After a short introduction on the welcome page, the participants were asked about sociodemographic variables. Next, mobility habits were assessed. Furthermore, mobility-centered needs at home (i.e., pain points, stress level, time and type of information and interest in vehicle-centered information) and non-mobility-centered additional digital needs (e.g., news, preparing grocery shopping) that are associated to the situation in which travelers inform themselves about their mobility options at home were assessed. Figure 3.1 summarizes the overall structure of the pre-study. According to the structure of the online survey, the following paragraphs concentrate on the method used to assess (1) mobility habits, (2) mobility-centered needs at home and (3) additional digital needs at home. Finally, this section contains the description of the sample of participants.

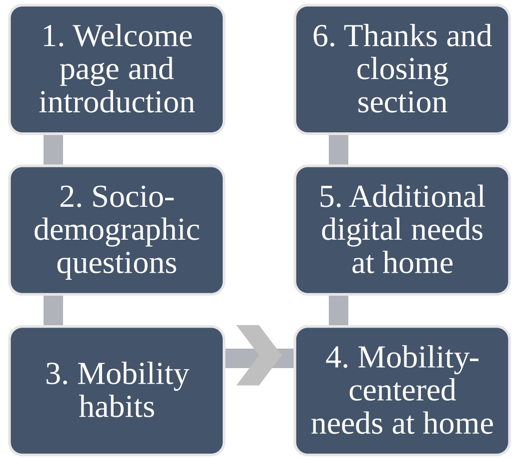


Figure 3.1 Overall Structure of the Online Pre-Study (own illustration).

3.2.1 Mobility Habits

Referring to mobility habits, this thesis regards the traveler's everyday habits concerning the use of different means of transport. Since the pre-study considered in this chapter concentrates on actual mobility habits in a present scenario the survey assessed the participants' regular use of a private car, carsharing, electric cars, and public transport. For each of the four modes, the survey contained an item that assessed the frequency with which the mode is used (i.e., not at all, once a year, every three months, once a month, once a week, multiple times per week or daily). Table 3.1 summarizes the item content and answer options of the whole survey.

3.2.2 Mobility-centered Needs at Home

Referring to mobility-centered needs at home, this thesis regards the situation in which travelers inform themselves about their mobility options at home (e.g., going by car or using public transport). This includes taking into account multiple decision-relevant aspects (e.g., duration of the mobility option and traffic) and finally choosing one mobility option (e.g., going to work by car and not using public transport). This paragraph describes the items regarding mobility-centered needs at home that were integrated into the survey. The item content and answer options of the whole survey can be found in Table 3.1.

In order to address mobility-centered needs at home inductively, the survey contained an open question concerning problems the participants have to face during this decision-making process (i.e., "Which problems occur to you when you concern yourself with your mobility options on (a) workdays and (b) weekends?"). Additionally, the survey contained a single item focusing on the stress level the participant had to suffer from while choosing the right mobility option on workdays and weekends. The participant's mobility-centered stress level was assessed using a five-point Likert-Scale, ranging from 1 = *not at all* to 5 = *extremely*.

Furthermore, in order to address mobility-centered needs at home deductively, the survey contained several closed questions. This part of the survey assessed the time at which participants inform themselves about their mobility options at home. Here, the following five categories were distinguished: (1) while leaving home, (2) max. 10 minutes before, (3) max. 20

minutes before, (4) more than 20 minutes before leaving home and (5) the day before. With regard to the three constructs mobility-centered problems, stress level and information time, the survey differentiated between the two contexts workdays and weekends and assessed each of the three constructs for both contexts. It is important to distinguish between mobility habits and mobility-centered needs on workdays during commuting and on weekends when the purpose of most trips is to reach leisure time activities because choice models have shown that the parameters influencing the traveler's mode choice differ depending on the purpose of the trip (see literature reviews in Chapter 2.1.2 and Chapter 2.2).

Besides differentiating between workdays and weekdays, the survey also differentiated four different route purposes, namely (1) commuting, (2) purchases & finishes (e.g., supermarket and pharmacy), (3) hobbies & leisure time activities (e.g., concerts and sports events) and (4) appointments such as meeting with friends. Regarding each of the four different route purposes, the survey assessed the frequency with which the participants inform themselves about their mobility options whenever travelling with that purpose. An interval of six frequencies was distinguished, namely (1) never, (2) once, (3) at the beginning, (4) regularly, (5) in specific situations, and (6) always.

Additionally, the type of information that is collected by the participant was assessed with a multiple-choice item. This part of the survey distinguished between eight categories, namely (1) the traffic situation, (2) weather on the route, (3) price of the mobility option, (4) duration, (5) complexity of a route (e.g., how often travelers have to change trains), (6) alternative routes, (7) departure times and (8) no information at all. Further multiple-choice questions referred to the need of accessing vehicle-centered information at home without leaving the house. This part of the survey assessed the interest in (1) temperature and cooling, (2) windows, doors and light, (3) mileage, (4) range and tank wealth or rather charging status, (5) service appointments (e.g., service or oil level), (6) routing, navigation or traffic news (7) current whereabouts of the car and (8) the effectiveness of past trips (e.g., consumption). Again, participants were also able to answer that they were not interested in any of the information. Referring to the closed questions regarding the type of information and the interest in vehicle-centered information at home, the participants were also asked to list other additional needs they have which were not covered through the answer options listed above (see Table 3.1).

3.2.3 Additional Digital Needs at Home

Referring to non-mobility-centered needs at home, this thesis regards needs, which are associated with the situation in which travelers inform themselves about their mobility options at home but are not directly connected to the topic of mobility. This paragraph describes the items regarding additional digital needs at home that were integrated into the survey.

In order to assess non-mobility needs at home, the survey contained a multiple-choice question with a list of 19 needs (see Table 3.6). For this list, the most popular app store categories [186] were included in a matrix in the survey while mobility-centered categories (i.e., navigation) were excluded. Similar to the assessment of mobility-centered problems, stress level and information time, the two contexts workday and weekend were distinguished with regard to the list of the 19 potential needs (i.e., "Which of the following digital services are you interested in when you inform yourself about your mobility options on (a) workdays and (b) weekends?").

Furthermore, the survey assessed which smart home features the participants are already using and which they want to use in the future. Here, the survey contained a multiple-choice item to assess the use of and interest in five different categories, namely (1) security features (e.g., video recordings, motion and smoke detectors), (2) energy balance (e.g., light and temperature control), (3) connected building services and equipment (e.g., blinds and washing machine), (4) connected entertainment technology (e.g., storage and usage of video content) and (5) connected car or other mobility options (e.g., load control). The participants were also able to answer that they do not use any of these features at all and/or that they are not interested in any of these features in the future. Moreover, the participants were asked about other additional non-mobility-centered needs and additional smart home features they use or they want to use in the future which are not covered through the answer options listed above. Table 3.1 summarizes the item content and answer options of the whole survey.

Table 3.1 List of Item Content and Answer Options of the Pre-Study (own illustration).

Item content	**Answer option**
Mobility habits	
Frequency of use of present means of transport: (1) private car, (2) carsharing, (3) electric cars, and (4) public transport	**Ordinal scales:** (1) not at all, (2) once a year, (3) every three months, (4) once a month, (5) once a week, (6) multiple times per week or daily
Mobility-centered needs at home	
Pre-trip pain points: "Which problems occur to you when you concern yourself with your mobility options on (a) workdays and (b) weekends?"	**Open text**
Pre-trip stress level: on workdays and weekends during pre-trip information search and decision-making process	**Rating scales:** five-point Likert-Scale, ranging from 1 = *not at all* to 5 = *extremely*
Pre-trip information frequency: depending on route purpose, i.e., (1) commuting, (2) purchases & finishes, (3) hobbies & leisure time activities, and (4) appointments such as meeting with friends	**Ordinal scales:** (1) never, (2) once, (3) at the beginning, (4) regularly, (5) in specific situations, and (6) always
Pre-trip information time: (1) while leaving home, (2) max. 10 minutes before, (3) max. 20 minutes before, (4) more than 20 minutes before leaving home, and (5) the day before	**Multiple-choice items:** yes vs. no
Type of pre-trip information: (1) the traffic situation, (2) weather on the route, (3) price of the mobility option, (4) duration, (5) complexity of a route, (6) alternative routes, (7) departure times, and (8) no information at all	**Multiple-choice items:** yes vs. no **+ open text**

Item content	Answer option
Vehicle-centered information: (1) temperature and cooling, (2) windows, doors and light, (3) mileage, (4) range and tank wealth or rather charging status, (5) service appointments, (6) routing, navigation or traffic news (7) current whereabouts of the car, and (8) the effectiveness of past trips	**Multiple-choice items:** yes vs. no **+ open text**
Additional digital needs at home	
Digital services: list of 19 most popular app store categories (see Table 3.6)	**Multiple-choice items:** yes vs. no **+ open text**
Present and future use of smart home features: (1) security features, (2) energy balance, (3) connected building services and equipment, (4) connected entertainment technology, and (5) connected car or other mobility options	**Multiple-choice items:** yes vs. no **+ open text**

3.2.4 Participants

Employees of a local car manufacturer were invited to answer the online survey via e-mail. Moreover, the link connected to the online survey was posted in different social networks (i.e., Facebook, Xing, and Nebenan.de) by employees of a local car manufacturer and by people without any connection to the car manufacturer (i.e., other young professionals and students). After the recruiting phase in April 2016, n = 164 participants answered the survey completely. All participants answered the survey in German. Only full data sets were included in the analysis. Six participants were excluded from the analysis because of an outlying age (i.e., 2, 17 and 73 years), because of outliers in their way to work (i.e., 300km and 350km) and because of inappropriate answers in free text fields (e.g., brain and flower).

Hence, further analysis was made with n = 158 participants. Among these participants, 50.63% are male (n = 80) and 49.37% are female (n = 78). Their age ranges from 20 to 63 years (M = 32.66, SD = 10.47). Most of the participants were employees and PhD students and approximately half of all participants are in an employment relationship with the local car manufacturer (n = 84; 53.16%). Moreover, most of the participants live in a large city with more than 500,000 inhabitants (n = 90; 56.96%), in a shared apartment (n = 41; 25.95%) or in an apartment together with their partner (n = 54; 34.18%) or family with children (n = 24; 15.19%). Nearly all participants (n = 151; 95.57%) own a car. However, only four of them own an electric car (2.53%) and only one more participant was planning to buy an electric car in 2018 (0.63%).

In order to judge the participants' technology affinity, the survey contained items that assessed their daily smartphone usage and their yearly consumption of digital gadgets. Nearly all participants own a smartphone (n = 155; 98.10%) which they use at least two hours per day. Moreover, most of the participants spend 200-1000 Euro for digital gadgets each year. Thus, in sum, the sample can be considered as technology-oriented and digital-oriented. Table 3.2 presents more details about the sample of the present pre-study.

Table 3.2 Demographic Characteristics of the Sample of the Pre-Study (own illustration).

	n	%			n	%
Final sample of participants	158	100				
Gender				**Connection to BMW**		
Male	80	50.63		External	74	46.84
Female	78	49.37		Internal	84	53.16
Occupation status				**Net-Income (Euro/Month)**		
Employees	77	48.70		≤ 1000	26	16.46
PhD Students	46	29.10		1001 - 2000	70	44.30
In education (Pupil, Trainee)	1	0.60		2001 - 3000	29	18.35
Students	30	19.00		3001 - 4000	20	12.66
Retired	3	1.90		≥ 4000	13	8.23
Unemployed	1	0.60				
Place of residence (Inhabitants)				**Household situation**		
Large city (> 500.000)	90	56.96		Single	39	24.68
Medium city (>100.000- 99.999)	26	16.46		Shared apartment	41	25.95
Small city (20.000 - 99.999)	15	9.49		With partner	54	34.18
Town (5.000 - 19.999)	10	6.33		With partner and child	24	15.19
Village (< 5.000)	17	10.76				
Car class of private car				**Electric car ownership**		
Small car	78	51.66		Yes	4	2.53
Mid-range car	65	43.05		Plan to Buy Next Year	1	0.63
Upper-range car	6	3.97		No	153	96.84
Sports car	2	1.32				
Daily smartphone usage				**Digital gadget consumption (Euro)**		
Not at all	3	1.90		Less than 200	58	36.71
Less than 1 hour	27	17.09		200 - 600	57	36.08
1 - 2 hours	54	34.18		601 - 1000	22	13.92
2 - 3 hours	41	25.95		1001 - 1400	12	7.59
3 - 4 hours	17	10.76		1401 - 1800	5	3.16
More than 4 hours	16	10.13		More than 1800	4	2.53
	Min	**Max**		**Mean**	**SD**	
Age	20	63		32.66	10.47	
Commuting (km)	0	90		15.19	17.25	

3.3 Theory of the Applied Data Analysis

This chapter focuses on the methods used to analyze the collected data of the pre-study. The data was collected with the help of the online survey tool LimeSurvey [119]. Microsoft Excel (2013) was used for preparatory analysis. This includes merging data sets and controlling values. RStudio 0.98.1102 [152] was used for higher level analysis. The data was mainly analyzed using qualitative clustering, descriptive statistics, and deductive statistical test procedures such as paired *t*-tests and chi-square tests. The theory of the applied data analysis will be described in the following paragraphs.

3.3.1 Qualitative Clustering and Inter-Rater Reliability

As described above, the survey assessed the participants' mobility-centered problems and pain points with the help of open questions. Thus, the resulting free text answers contained qualitative information. In order to analyze the free text answers, two independent raters clustered the participants' answers qualitatively and built conceptual categories. The qualitative clustering was based on state-of-the-art guidelines for qualitative data analysis [48].

Afterwards, the inter-rater-reliability of the qualitative clustering was checked with Cohen's Kappa [46]. Cohen's Kappa relativizes actual agreement by chance agreement [213]. Kappa ranges from -1 to 1, indicating excellent agreement until values above 0.75 [45]. The following formula illustrates the estimation of the agreement coefficient for nominal scales: Cohen's Kappa [46, p. 40], in which:

- p_o = the proportion of units in which the raters agreed
- p_c = the proportion of units for which agreement is expected by chance.

$$K = \frac{p_o - p_c}{1 - p_c} \tag{3.1}$$

3.3.2 Paired t-Tests

Paired *t*-tests were used to identify significant differences between two group means of metric study variables. More specifically, the participants' stress level was examined with regard to differences between their group means on workdays and on weekends. Since both scores, i.e., on workday and weekend, were assessed in the same sample, the data has to be considered as paired [68]. Table 3.3 illustrates the possible testing procedures of paired *t*-tests and The following formula illustrates the estimation of the test statistic T [90, p. 190], in which:

- $D_i = X_i - Y_i$ for each $i = 1, \ldots, n$
- $X_1, \ldots, X_n$ i.i.d. with $X \sim N(\mu_x, \sigma_x)$
- $Y_1, \ldots, Y_n$ i.i.d. with $Y \sim N(\mu_y, \sigma_y)$
- T follows a $t(n-1)$-distribution.

$$T = \frac{\bar{D} - \delta_0}{SD / \sqrt{n}} \tag{3.2}$$

Table 3.3 Testing Procedures for Paired *t*-Tests (Adapted from [90])

Hypothesis	**Decision**
$H_0: \mu_X - \mu_Y = \delta_0$ vs. $H_1: \mu_X - \mu_Y \neq \delta_0$	$\lvert t \rvert > t_{1-\alpha/2}(n-1)$
$H_0: \mu_X - \mu_Y \leq \delta_0$ vs. $H_1: \mu_X - \mu_Y > \delta_0$	$t > t_{1-\alpha}(n-1)$
$H_0: \mu_X - \mu_Y \geq \delta_0$ vs. $H_1: \mu_X - \mu_Y < \delta_0$	$t < t_{\alpha}(n-1)$

T-tests require some assumptions, which were checked in a preparatory analysis. The normal distribution was checked with the Shapiro-Wilk tests of normality [91]. This test compares the distribution of the variable in the current sample and the distribution of this variable in a normally distributed theoretical sample. The test result was significant ($p < .001$). Consequently, the stress scores cannot be assumed as distributed normally. Since the central limit theorem expresses that the assumption of normality can be assumed in a sample with $N > 30$, parametric analysis is still justified in this case. Moreover, homoscedasticity was checked with standardized residual plots, which is a common method to examine equal variances at different levels of a variable. All plots indicated a moderately equal spread of residuals. Therefore, the assumption of homoscedasticity is considered as fulfilled in this sample [68].

The significance level for *t*-tests was defined as $\alpha = .05$. If other significance levels were used, they are listed explicitly in the results section.

3.3.3 Chi-square Test of Independence of Categorial Variables

Chi-square tests were used to identify significant differences between the frequency distributions of nominal variables. More specifically, chi-square-tests were used to identify significant differences between additional needs on workdays versus additional needs on weekends. Therefore, the answers (yes vs. no) of all participants were aggregated in two frequency matrices for each need listed in Table 3.6. One matrix for needs on workdays and one matrix for needs on weekends. Then the equality of both matrices was checked for each need. Significant results indicate differences between needs on workdays and weekends [4]. Since all cells contained frequencies greater than $n = 5$, no assumptions will be violated. Table 3.4 illustrates the hypotheses tested by chi-square tests. The following formula illustrates the estimation of the test statistic χ^2 of the Chi-square Test of Independence of Categorial Variables [92, p. 138], in which the parameters are defined by the k*m matrix for variable X with k categories and variable Y with m categories:

		Y				
		b_1	**b_2**	**…**	**b_m**	**Total**
X	**a_1**	n_{11}	n_{12}	…	n_{1m}	$n_{1.}$
	a_2	n_{21}	n_{22}	…	n_{2m}	$n_{2.}$
	…	…	…	…	…	…
	a_k	n_{k1}	n_{k2}	…	n_{km}	$n_{k.}$
	Total	$n_{.1}$	$n_{.2}$	…	$n_{.m}$	n

- $X_1, ..., X_n$ i.i.d.
- $Y_1, ..., Y_n$ i.i.d.
- χ^2 follows a $((k-1)(m-1))$-distribution

$$\chi^2 = \sum_{i=1}^{k} \sum_{j=1}^{m} \frac{(n_{ij} - \frac{ni.*n.j}{n})^2}{\frac{ni.*n.j}{n}} \tag{3.3}$$

Table 3.4 Hypotheses tested by Chi-square Test of Independence (Adapted from [90]).

Hypothesis	Decision
H_0: $P(X = a_i, Y = b_j) = P(X = a_i)P(Y = b_j)$ for each i, j	$\chi^2 > \chi^2\ 1-\alpha((k-1)\times(m-1))$
H_1: $P(X = a_i, \mathrm{Y} = \mathrm{b_j}) \neq P(X = a_i)P(Y = b_j)$ for at least one pair	

The significance level for chi-square tests was defined as $\alpha = .05$. If other significance levels were used, they are listed explicitly in the results section.

3.4 Results of the Pre-Study

This chapter summarizes the results of the pre-study. The results will be presented in the same order as the data for the different parts of the questionnaire was collected (see Figure 3.1). Hence, the following paragraphs will first describe the results concerning the participants' current mobility habits. Next, the results of the main part of the survey will be summarized, i.e., the results concerning mobility-centered needs at home. Finally, the results regarding additional digital needs at home will be outlined.

3.4.1 Mobility Habits

In order to better understand the main result of this pre-study concerning the participants' mobility-centered need at home, it is important to get an overview about the participants' current mobility habits and modal decisions (i.e., how often they use which mode of transport). The following results on the participants' mobility habits will help to put the results regarding mobility-centered needs at home into a context.

Nearly all participants who took part in the pre-study (n = 151; 95.57%) own a car. However, only four of them own an electric car (2.53%) and only one more participant was planning to buy an electric car in 2018 (0.63%). Regarding private car usage most participants reported that they use their car daily (n = 43; 27.22%), multiple times per week (n = 47; 29.75%), once a week (n = 37; 23.42%) or at least once a month (n = 20; 12.66%). Only four participants answered that they use their car only once every three months (n = 3; 1.90%) or even only once a year (n = 1; 0.63%).

With regard to other mobility options besides private cars, 33.54% of the participants use public transport daily (n = 53), 24.68% use it multiple times per week (n = 39), 8.86% once a week (n = 14), 15.19% once a month (n = 24), 10.76% once every three month (n = 17), 3.80% once a year (n = 6) and only 3.16% do not use public transport at all (n = 5). Furthermore, 35.44% (n = 56) of the participants reported that they use carsharing and 31.65% (n = 50) of them answered that they regularly use electric cars.

Moreover, the sample does not include any travelers who use their private car mono-modally, use electric cars mono-modally or use carsharing mono-modally. Thirty-three of the participants (20.89%) even use all four means of transport alternately (i.e., private car, carsharing, electric cars, and public transport). However, the sample includes five travelers (3.16%) that use public transport mono-modally. Nevertheless, 96.84% of the participants can be considered as multi-modal travelers which use their private car and public transport.

In sum, except for the five mono-modal public transport users, the sample represents a group of multi-modal travelers. While some of the questioned travelers also use carsharing and electric cars, private cars and public transport are still the two dominant modes in the present sample. In conclusion, the present sample can provide interesting insights into multi-modal traveler's mobility-centered needs at home which will be addressed in the next section because they show a multi-modal mobility behavior which requires planning including modal and temporal mobility decisions. Figure 3.2 summarizes the current mobility habits of the sample considered in the pre-study.

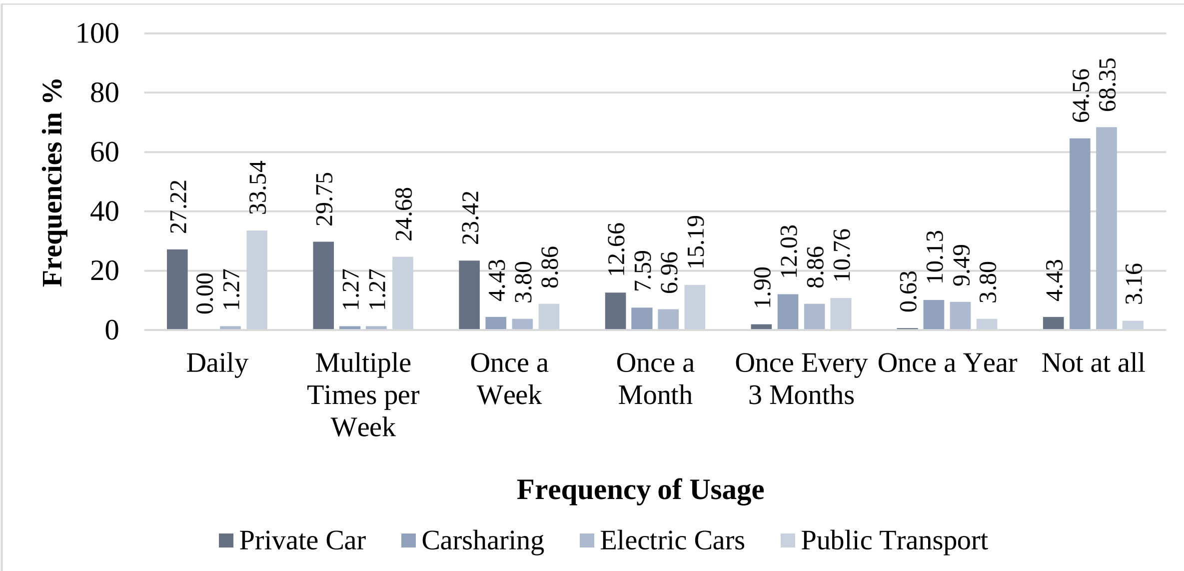


Figure 3.2 Current Mobility Habits of the Sample of the Pre-Study (own illustration).

3.4.2 Mobility-centered Needs at Home

This section describes the results of the main part of the survey, namely the results concerning the participants' mobility-centered needs at home. Concerning mobility-centered needs at home, this thesis regards mobility-centered pain points and the stress level the participants experience during informing themselves about their mobility options at home. Furthermore, the situation in which travelers inform themselves about their mobility options at home will be elaborated in detail concerning the following aspects:

- When? - Information time
- How often? - Frequency of information collection depending on the purpose of the trip
- What? - Type of mobility-centered and vehicle-centered information.

The results will be presented in the same order as the data of this part of the questionnaire was collected (see Table 3.1). The insights into mobility-centered needs at home gained in this chapter will be implemented in a pre-trip prototype which will be described in Chapter 4.

Pain Points and Stress Level. The coding of the free text answers revealed six problem categories that appeared on both, workdays and weekends and four categories that only appeared on workdays. Two independent raters showed an excellent agreement in the qualitative clustering analysis ($K_{\text{workdays}} = 0.75$, p <.001; $K_{\text{weekends}} = 0.82$, p <.001). In both conditions, i.e., on workdays and on weekends, the availability of information is the largest category ($n_{workdays}$ = 30; $n_{weekends}$ = 7). Table 3.5 summarizes the results on mobility-centered problems and illustrates all pain points identified on workdays and/or weekends.

The participants' mobility-centered stress level was analyzed using paired t-tests. The t-tests were used to identify significant differences between the group means of the stress level on workdays and on weekends. The average stress level (see Figure 3.3) while choosing mobility options at home on workdays (M = 2.35, SD = 1.09) is significantly higher than on weekends (M = 1.82, SD = 0.90, $t(303) = 4.73$, p <.001).

Table 3.5 Mobility-centered Problems at Home on Workdays (n_{wo}) and on Weekends (n_{we}) (own illustration pre-published in [160, p. 5]).

Problem	n_{wo}	**Problem**	n_{we}
Availability of information	30	Availability of information	7
Time	4	Time	6
Weather	4		
Lack of offers	3	Lack of offers	4
Traffic jams	3	Traffic jams	4
Comfort	2		
Prioritizing	2		
Stress	2		
Decision problems	1	Decision problems	2
Costs	1	Costs	5
Other	9	Other	1

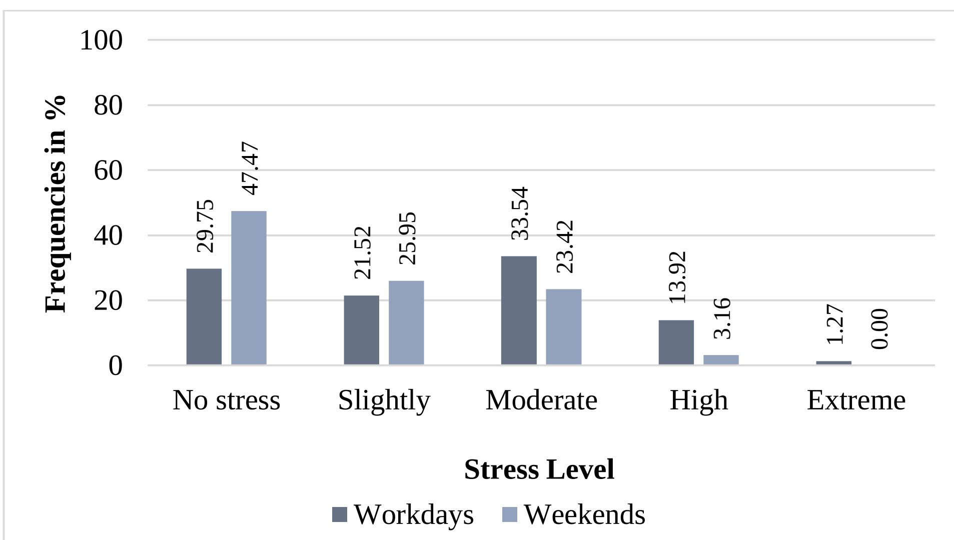


Figure 3.3 Mobility-centered Stress Level at Home on Workdays and on Weekends (own illustration).

Information Time. Figure 3.4 illustrates the results concerning the time when travelers inform themselves about their mobility options pre-trip. The results indicate that on workdays most travelers either use pre-trip ISs while leaving or very shortly before leaving (i.e., 10 minutes pre-trip) or very long before starting the trip (i.e., the day before). Significantly fewer travelers inform themselves in the interval in between on workdays (i.e., 20 minutes pre-trip or more than 20 minutes pre-trip). Contrary, on weekends most travelers use pre-trip ISs more than 20 minutes before the trip (n = 57; 36.08%) or even the day before the trip (n = 45; 28.48%). Furthermore, regarding the differences between information time on workdays and weekends, all tests between workdays and weekends are significant ($\chi^2_{\text{while leaving}} = 23.03$, $\chi^2_{\text{10 min before}} = 29.92$, $\chi^2_{\text{20 min before}} = 20.58$, $\chi_{\text{2more than 20 min before}} = 32.87$, $\chi^2_{\text{the day before}} = 30.72$, $p < .001$).

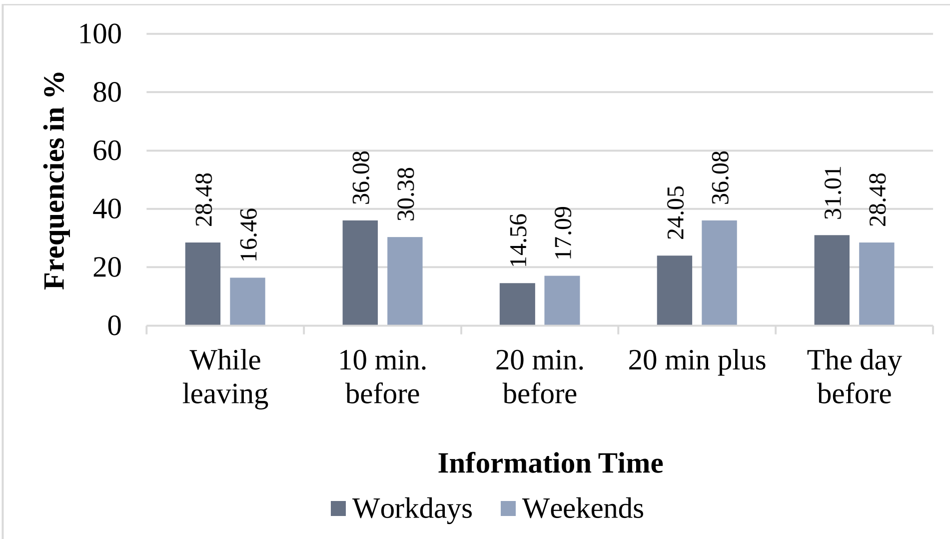


Figure 3.4 Mobility-centered Information Time at Home on Workdays and on Weekends (own illustration).

Frequency of Pre-trip Information Collection Depending on the Purpose of the Route. Besides differentiating between workdays and weekdays, the survey also differentiated four different route purposes, namely (1) commuting, (2) travelling in order to carry out purchases and finishes (e.g., supermarket and pharmacy), (3) travelling in order to practice hobbies and reach leisure time activities (e.g., concerts and sports events) and (4) travelling in order to reach appointments such as meeting with friends. Figure 3.5 shows the frequencies with which travelers inform themselves about their mobility options pre-trip depending on these four different kinds of route purposes. With regard to all four route purposes, the information behavior of the respondents covers the entire range of the information frequency from never to always. Looking at the maxima, travelling in order to reach appointments such as meetings with friends (n = 32, 20.25%) and travelling in order to practice hobbies or reach leisure time activities (n = 30, 18.99%) are the two route purposes with the highest number of answers stating that the respondents always inform themselves about their mobility options on these trips. In contrast, travelling in order to carry out purchases and finishes is the route purpose with the highest number of answers stating that the respondents never (n = 60, 37.97%) or only once (n = 36, 22.79%) use pre-trip ISs in order to inform themselves about their mobility options pre-trip. The frequencies for all other combinations of information frequencies and route purposes can be found in Figure 3.5.

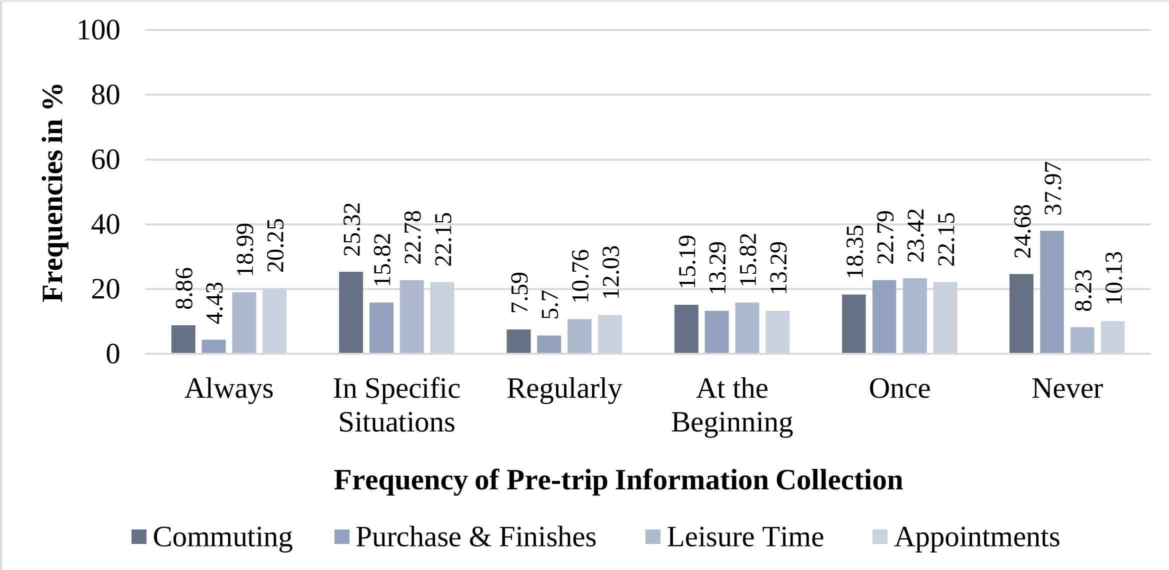


Figure 3.5 Frequency of Pre-trip Information Collection Depending on the Purpose of the Route (own illustration).

Type of Information. Finally, the results regarding the information type will be presented. Here, two groups are distinguished, namely mobility-centered information (i.e., information on a route independent from the mode of transport such as departure times) and vehicle-centered information (i.e., information on the status of the private vehicle that can be assessed in-house).

Regarding the type of mobility-centered information, 80.38% informed themselves about departure times, 75.95% about the duration of the mobility option, 68.99% about the complexity of the route and 65.19% about the traffic situation. Alternative routes were accessed by 48.10% of the participants, prices by 37.34% and the weather on the route by 35.44%. Five participants listed additional types of information in the free text answer options. Two participants listed (1) parking information whereas (2) charging information, (3) duration of the trip and (4) time of arrival and how to pick up other people were each listed by one participant only. Only 1.90% of the respondents did not access any information beforehand. Figure 3.6 visualizes the results regarding the desired type of mobility-centered information.

Concerning the access of vehicle-centered information at home, the survey showed that 63.29% of the participants are interested in their range, tank fill or charging status, 51.27% in the current whereabouts of the car and 50.00% in routing, navigation and traffic reports. Moreover, 42.41% of the participants would like to be informed about the status of windows, doors, and light as well as about upcoming service appointments, 31.01% about temperature and cooling, 25.32% about the effectiveness of past trips and 18.35% about the mileage. Only one participant listed additional vehicle-centered information, namely information about damages to the car. Only 17.09% of the participants do not want to access any vehicle-centered information at home. Figure 3.7 visualizes the results concerning the desire to access vehicle-centered information at home in a bar chart.

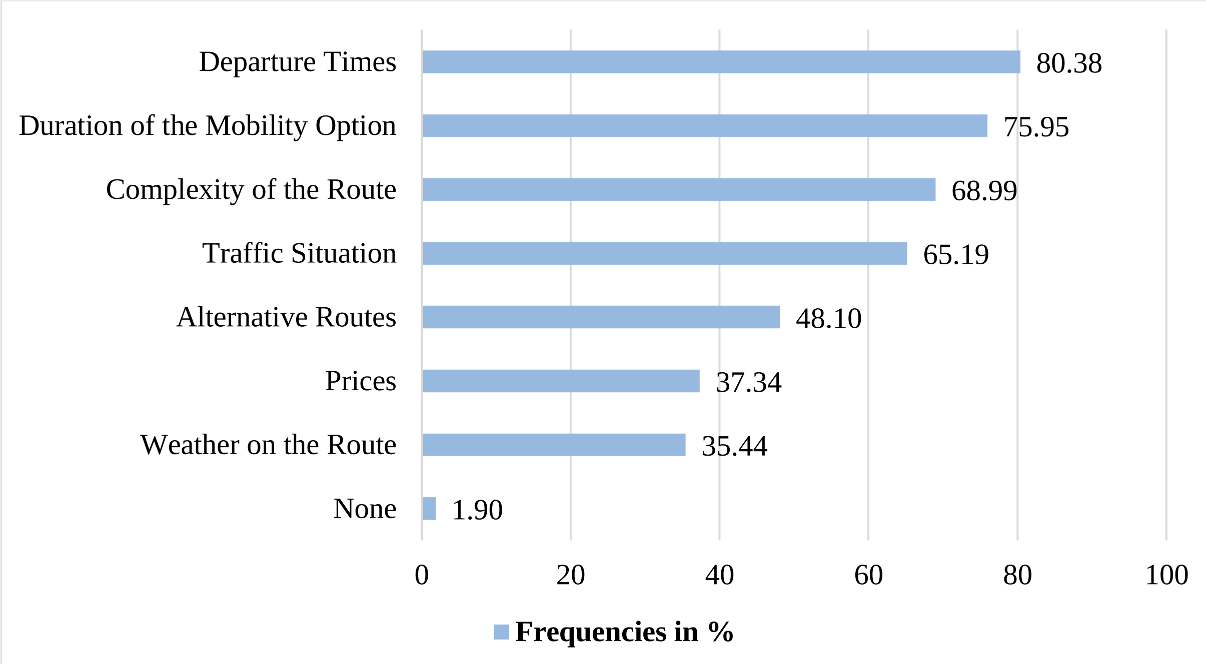


Figure 3.6 Type of Mobility-Centered Information that is Accessed Pre-trip (own illustration).

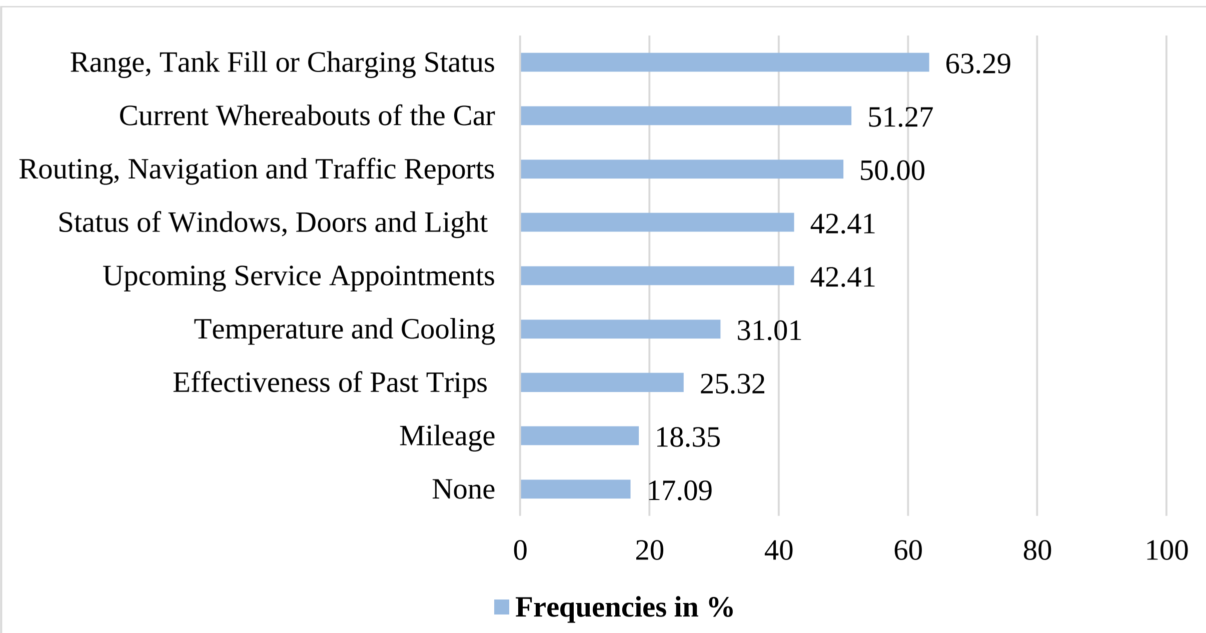


Figure 3.7 Vehicle-centered Information Travelers Would Like to Access at Home (own illustration).

Summarizing, this section has presented the results concerning mobility-centered needs at home that were assessed in the pre-study in order to build an empirical basis for the development of the pre-trip prototype that will be described in Chapter 4. Before discussing the results described in this section, the next chapter describes the results concerning additional digital needs at home that were gained in the pre-study.

3.4.3 Additional Digital Needs at Home

In order to fully understand the situation in which travelers use pre-trip ISs at home and inform themselves about their mobility options, it is important to investigate which additional and not necessarily mobility-centered needs travelers have in this situation. These insights will help to look at pre-trip situations entirely and develop and design pre-trip ISs according to the traveler's needs. Therefore, this section describes the results regarding additional digital needs at home that were collected in the pre-study. Thereby, the following paragraphs first focus on the analysis of additional digital needs based on app store categories. Afterwards, the analysis of current and future use of smart home features is described.

As explained in the method section of this chapter (see Chapter 3.2.3) additional digital needs in pre-trip situations were assessed using a list of categories of digital services from the app store [186]. Table 3.6 summarizes the results concerning the list of the 19 potential additional digital needs at home. On workdays, the top three needs are (1) news, (2) messages and (3) music. Besides music and messages, on weekends, the top three needs are (1) food and drinks, (2) sports and leisure time activities and (3) travelling. Chi-square-tests were used to identify differences between the frequency distribution of desired needs on workdays and weekends. All tests are significant (p <.001). Only one participant listed an additional need that was not covered by the 19 pre-determined categories, namely information about what the own children are doing. All frequencies and chi-square-tests concerning the differences in additional digital needs on workdays and weekends can be found in Table 3.6.

Table 3.6 Non-mobility-centered Additional Needs on Workdays (nwo) and Weekends (nwe) (own illustration pre-published in [160, p. 6]).

Needs	n_{wo}	%	n_{we}	%	χ^2	df
News (e.g., daily newspaper)	97	61.39	79	50.00	58.62	1
Messages from social contacts (e.g., e-mail, text messages)	92	58.23	84	53.16	39.93	1
Listening to music	89	56.33	85	53.80	55.78	1
Calendar or personal agenda	74	46.84	65	41.14	67.95	1
Food and drinks (e.g., recipes, shopping lists)	70	44.30	84	53.16	55.85	1
Sports & leisure time activities (e.g., event recommendations)	65	41.14	81	51.27	56.20	1
Social networks (e.g., Facebook, Xing)	61	38.61	60	37.97	37.03	1
Travelling (e.g., offers)	54	34.18	81	51.27	67.26	1
Health and fitness (e.g., fitness tips, own sporting activities)	45	28.48	49	31.01	64.21	1
Entertainment (e.g., TV program, books, puzzles)	38	24.05	55	34.81	66.76	1
Photo and video (e.g., own gallery)	37	23.42	43	27.22	53.32	1
Business (e.g., magazines, headlines)	37	23.42	26	16.46	78.63	1
Lifestyle (e.g., fashion, deals)	33	20.89	39	24.68	65.19	1
Parents & family (e.g., event recommendations)	26	16.46	38	24.05	55.80	1
Literature (e.g., book proposals, journals)	25	15.82	28	17.72	44.23	1

Needs	n_{wo}	**%**	n_{we}	**%**	χ^2	**df**
Home and garden (e.g., design tips)	23	14.56	32	20.25	69.14	1
Finance (e.g., share prices)	22	13.92	23	14.56	51.38	1
Education (e.g., language trainer or brain teasers)	22	13.92	27	17.09	77.18	1
Art (e.g., event recommendations)	21	13.29	30	18.99	56.71	1
None	16	10.13	19	12.03	103.96	1

Besides the analysis of additional digital needs based on app store categories, the current and future use of smart home features was analyzed. The results of current and future use of smart home features show that the most wanted feature for the future is (1) energy balance (66.46%; current: 5.70%), followed by (2) connected building services and equipment (54.43%; current: 3.80%), (3) connected entertainment technology (43.67%; current: 25.95%), (4) connected car and mobility (43.04%; current: 9.49%) and security features (38.61%; current: 8.23%). Only four participants listed additional smart home features they would like to use in the future, namely (1) controlling the garage gate, (2) monitoring the consumption of energy and water, (3) opening doors automatically and (4) taking parcels and opening the door for workman when nobody is at home. Only 17.09% of the participants answered that they are not interested in using smart home features in the future, whereas currently 65.82% do not use any smart home features. Figure 3.8 visualizes the results concerning the current and future use of smart home features in a bar chart.

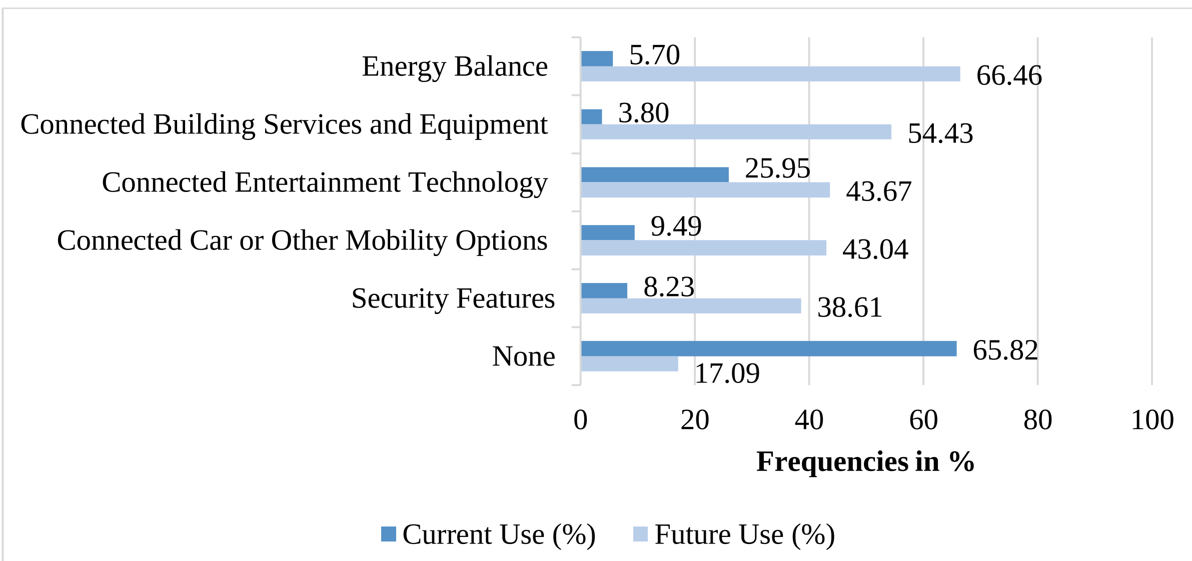


Figure 3.8 Current vs. Future Use of Smart Home Features (own illustration).

In conclusion, this section has presented the results concerning additional digital needs at home. Besides mobility-centered needs, the survey also contained additional non-mobility-centered digital needs in order to understand the situation in which travelers inform themselves about their mobility options at home entirely. Together with the insights presented in Chapter 3.4.2, the results presented in the present chapter build an empirical basis for the development of the pre-trip prototype that will be described in Chapter 4. Before describing the implementation, the results of the pre-study will be discussed in the following paragraphs.

3.5 Discussion of Results

This chapter discusses the results of the pre-study described in Chapter 3. The following paragraphs will discuss the core findings of the pre-study with respect to its impact on the user-centered development, design and innovation of in-house pre-trip IS. After discussing the core findings of the pre-study, possible limitations of the study will be discussed and ideas for future research will be elaborated. Finally, the discussion ends with a conclusion on the theoretical and practical implications of the results presented in this chapter. The conclusion leads to the next chapter (i.e., Chapter 4) in which the results of the pre-study will be implemented in a pre-trip prototype.

3.5.1 Core Findings

The aim of this chapter and the pre-study presented in this chapter was to provide an initial step towards formulating requirements for pre-trip ISs for the traveler's home. Therefore, this chapter focuses on the situation in which travelers inform themselves about their mobility options at home. With the help of an online survey the most pressing pain points, the traveler's stress level, their mobility-centered pragmatic needs (e.g., time and type of information) and their non-mobility-centered additional digital needs (e.g., news, listening to music) in the pre-trip situation were assessed.

In summary, the survey showed that travelers most suffer from a lack of availability of information about their mobility options. This means that current pre-trip ISs do not satisfy the travelers' need for reliable information about different mobility options at home whenever they need them without putting a considerable amount of effort in the search for information. Additionally, the pre-study identified more mobility-centered problems like time, weather, lack of offers and traffic jams, which were, however, mentioned less often. Concerning the traveler's stress level, the results show that searching for mobility options at home is associated with stress for most travelers. On workdays, this stress level is significantly higher than on weekends. Therefore, smart in-house pre-trip ISs should help the travelers leaving their homes by finding the optimal mobility option and providing it proactively. Proactively presenting the needed information from a reliable data source could reduce the traveler's stress level because the service would reduce the traveler's workload for getting reliable mobility-centered information and make mobility-centered decisions.

Furthermore, the timing of information seems to be crucial for in-house pre-trip IS. The time slot in which the traveler is interested in mobility information is rather small and is different on workdays and on weekends. Thus, a smart in-house pre-trip IS should communicate with other connected information technology in order to infer the traveler's actual needs and habits and provide specific information. For example, the service should retrieve the travelers' personal agenda from their digital calendar and make recommendations concerning the travelers' departure time and the fastest mode of transport proactively. Moreover, the digital calendar can tell the service whether it is a working day, weekend or a holiday for the traveler. Based on this information, the smart in-house mobility service could display the appropriate information for the appropriate kind of day. Another reference to a system that can currently detect this kind of intelligent information is a wearable fitness tracker. For example, the wearable fitness tracker could tell the service weather the travelers have already worked out today or whether they could still be animated to work out through sports and leisure time recommendations.

Additionally, the type of information that is desired at home (e.g., departure times, durations) and desired vehicle-centered information (e.g., tank fill) have to be included in the requirements as well. The results of the pre-study highlight that most travelers inform themselves about multiple decision-relevant aspects. Hence, smart in-house pre-trip ISs should combine multiple types of information into one service instead of providing solutions that focus only on one certain information type, for example, parking information [176]. Thus, travelers can get all the information they need from one mobility ecosystem which they experience as one combined service.

Referring to the non-mobility-centered additional digital needs associated to the situation in which travelers inform themselves about their mobility options at home, the result show that travelers are interested in several non-mobility needs in this situation. Moreover, the pre-study identified significant differences between these needs on workdays and weekends. For example, on workdays, the participants expressed a higher interest in news (e.g., daily newspaper), their calendar or personal agenda and business-related information (e.g., magazines, headlines) compared to weekends. On weekends, however, the participants expressed a higher interest in information concerning food and drinks (e.g., recipes, shopping list), sports and leisure time activities (e.g., event recommendations), entertainment (e.g., TV program, books) and event recommendations for parents and families compared to workdays. Thus, on workdays, the participants focused on information-based hard facts whereas on weekends they want to be stimulated and desire more hedonic features. Moreover, the results show that on workdays the travelers want to be informed about the world around them in terms of general news and messages from social contacts. This might hint to a need to be reconnected to the world after relaxing at home during the weekend or enjoying a weekend full of leisure time activities. Additionally, the travelers seem to be interested in music. This might be connected to the elevated stress level that was found while choosing the right mobility option. Music might have a relaxing function in this case. Listening to music could, however, also be habitual while commuting. Besides a need for music and messages, the travelers desire different information on weekends. The travelers mainly demand recommendations for recipes and events which will help them enjoy their weekends. Thus, smart in-house pre-trip ISs should be aware of the current day and provide tailored information to the travelers. In sum, providing different information on workdays and weekends is a technically simple way to create benefit for the customer.

The second non-mobility-centered aspect is the current and future use of smart home features. Since smart in-house pre-trip ISs might become a service component in future smart home ecosystems, it is important to discuss the current and future use of smart home services in the present sample. Here, the results stress that most of the participants do not use smart home features like energy balance currently but are highly interested in using these features in future. Similar to previous research [149] this indicates that we should focus on user-centered design and user tests of smart home services in order to enhance the attractiveness of these services for the user.

In sum, the core findings of the pre-study provide insights into concrete types of pre-trip information and vehicle-centered information that should be presented individually tailored and proactively to the travelers in a timely manner. Moreover, the pre-study highlights that combining purely functional mobility-centered information with additional hedonic service qualities might be a promising strategy to motivate travelers to use pre-trip ISs and maybe also change their mobility behavior and modal decisions based on pre-trip IS. The ideas gained from the pre-study will be implemented into a prototype and evaluated concerning the influence on the traveler's hedonic motivation and behavior later on in Chapter 4 and 5 of this thesis. Before implementing and evaluating the results, it is important to discuss possible limitations of the pre-study. Therefore, the following paragraphs concentrate on possible limitations and ideas for future research.

3.5.2 Limitations and Future Research

Although the core findings of the pre-study present an early considerable insight into functional needs for smart in-house pre-trip IS, the results underlie some restrictions. First, the participants were asked to think about the situation in which they inform themselves about their mobility options at home. Thus, the results are limited to the situations in which the traveler comes home, is at home or leaves home and are not generalizable to more situations (e.g., leaving work). Hence, future research should focus on more situations in which mobility-centered information search is relevant and look at differences between the needs in different situations.

One more aspect is the form of expression of the identified use cases. The study presented here gives no insights into how to implement demanded functions such as recommendations on food and drinks. Consequently, open questions concerning the technical transfer, the practical implementation and the evaluation of prototypes should be addressed in future research. These two aspects will be addressed in Chapter 4 and 5 of this thesis.

Furthermore, future research should consider moderating variables for mobility-centered information search and mobility-centered problems. For example, the study showed that most participants experience the situation in which they inform themselves about their mobility options as stressful. Additionally, the results show that the participants' stress level in this situation is on workdays significantly higher than on weekends. Nevertheless, 29.75% of the participants do not experience any stress in this situation at home on workdays (on weekends: 47.47%). Consequently, future studies should explore the reasons why certain participants do not experience any stress in this situation. Possibly, people who do not experience mobility-centered information search as stressful, use a certain mobility option more often (e.g., train) or have a fixed way to work and do not have to inform themselves about their mobility options every morning.

3.5.3 Conclusion

In conclusion, this chapter is a first step to formulate user-centered requirements for smart in-house pre-trip ISs. First of all, the results express that different pressing use cases should be bundled in one service so that the service is important in more than one scenario solely. This becomes obvious since user needs differ between workdays and weekends and the service should be of use in most parts of the traveler's everyday life to facilitate user retention. Hence, in contrast to a lot of pre-trip ISs and other mobility services that are currently available [see 135,167,176], smart in-house pre-trip ISs should be improved through the combination of multiple functions. This includes the combination of information-based hard facts (e.g., temporally optimized route by car) and more stimulating functions that maximize customer benefit through creating joy of use and a positive user experience (e.g., listening to music, recommendation for leisure time). All information presented should be adjusted to the traveler's demands. Therefore, the smart service should adapt to individual user needs and habits (e.g. information time and type of information). After inferring the user's needs and habits in exchange with connected information technology like the traveler's digital calendar or wearable fitness applications, only individually desired information should be presented proactively in a timely manner. In order to provide seamless access to individually needed information at the individually right time, it is especially important to identify differences in the traveler's behavior between workdays and weekends which includes the differentiation of different route purposes and travelling with different levels of time pressure. Figure 3.9 summarizes the core implications of the pre-study, namely the potential of combining a balance of pragmatic and hedonic product qualities in pre-trip ISs.

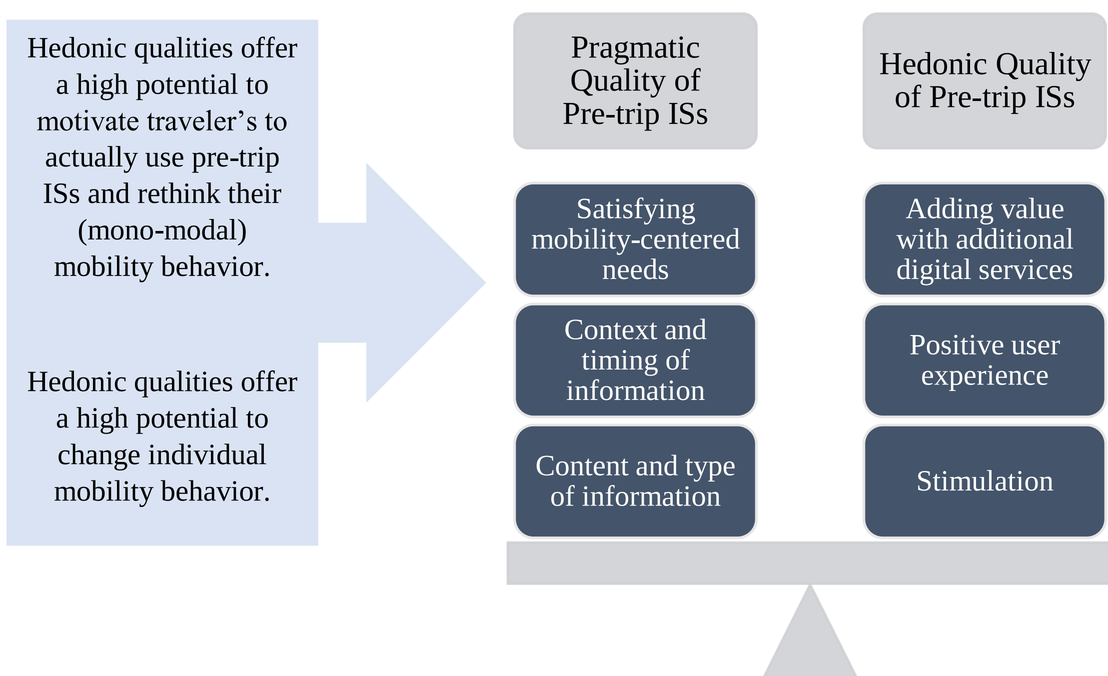


Figure 3.9 Summary of Implications of the Pre-Study: The Potential of a Balance of Pragmatic and Hedonic Qualities in Pre-trip ISs (own illustration).

4 Development of the Pre-trip Prototype

This chapter describes the development of a pre-trip prototype. The pre-trip prototype was built based on the results of the pre-study presented and discussed in Chapter 3. Consequently, this chapter elaborates how the insights gained in the pre-study were used to develop and design a pre-trip prototype in a user-centered manner. Thereby, together with Chapter 3, this chapter contributes to answering research question one (i.e., which information is desired by users in pre-trip information systems?). Chapter 3 contributes to research question one by providing the theoretical and empirical basis for an implementation whereas the present chapter contributes to research question one by actually implementing the gained insights. The basic construct of the implementation is based on the BMW Connected Mirror show case. The show case was presented at the Consumer Electronics Show (CES) in Las Vegas (USA) in January 2016 [101]. The content of the show case will be described in more detail in the following paragraphs. Moreover, considering the further outline of this thesis, the pre-trip prototype described underneath will serve as the basis for the evaluation presented in Chapter 5. Hence, the pre-trip prototype is the basis for answering research question two (i.e., which factors motivate travelers to accept and use pre-trip IS?). The following paragraphs will describe the pre-trip prototype's hardware, software, and operation. Each feature will be described in detail and each user interface will be visualized (see Figure 4.2 to Figure 4.7). An overall picture of the prototype can be found in Figure 4.1. Main parts of this chapter were already published in two conference proceedings [161,214].

4.1 Description of Overall Approach: The BMW Connected Mirror

This chapter aims to extend the previous results by an implementation of the identified user needs into a pre-trip prototype. In the online survey described in Chapter 3, mobility-centered needs at home (i.e., pain points, stress level, time and type of information and interest in vehicle-centered information) and non-mobility-centered additional needs (e.g., news, preparing grocery shopping) that are associated to the situation in which travelers inform themselves about their mobility options at home were assessed. A detailed description of the results of the online survey can be found above and in the journal paper on which Chapter 3 relays on [160].

The result of the pre-study (see Chapter 3) showed that travelers most suffer from a lack of availability of information about their mobility options. This means that current in-house pre-trip ISs and further digital mobility services do not satisfy the travelers' need for reliable information about different mobility options at home whenever they need them without putting a considerable amount of effort in the search for information. The pre-study showed that searching for mobility options at home is associated with stress for most travelers. Proactively presenting the needed information from a reliable data source could reduce the travelers' stress level because the service would reduce the travelers' workload for getting mobility-centered information and making modal and temporal decisions. Based on these insights, the features were implemented into exemplary hardware (i.e., smart mirror) on which information can be derived in passing (e.g., while brushing your teeth or while putting on the jacket) and without actively inquiring it (i.e., without starting an application and entering information). Therefore, a smart mirror, namely the BMW Connected Mirror, was chosen as the basic framework for the pre-trip prototype presented in this chapter. The following paragraphs will describe the key components and characteristics of the BMW Connected Mirror, including its hardware, operation, and software.

The BMW Connected Mirror. The BMW Connected Mirror is the exemplary smart mirror pre-trip prototype considered in this thesis. Figure 4.1 portrays the BMW Connected Mirror in the BMW World in Munich (Germany). It was first introduced to the market in January 2016 as a show case at the Consumer Electronics Show (CES) in Las Vegas (USA). The presentation of the BMW Connected Mirror at the CES contained an illustration of the time of day, weather information, digital calendar, routing information, and vehicle-centered information. In addition, a link with other smart home services such as effective energy management was demonstrated [101]. In sum, the BMW Connected Mirror was presented as a show case of a future in-house mobility touchpoint in an overall BMW mobility ecosystem.

Hardware. The BMW Connected Mirror is an interactive smart home product in the form of a full body mirror. The mirrored display surface of the BMW Connected Mirror enables the smooth integration of a user interface in addition to the primary mirror function. Hence, information can be derived in passing and without actively inquiring it. The mirror display consists of an organic light emitting diode (OLED) display produced by Samsung. At the time of the prototype development, this specific OLED display was not yet available on the market. However, an early prototype of the display was installed in the BMW Connected Mirror in cooperation with Samsung. The OLED display is 55 inches tall. The further hardware of the BMW Connected Mirror consists of a frame in bamboo wood look and aluminum ornaments in the BMW i-Design (see Figure 4.1). Since a bamboo itself is too small to produce the whole frame out of one single piece of bamboo wood, the frame was made out of synthetic substances and painted in bamboo wood look. The BMW Connected Mirror in this design is unique and is currently exhibited in the BMW World in Munich.

Operating. The Connected Mirror prototype is operated by gesture control. Gesture control was selected as the form of operation because operating by touch is not compatible in the context of a mirror display. More specifically, touching the display would leave marks on the surface of the display each time operating and touching it. In order to enable gesture control, a Kinect was installed above the BMW Connected Mirror (see the black box on the ceiling in Figure 4.1). Originally, the Kinect is an input device produced by Microsoft for the video game consoles Xbox 360, Xbox One and Microsoft Windows personal computers. The Kinect includes a line of three-dimensional motion sensors. The sensing and tracking of motion enable users to control and interact with their video game console or their personal computer without any game controller. Hence, the control and interaction can be operated through a natural user interface using gestures [131]. The connection of the Kinect and the Adobe Experience Design prototype described in the following relies on a C# syntax. More details concerning the general function of a sensor that detects the position of an object and then enables the object to control graphical elements on a smart mirror were published in a patent in the course of the development of the BMW Connected Mirror by the inventors Goffart, Gusenbauer and Mangel [78].

Software. For the present thesis, the original show case of the BMW Connected Mirror was edited and extended with regard to its preliminary show case functions. For this purpose, the prototyping software Adobe Experience Design CC (Beta) was used [3]. Adobe Experience Design enables designers and product developers to design user interfaces of prototypes without programming knowledge. User interfaces developed and designed with the help of Adobe Experience Design make it possible to experience user journeys and product features in the same ways as users would experience their journey and features in a fully developed product or service. The different user interfaces that were designed in Adobe Experience Design for the present thesis will be explained in detail in the next section (Chapter 4.2). Moreover, the user interfaces are visualized in the following in Figure 4.2 to Figure 4.7.

Figure 4.1 The BMW Connected Mirror in the BMW World in Munich, Germany (own illustration pre published in [214, p. 3]).

4.2 Description of User Interfaces

After describing the pre-trip prototype's hardware, software and operation in Chapter 4.1, Chapter 4.2 now illustrates in detail the different user interfaces that were created using the prototyping software Adobe Experience Design CC (Beta). The user interfaces were developed based on the CES show case presented in Las Vegas in January 2016 and the results of the pre-study (see Chapter 3). The implementation of the results of the pre-study into a pre-trip prototype contributes to research question one (i.e., which information is desired by users in pre-trip information systems?) and simultaneously prepares the ground for answering research question two (i.e., which factors motivate travelers to accept and use pre-trip IS?). Based on the core findings from the pre-study, pragmatic (i.e., information-based qualities) and hedonic (i.e., stimulation- and pleasure-oriented) qualities were combined in the pre-trip prototype. The following paragraphs first describe and then visualize each user interface developed for the present thesis (see Figure 4.2 to Figure 4.7).

Start Screen. A user interface with a toolbar on the left side and information on the date, time of day and weather at the top of the display was created as the start screen of the pre-trip prototype. On this screen, the user is able to use the BMW Connected Mirror as a mirror (e.g., for putting on the jacket before going outside). At the same time, the user is able to enter one of the following user interfaces from the toolbar on the left side by gesture control.

User Interface "Agenda". The user interface "Agenda" was meant to retrieve the users' personal agenda including dates and locations of upcoming meetings from their digital calendar. The calendar integration enables the proactive presentation of intelligent pre-trip information. For example, the digital calendar can tell the pre-trip service whether it is a working day, weekend or a holiday for the user. Based on this information, the smart in-house mobility service could display the appropriate information for the appropriate kind of day, time and situation. Based on the location information, the calendar integration enables the routing feature which will be explained in the following. The agenda interface is visualized in Figure 4.2.

User Interface "MyMobility – Multimodality". The most pressing pain point identified in the pre-study in Chapter 3 is the availability of information. Moreover, the literature review and market analysis presented in the theoretical background of this thesis (see Chapter 2.1.2 and Chapter 2.3) has highlighted that pre-trip ISs should bundle and compare information regarding multiple means of transport in order to foster multi-modal mobility behavior and changes in modal decisions. Therefore, the core interface of the pre-trip prototype contains multi-modal mobility information. Since this chapter concentrates on mobility behavior in a present scenario, the interface regarded here contains three different mobility options which are currently available on the market, namely, carsharing, private car usage, and public transport. For each of the three modal alternatives, the different routing options to reach the next calendar appointment were offered including the duration of the mobility options as well as reasons for delays. This interface is visualized in Figure 4.3. A more detailed user interface concentrating on the exact routing with one of the three different means of transport (i.e., carsharing, private car, and public transport) could be reached through choosing one of the three alternatives on this layer of the interface. The routing interface will be explained in more detail in the following paragraphs. Later chapters of this thesis also include future scenarios of mobility planning and travelling with future means of transport (i.e., robo-taxis and ridepooling; see Chapter 6).

User Interface "MyMobility – Vehicle Status. The literature review, as well as the pre-study showed that German mobility is still characterized by a dominance of private car usage. Additionally, the pre-study has highlighted the travelers' interest in vehicle-centered information at home. Therefore, a user interface with vehicle-centered information such as tank fill, in-car temperature, and lock status was included in the pre-tip prototype. A scenario with an electric vehicle (i.e., BMW i3) was selected for the vehicle-centered information interface. This scenario was selected in order to illustrate the possible scope of a holistic pre-trip IS that could also manage the charging of an electric car with solar energy at home. This connection to smart home features will be explained in more detail in the paragraph regarding the "Home Status" user interface. This interface is visualized in Figure 4.3.

User Interface "MyMobility – Routing". As explained above the pre-trip prototype provided three different modal alternatives, namely carsharing, private car and public transport. After a short preview of travel durations and reasons for possible delays, the users were able to choose one of the modal alternatives and retrieve information about the exact routing to reach the next calendar appointment. Based on the insights into information types from the pre-study, the routing interface includes information on the departure time, duration of the mobility option, traffic situation and reasons for delays. This interface is visualized in Figure 4.4.

User Interface "Home Status". Based on the high interest in using smart home features in the future that was identified in the pre-study, an interface with smart home connections was integrated into the pre-trip prototype. This interface contains status information about the entire smart home area, including missed calls, completion of the pre-programmed laundry, lawn watering as well as an overview of the current energy management. This interface is visualized in Figure 4.5.

The interfaces described above mostly satisfy functional needs of the traveler regarding their trip planning and smart home monitoring. These interfaces are based on the show case of the BMW Connected Mirror presented at the CES in January 2016 in Las Vegas, USA [101]. One of the core findings of the pre-study was that travelers might be motivated to use pre-trip ISs more frequently if the system combined pragmatic (i.e., information-based qualities) as well as hedonic (i.e., stimulation- and pleasure-oriented) qualities. Therefore, the following two hedonic features were integrated into the pre-trip prototype. These interfaces were developed originally for this thesis.

User Interface "Discover". This menu item was specifically designed to address the users' need for stimulation by constantly surprising them with new recommendations for activities and events that might be interesting to explore. Based on the users' individual preferences, this interface was meant to suggest new events and activities such as a concert of their favorite musician or the reopening of a fine restaurant. This interface is visualized in Figure 4.6.

User Interface "Family & Friends". This menu item was specifically implemented to address the users' need for relatedness to their family and friends. The implemented features should make the users feel close to people who are important to them. This interface contained an interactive memo board on which authorized users could leave small messages directly or through a third-party communication service (e.g., WhatsApp). Moreover, a slide show generated from social media or photos stored and shared in a cloud was included here. This interface is visualized in Figure 4.7.

Summarizing, the interfaces described above combine pre-trip information with additional digital information and recommendation. Thereby, the pre-trip prototype considered in this thesis is meant to satisfy both, functional mobility-centered and vehicle-centered needs of the traveler and additional digital pleasure-oriented motives. The implementation of the results of the pre-study into a pre-trip prototype on the BMW Connected Mirror prepares the ground for answering research question two (i.e., which factors motivate travelers to accept and use pre-trip IS?). Therefore, the implemented features and designed user interfaces will be evaluated in detail in the next chapter. More specifically, the next chapter will elaborate on how users evaluate the technology acceptance of the pre-trip prototype. Thereby, the chapter focuses on the influencing factors that predict the users' intrinsic and extrinsic motivation to use pre-trip IS.

Figure 4.2 User Interface "Agenda" of the BMW Connected Mirror (own illustration).

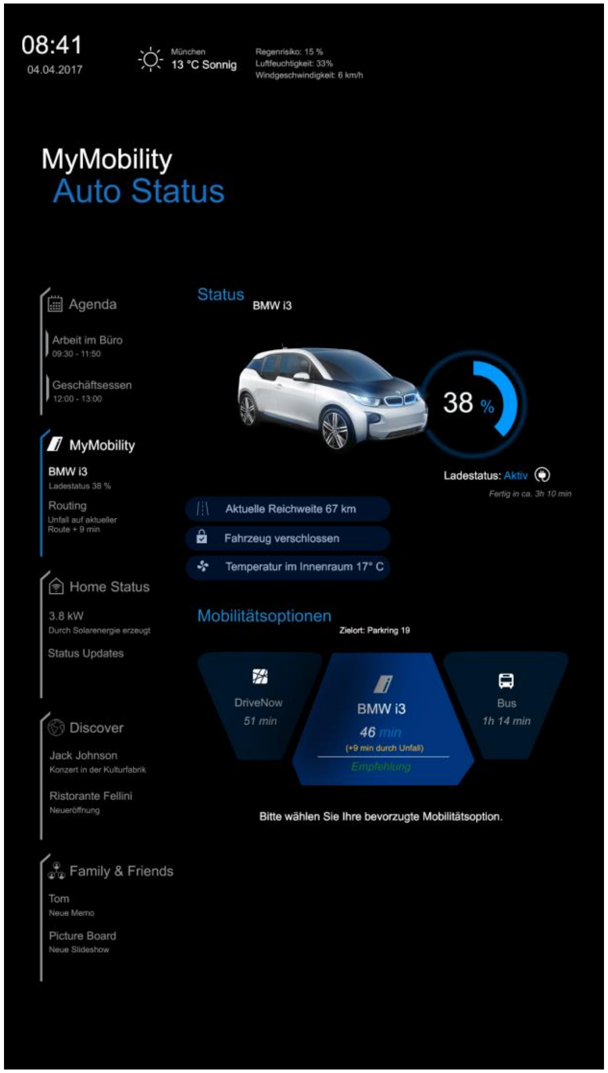


Figure 4.3 User Interfaces "My Mobility – Vehicle Status" and "My Mobility – Multimodality" of the BMW Connected Mirror (own illustration pre published in [214, p. 3]).

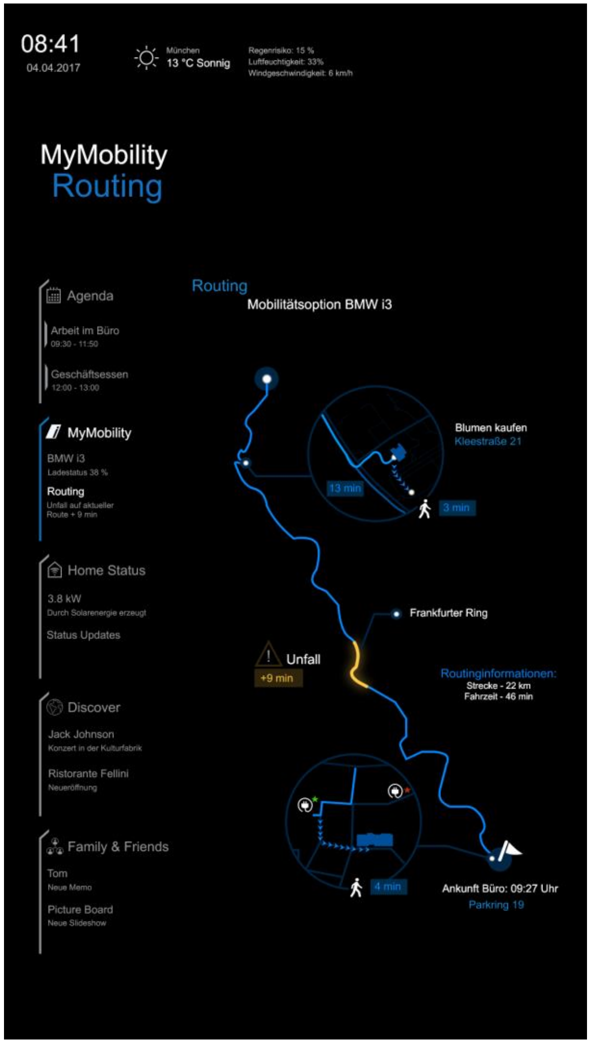


Figure 4.4 User Interface "My Mobility - Routing" of the BMW Connected Mirror (own illustration).

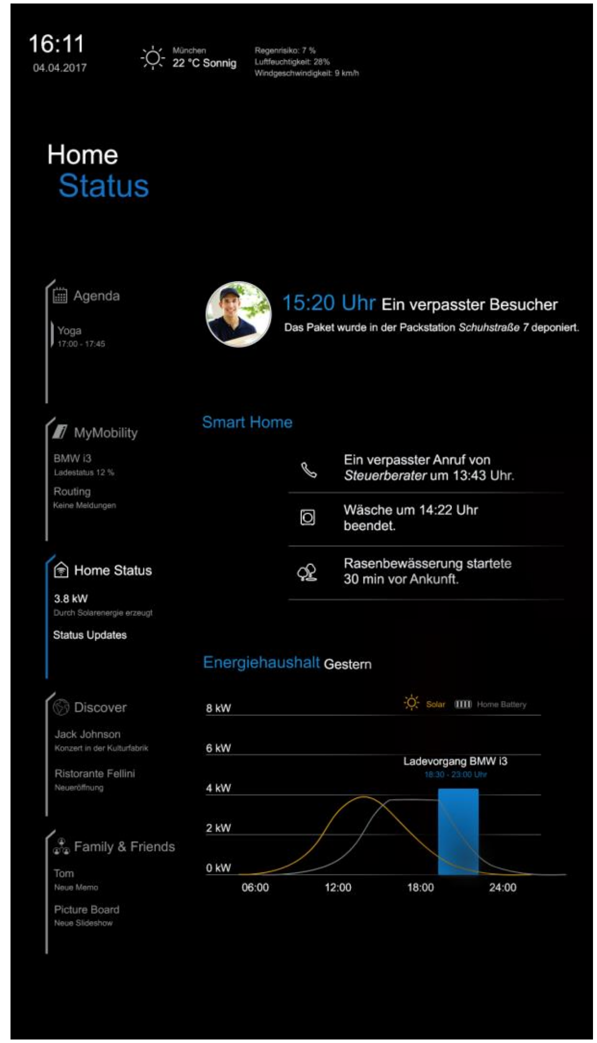


Figure 4.5 User Interface "Home Status" of the BMW Connected Mirror (own illustration).

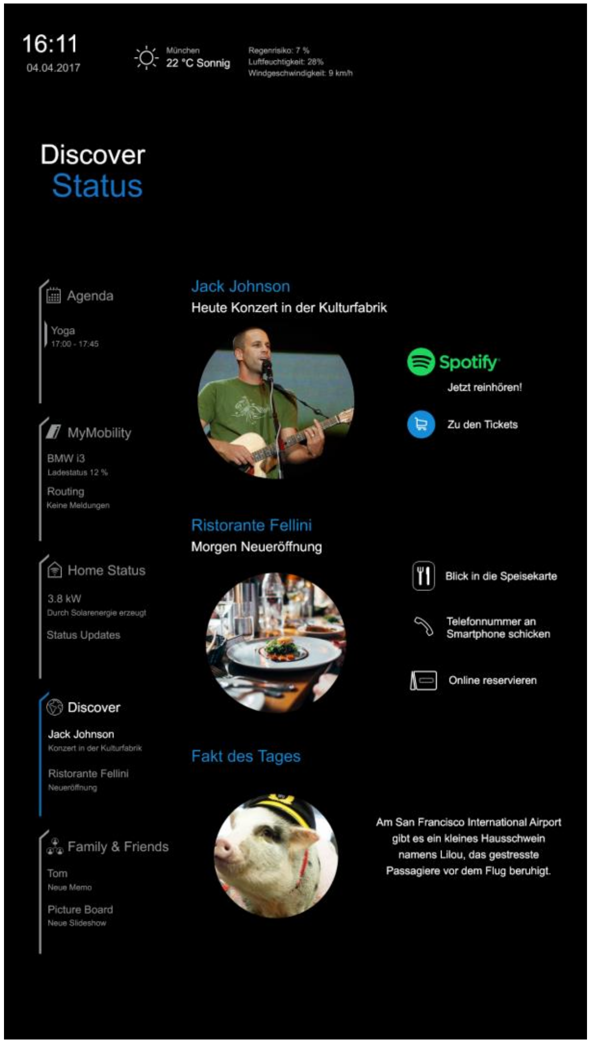


Figure 4.6 User Interface "Discover" of the BMW Connected Mirror (own illustration).

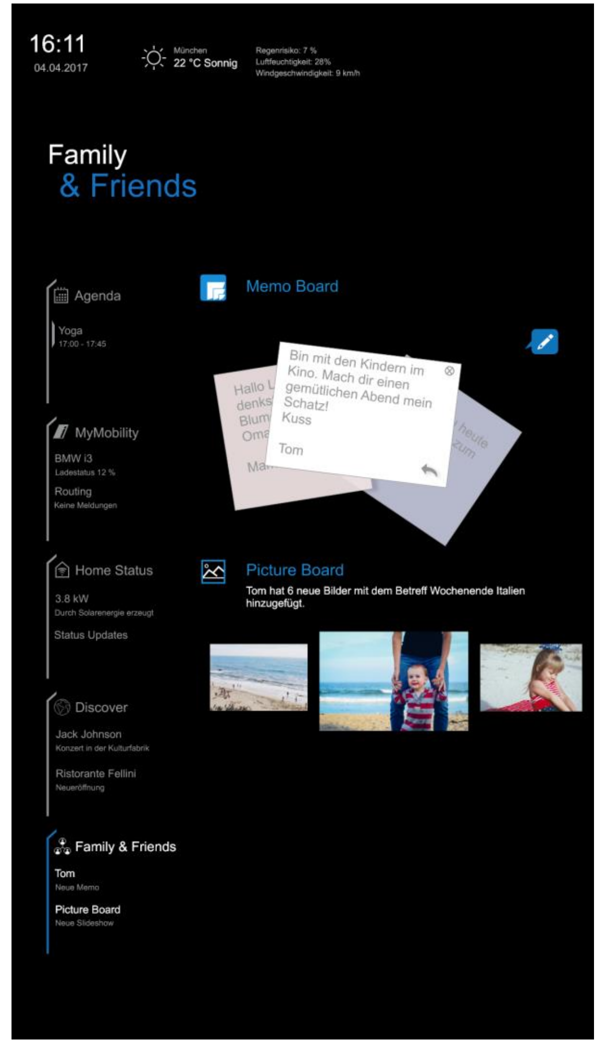


Figure 4.7 User Interface "Family & Friends" of the BMW Connected Mirror (own illustration).

5 Technology Acceptance of Pre-trip Information Systems

As stated in the introduction, the progressing traffic collapse burdens the economy, the environment, and each individual traveler. Especially in urban areas, transportation systems and infrastructure are under high pressure to satisfy the constantly rising mobility demand and the growing complexity of mobility options (see Chapter 1.1). Counteracting the progressing traffic collapse requires both, changes on traffic system and strategy level as well as changes on the individual behavioral level. For the latter, intelligent traveler ISs, and among them especially pre-trip ISs, play an important role. As explained in detail in Chapter 2.3.2, the development of technologies for locating and tracking mobile phones in the early 2000s has revolutionized the market of ITS [222]. Based on these technological developments, innovative digital mobility and especially location-based services have entered the ITS market. Consequently, digital mobility and especially location-based services have expanded the field of ITS by appearing in cars and on smartphones and became a strong influencing factor on travel behavior [71]. Hence, from the technical perspective, a huge variety of digital mobility services that constantly improve themselves on a crowdsourcing-basis are available on the transportation market. However, the pure availability of technically functioning services does not yet solve the problem of the progressing traffic collapse. The remaining key challenge is to motivate travelers to actually accept and use these services before their trips and to make them rethink their mobility habits and decisions based on the provided information [124,125]. Therefore, this chapter aims to answer the second of the three research questions introduced at the beginning of this thesis (see Chapter 1.1):

- Research Question 2: Which factors motivate travelers to accept and use pre-trip ISs?

In order to answer research question two, this chapter focuses on the technology acceptance of pre-trip ISs. The results of the pre-study presented and discussed in Chapter 3 formed the basis for the implementation described in Chapter 4. Subsequently, the present chapter aims to evaluate the pre-trip prototype with regard to its technology acceptance. Thereby, the aim is to achieve a deeper understanding of factors that motivate travelers to use pre-trip ISs. Therefore, the pre-trip prototype described in Chapter 4 is used to conduct a user study (n = 548). The results of this study are analyzed in order to draw conclusions on the factors that determine the technology acceptance in terms of use, satisfaction and loyalty towards pre-trip ISs.

This chapter proceeds as follows: Chapter 5.1 starts with an introduction to the state-of-the-art methods used for modelling and evaluating the acceptance and use of ISs and emerging technologies. This includes a literature review on the Unified Theory of Acceptance and Use of Technology II (i.e., UTAUT2: [203]), which is a frequently applied framework for analyzing technology acceptance from the field of IS research (see Chapter 5.1.1). Afterwards, Chapter 5.1.2 provides a literature review on further outcome variables of technology acceptance. While the UTAUT2 only focuses on behavioral intention and use behavior as outcome variables of technology acceptance, Chapter 5.1.2 also identifies satisfaction and loyalty as useful extensions for the UTAUT2. Based on the literature review on UTAUT2 and further outcome variables of technology acceptance (i.e., satisfaction and loyalty) hypotheses about the relationships within UTAUT2 as well as satisfaction and loyalty are derived for the context of pre-trip ISs.

Later on, Chapter 5.1.3 elaborates the theory of the state-of-the-art data analysis that needs to be applied in order to investigate the technology acceptance of pre-trip ISs. Here, structured equation modelling (SEM) via partial least squares (PLS) is identified as an acknowledged and commonly used method for modelling technology acceptance and use. Hence, a systematic procedure for applying PLS-SEM will be elaborated. Finally, Chapter 5.1.4 summarizes the literature reviews on the conceptual and statistical methods for evaluating technology acceptance and combines the insights in an overall approach and goals of a user study that is conducted in order to answer research question two.

Next, in the method and design section (see Chapter 5.2), it will be explained in detail, which material and variables were used in the user study (see Chapter 5.2.1). This also includes a description of the sample of participants (see Chapter 5.2.2) and the applied data analysis (see Chapter 0). Afterwards, the results of the user study are presented in Chapter 5.3 and discussed in Chapter 5.4. Main parts of this chapter were already presented at a scientific conference [159] and published in three conference proceedings [158,161,214].

5.1 Methods for Evaluating Technology Acceptance

The following sections concentrate on state-of-the-art methods for modelling and evaluating the acceptance of new ISs. This includes a description of the Unified Theory of Acceptance and Use of Technology II (i.e., UTAUT2: [203]) and the definition of all belonging constructs. Moreover, Chapter 5.1.1 contains a literature review on the previous fields of application of the UTAUT2. Based on this literature review, the hypotheses for the present analysis will be derived.

Since the UTAUT2 only focuses on behavioral intention and use behavior, Chapter 5.1.2 focuses on additional outcome variables of technology acceptance, namely satisfaction and loyalty. Based on a literature review on satisfaction and loyalty as outcome variables in the context of technology acceptance, further hypotheses for the subsequent data analysis will be derived. Finally, Figure 5.5 summarizes all hypotheses considered in this chapter into one research model.

After providing the state of the art concerning methods for modelling and evaluating the acceptance of new ISs and deriving the hypotheses for the evaluation of the pre-trip prototype, Chapter 5.1.3 elaborates the theory of the applied statistical models. Here, the procedure of structured equation modelling (SEM) via partial least squares (PLS) will be described.

5.1.1 The Unified Theory of Acceptance and Use of Technology II

This section provides an overview of state-of-the-art frameworks for evaluating the acceptance and use of new ISs. Modelling and evaluating the users' acceptance of new information technology (IT) is a frequently discussed topic in research on information systems and emerging technologies. Past research revealed several models that include relevant variables for predicting technology acceptance in terms of behavioral intention and use behavior [54,201,203,204]. Among these models, this chapter concentrate on the latest adaption of the Unified Theory of Acceptance and Use of Technology (i.e., UTAUT2: [203]). The UTAUT2 aggregates the insights from the research on the Technology Acceptance Model (i.e., TAM: [54]) and the former Unified Theory of Acceptance and Use of Technology (i.e., UTAUT: [201]) and applies these insights to the context of the consumers' voluntary use of technology. The UTAUT2 predicts the consumers' behavioral intention and use behavior based on their performance expectancy, effort expectancy, expected social influence, facilitating conditions, habit, price value and hedonic motivation (for definitions see Table 5.1). The consumers' age, gender, and experience moderate these connections. Compared to the UTAUT, the UTAUT2 contains hedonic motivation, price value, and habit as additional predictors for behavioral intention. Moreover, UTAUT2 concentrates on voluntary technology use instead of mandatory technology use in the organizational context (see UTAUT). Figure 5.1 illustrates the components of UTAUT2 and their relationship to each other.

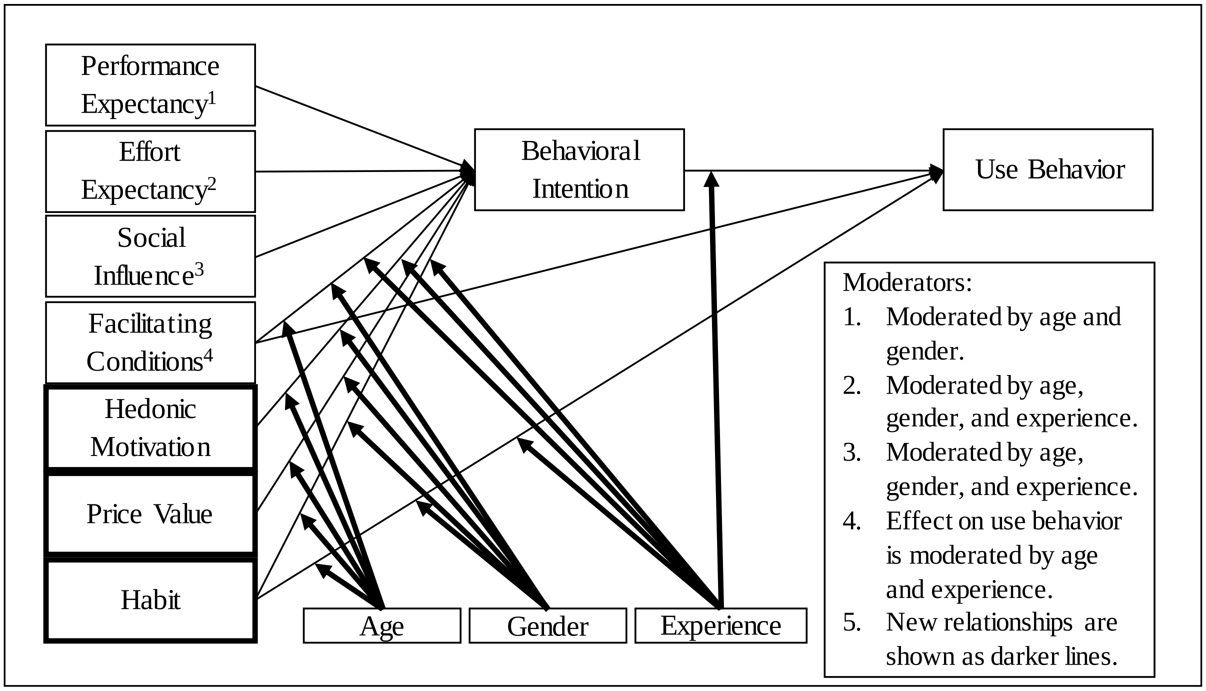


Figure 5.1 Unified Theory of Acceptance and Use of Technology II (Adapted from: [203, p. 160]).

Table 5.1 Definitions of the Components of UTAUT2 (own illustration).

Construct	Definition
Performance expectancy	"[The] degree to which an individual believes that using the system will help him or her to attain gains in (…) performance." [201, p. 447]
Effort expectancy	"[The] degree of ease associated with the use of the system." [201, p. 450]
Social influence	"[The] degree to which an individual perceives that important others believe he or she should use the new system." [201, p. 451]
Facilitating conditions	"[The] degree to which an individual believes that an organizational and technical infrastructure exists to support use of the system." [201, p. 453]
Habit	"[A] perceptual construct that reflects the results of prior experiences." [203, p. 161]

Construct	Definition
Price value	"The consumers' cognitive tradeoff between the perceived benefits of the applications and the monetary cost for using them (…) The price value is positive when the benefits of using a technology are perceived to be greater than the monetary cost and such price value has a positive impact on intention." [203, p. 161]
Hedonic motivation	"[The] fun or pleasure derived from using a technology" [203, p. 161]
Behavioral intention	The intention to use a specific technology in the future [see 201].

After describing the overall structure of the UTAUT2 and defining its components, the following section provides an overview of the fields of application of the UTAUT2. The UTAUT2 has already proved itself as a useful model for technology acceptance for a wide range of different consumer products. For example, the application of UTAUT2 to mobile banking [5,19] and mobile payment [108,133] on the one hand and the application of UTAUT2 to social network sites [87] on the other hand shows that UTAUT2 can be applied to both, pragmatic (i.e., mobile banking) and hedonic IT (i.e., social network sites). The strength of the influence of the single UTAUT2 components on the users' acceptance and use differs depending on the type of technology that is analyzed. For example, effort expectancy and facilitating conditions were identified as the two most important predictors for using a mobile health care system [61] while hedonic motivation and habit were identified as the two most important predictors for using mobile apps [89] and Instagram [102]. Table 5.2 gives an overview of the different fields of application of UTAUT2.

Table 5.2 Overview of the Fields of Application of UTAUT2 (own illustration).

Field of Application	Reference
Computer supported collaborative classrooms	Ali, Nair, & Hussain (2016) [7]
E-Government services	Krishnaraju, Mathew, & Sugumaran (2013) [111]
Electronic textbooks	Gerhart, Peak, & Prybutok (2015) [74]
Google glass	Salinas Segura & Thiesse (2015) [166]
Health and fitness apps	Yuan, Ma, Kanthawala, & Peng (2015) [221]
Instagram	Järvinen, Ohtonen, & Karjaluoto (2016) [102]
Internet banking	Arenas-Gaitán, Peral-Peral, & Ramón-Jerónimo (2015) [9]
Intelligent Traveler ISs	Lisson, Hall, Michalk, & Weinhardt (2017) [125]
Mobile apps	Hew, Lee, Ooi, & Wei (2015) [89]
Mobile banking	Alalwan et al. (2017) [5]; Baptista & Oliveira (2015) [19]
Mobile health care system	Dwivedi, Shareef, Simintiras, Lal, & Weerakkody (2016) [61]
Mobile internet	Venkatesh et al. (2012) [203]
Mobile payment	Khalilzadeh et al. (2017) [108]; Morosan & DeFranco (2016) [133]; Oliveira, Thomas, Baptista, & Campos (2016) [143]
Mobile TV	Wong, Wei-Han Tan, Loke, & Ooi (2014) [216]

Field of Application	Reference
Online shopping	Escobar-Rodríguez & Carvajal-Trujillo, (2013) [65]; Pascual-Miguel, Agudo-Peregrina, & Chaparro-Peláez (2015) [147]; Escobar-Rodríguez & Carvajal-Trujillo (2014) [66]
Persuasive environmentally sustainable systems	Brauer, Ebermann, & Kolbe (2016) [29]
Social network sites	Herrero et al. (2017) [87]
Smart shower meters	Kupfer, Ableitner, Schöb, & Tiefenbeck (2016) [114]
SMS commercials	Shareef, Dwivedi, Kumar, & Kumar (2017) [180]
Wearable devices	Gu, Wei, & Xu (2016) [80]
Wearable healthcare devices	Gao, Li, & Luo (2015) [73]

Although the UTAUT2 is a wide spread method to analyze the users' technology acceptance, the application of UTAUT2 components on intelligent traveler information systems (ITIS) is rare. Only few empirical studies address the technology acceptance of ITISs [e.g., 124,125]. For example, Lisson et al. [125] studied the acceptance of ITISs with an online study with n = 298 students of a German university. The sample included users as well as non-users of ITISs. The authors identified hedonic motivation, social influence, performance expectancy, and price value as the most important predictors for the participants' intention to use ITISs. With the help of performance expectancy, effort expectancy, social influence, hedonic motivation, price value, and habit, the authors were able to explain 34.4% of the variance of the users' behavioral intention and 12.4% of the users' stated use behavior.

In sum, the UTAUT2 is a well-established framework for evaluating the intended and actual use of different technologies. Thereby, the relative importance of the different components (see Table 5.1) for explaining variance in the users' behavioral intention differs depending on the concrete IS that is studied. The rare application of technology acceptance frameworks in the context of transportation research highlights the need to study the influence of the components of UTAUT2 on the users' intention to use pre-trip ISs. Therefore, the following paragraph focuses on the application of the UTAUT2 on pre-trip ISs and derives hypotheses concerning the influence of the model parameters on the participants' intention to use pre-trip ISs.

Since this thesis examines a pre-trip prototype that is not available on the consumer market, the constructs habit and facilitating conditions were excluded from further analysis. Similar to previous studies [e.g., 114,166], it can be argued that it is not suitable to assess the original UTAUT2 items for the users' habit to use a certain technology in the context of new technology that is not already available on the market. Since recent approaches to change the wording of the original UTAUT2 items for habit did not result in items with acceptable quality criteria [114], the construct habit was excluded from the analysis. Again, due to the novelty of the regarded technology, the construct facilitating conditions was also excluded from the analysis.

Based on previous research described above it is predicted that the components of UTAUT2 have a positive influence on the intention to use pre-trip ISs (H = Hypothesis):

- H1: Performance expectancy has a positive effect on the intention to use pre-trip ISs.

- H2: Effort expectancy has a positive effect on the intention to use pre-trip ISs.
- H3: Social influence has a positive effect on the intention to use pre-trip ISs.
- H4: Hedonic motivation has a positive effect on the intention to use pre-trip ISs.
- H5: Price value has a positive effect on the intention to use pre-trip ISs.

5.1.2 Outcome Variables in Technology Acceptance

Besides extending the research on UTAUT2 by the application of the technology acceptance framework to a pre-trip IS, this thesis also extends the research on UTAUT2 by the integration of two more outcome variables, namely satisfaction and loyalty. Therefore, the following paragraphs focus on evaluating technology acceptance as a multi-faceted construct and the importance of integrating satisfaction and loyalty as facets of technology acceptance of pre-trip ISs. The literature review presented above has to main goals, namely (1) providing well founded definitions of satisfaction and loyalty in the context of technology acceptance and (2) providing the basis for deriving hypotheses about the antecedents of satisfaction and loyalty as facets of technology acceptance in the context of pre-trip ISs. Since the application of technology acceptance models in the context of mobility, ITISs and pre-trip ISs is rare, this section reviews literature from the overall field of technology acceptance which includes different ISs (e.g., web-based learning programs and mobile banking).

Satisfaction. Satisfaction was integrated as a facet of technology acceptance into the present research because according to the international standard of usability, i.e., ISO 9241 [59], satisfaction is one of the three core elements of usability besides efficiency and effectiveness. Since perceived usability is a core element of a users' technology acceptance, it is important to measure technology acceptance in terms of user satisfaction. According to Lindgaard and Dudek [123], this thesis defines satisfaction as the "subjective sum of the interactive experience" (p. 430) with a technology. This definition includes that a high user satisfaction goes along with the users' impression that it is a wise and right decision to use the technology and that they enjoy the whole interaction with the system [57]. Furthermore, it is important to include satisfaction as an outcome variable of the acceptance of a technology because previous research has argued that satisfaction is a core component of the success of ISs. More precisely, the users' satisfaction can be seen as an antecedent of the users' behavioral intention. This means that the users' behavioral intention is influenced positively by a high satisfaction of the user which can again be achieved through a positive user experience during the interaction with the system [55]. The positive influence of satisfaction on usage intention was supported in several empirical studies [e.g., 117,157,192]. For example, Lee [117] studied web-based learning programs and found that satisfaction had the highest effect on the users' continuance intention compared to perceived usefulness, attitude, concentration, subjective norm and perceived behavioral control. Based on these insights, this thesis hypothesizes the following:

- H6: Satisfaction has a positive influence on the intention to use pre-trip ISs

Besides the positive influence of user satisfaction on behavioral intention, this thesis also integrates the antecedents of satisfaction into the present research model. Previous research has provided some insights into possible antecedents of user satisfaction [e.g., 117,157]. For example, Lee [117] showed that perceived usefulness and confirmation (i.e., a better user experience than expected) had significant positive effects on satisfaction in the context of e-learning. Similar results were found by Roca, Chiu and Martinez [157] also in the context of e-learning. Here, satisfaction had a positive influence on the users' continuance intention. Satisfaction was in turn predicted by perceived usefulness, information quality, confirmation, service quality, system quality, perceived ease of use and cognitive absorption. Another study, in the context of the continuance intention concerning online social networks, showed positive significant effects of perceived enjoyment, and perceived usefulness on user satisfaction [192].

Furthermore, the relationship between satisfaction and several UTAUT2 components was studied. For example, satisfaction and its relationship to the performance expectancy, effort expectancy, social influence and facilitating conditions was studied in the context of the adoption of an E-government technology [38]. While social influence did not have a significant effect on satisfaction with the technology, performance expectancy, effort expectancy and facilitating conditions showed significant positive effects on satisfaction. Similar results were found in the context of healthcare with regard to the acceptance of electronic patient record [129]. Again, social influence did not have a significant effect on satisfaction. Performance expectancy, effort expectancy and facilitating conditions, however, showed significant positive effects on satisfaction. Based on the related work summarized above, this thesis hypothesizes the following relationships between the UTAUT2 components and satisfaction:

- H7: Performance expectancy has a positive effect on the satisfaction with pre-trip ISs.
- H8: Effort expectancy has a positive effect on the satisfaction with pre-trip ISs.
- H9: Social influence has a positive effect on the satisfaction with pre-trip ISs.
- H10: Hedonic motivation has a positive effect on the satisfaction with pre-trip ISs.
- H11: Price value has a positive effect on the satisfaction with pre-trip ISs.

Loyalty. The following paragraph focuses on the integration of loyalty as a facet of technology acceptance. Generally, loyalty can be defined as the deep commitment of a user towards a product, service, brand or organization [144, p. 34]. This definition includes two main facets of loyalty, namely (1) loyalty in terms of the longitudinal usage or repurchase and (2) loyalty in terms of recommending a certain product, service or brand to others [115, p. 294]. This thesis concentrates on loyalty in terms of recommending a technology to others because loyalty in terms of usage intention is already assessed with the help of behavioral intention. Moreover, this thesis concentrates on a prototype which is not yet available on the market and is therefore not able to assess purchase behavior. Form an entrepreneurial view, it is important to focus on customer loyalty because loyalty is a core driver of economic success [156]. For example, a large benefit of loyal customers is the firms' savings with regard to investments in new customer acquisition [155].

With regard to the antecedents of loyalty, satisfaction is seen as a requirement for customer loyalty [e.g., 64,88]. Here, customer loyalty is seen as "a psychological character formed by sustained satisfaction of the customer" [153, p. 141]. For example, the relationship between satisfaction and loyalty was studied in the context of mobile application recommendation [218]. Here, the users' app continuance intention, the perceived hedonic benefits and their satisfaction with the app were the direct antecedents of their loyalty.

Moreover, previous research has identified behavioral intention as an antecedent of loyalty. For example, a recent study in the context of mobile banking integrated the users' behavioral intention to recommend (i.e., loyalty) into the UTAUT2. The results showed that the users' intention to adopt mobile banking had a significant positive effect on their intention to recommend mobile banking to others [143]. Here, the users' adoption intention was used as the only predictor for the users' loyalty and explained 61.3% of the variance in loyalty. Based on these findings, the authors argued that it is important to include loyalty or rather the recommendation intention as a facet of technology acceptance because loyalty gets even more important because of the enhanced discussion about new technologies among consumers via social media [143:411, p. 411]. Furthermore, by extending the UTAUT2 by loyalty, this thesis contributes to the recommendations of future research directions of Venkatesh et al. [204, p. 348], who argued that it is worthy to investigate the impact of technology use on further consumer outcomes such as brand loyalty. Based on the related work concerning loyalty and technology acceptance, this thesis hypothesizes the following relationships between loyalty, behavioral intention, and satisfaction:

- H12: Satisfaction has a positive influence on the loyalty towards pre-trip ISs.
- H13: Behavioral intention has a positive influence on the loyalty towards pre-trip ISs.

Moreover, based on the high dependence of behavioral intention on user satisfaction, this thesis investigates whether the direct effects of the UTAUT2 components (i.e., effort expectancy, performance expectancy, social influence, hedonic motivation, and price value) on behavioral intention are mediated by user satisfaction. Figure 5.2 illustrates all hypothesis integrated in one research model.

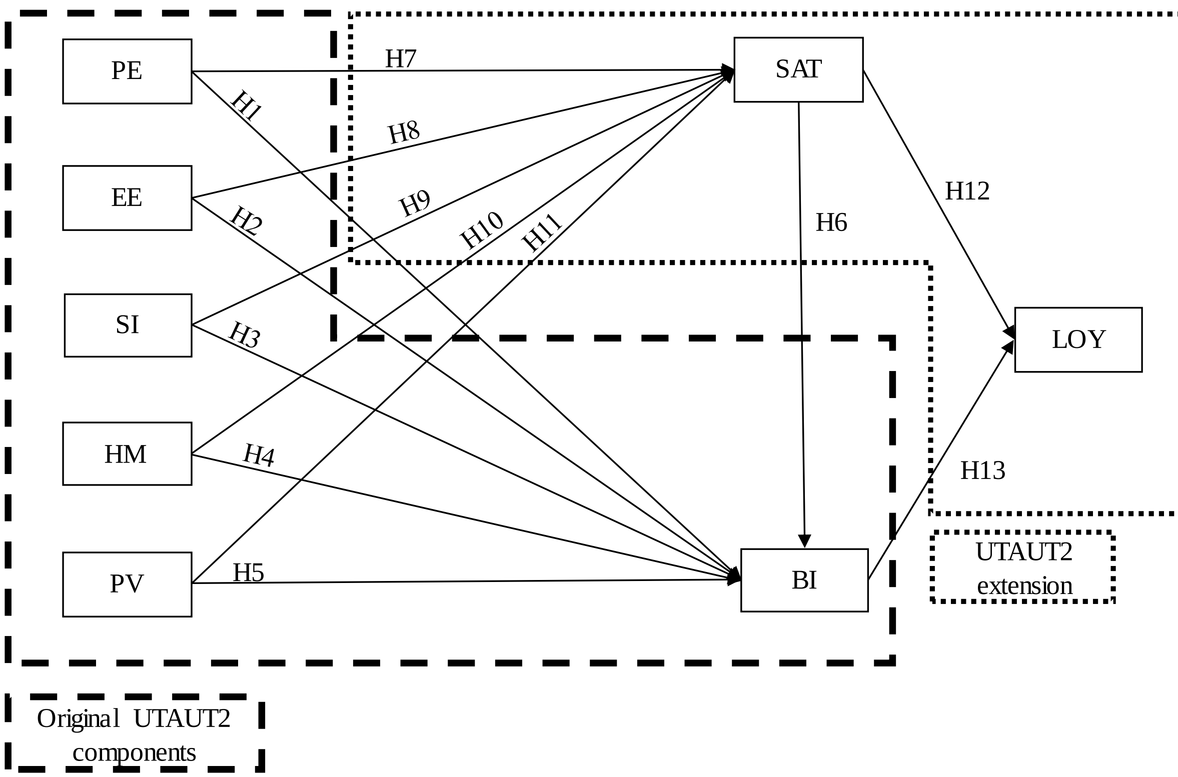


Figure 5.2 Research Model (own illustration: EE = Effort Expectancy, HM = Hedonic Motivation, PE = Performance Expectancy, PV = Price Value, SI = Social Influence, BI = Behavioral Intention, SAT = Satisfaction, LOY = Loyalty).

Summarizing, this thesis uses the technology acceptance framework UTAUT2 to investigate the technology acceptance and use in the context pre-trip ISs within the field of transportation research. In addition to the original UTAUT2 components (see Figure 5.1), satisfaction and loyalty were identified as fruitful extensions of UTAUT2. After reviewing the literature on UTAUT2 and further outcome variables of technology acceptance and deucing hypotheses on the relationships in the context of pre-trip ISs, the following paragraphs concentrate on the modelling techniques used to analyze these connections.

5.1.3 Theory of the Applied Statistical Models

This chapter provides a detailed overview of the state-of-the-art statistical means used for modelling technology acceptance. Generally, structured equation modelling (SEM) via partial least squares (PLS) is an acknowledged and commonly used method for modelling technology acceptance and use [e.g., 122,202,203]. Figure 5.3 summarizes the systematic procedure of applying PLS-SEM.

The first step of the procedure is focused in Chapter 5.1.2 and Chapter 5.2.1. The structural model considered in this chapter is already illustrated above in Chapter 5.1.2 (see Figure 5.2). The measurement model replenished the inner structural model among the manifest items used to assess the latent construct illustrated in the inner structural model in Figure 5.2. The items can be found in Chapter 5.2.1 (see Table 5.5). Taken together, the inner structural model and the outer measurement model represent the path model of the present user study. Step two, namely the data collection and examination will also be described in Chapter 5.2.

This chapter concentrates on the third and fourth step listed in Figure 5.3. After introducing the mathematical foundation of SEM, the following paragraphs focus on the theory of estimating PLS path models. This includes estimating the model as well as evaluating its reliability and validity. Moreover, the significance of effects is tested via Bootstrapping and the quality of the model is evaluated with the help of R^2, Q^2 and f^2. Finally, advanced PLS-SEM analyses such as mediator analysis will be described.

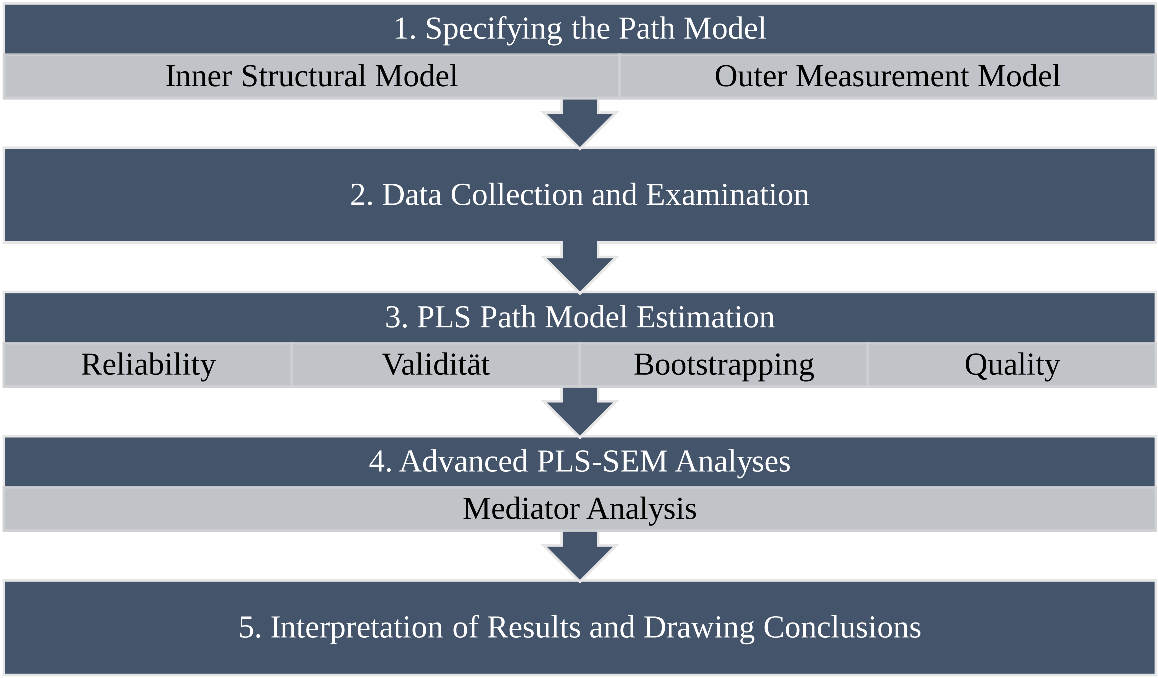


Figure 5.3 A Systematic Procedure for Applying PLS-SEM (Adapted from [82, p. 25]).

Mathematical Foundation. PLS-SEM belongs to the group of multivariate methods, i.e., PLS-SEM analyzes multiple variables simultaneously [82, p. 2]. Thereby, several variables are combined linearly in order to estimate a score for the variate value. The linear combination includes values of variables X_i (e.g., aggregated scores assessed with the help of a questionnaire) and weights β_i that influence with which relative importance the variables enter the equation [82, p. 4 ff.]. The mathematical foundation of PLS-SEM can be summarized as follows:

$$Variate\ value = \beta_1 \cdot X_1 + \beta_2 \cdot X_2 + \cdots + \beta_k \cdot X_k + \cdots + \beta_n \cdot X_n \tag{5.1}$$

Path Model Estimation. The PLS-SEM algorithm is used to estimate the path model. This algorithm estimates the model parameters (i.e., mainly the path coefficients) so that the explained variance of the dependent construct is maximized [82, p. 74 ff.]. Thereby, based on the recommendations of Hair et al. [82,83] the 'path weighting scheme' was chosen for the model estimation in this thesis. For the maximum iterations, the reference value of 300 was maintained and the stop criterion was set to 10e-7 [83, p. 93].

Evaluating the Reliability and Validity of the Model. After estimating the path model, the reliability and validity of the model need to be checked. In this step, the reliability, as well as the convergent and discriminant validity need to be checked. Table 5.3 summarizes the criteria that need to be applied in this step.

Table 5.3 Overview of Criteria for Reliability and Validity in the Context of PLS-SEM (own illustration).

Criteria	Definition	Convention	Source
Reliability (internal consistency of a scale)			
Cronbach's alpha	The inter-correlation of items from one scale	$\alpha > .70$	Hair et al. (2014) [82, p. 115]
Composite reliability	The inter-correlation of items from one scale which is weighted by outer loadings.	$\alpha > .70$	Hair et al. (2014) [82, p. 115]
Convergent validity			
Average Variance Extracted (AVE)	The amount of variance that is captured by the construct compared to the amount of variance that is captured by the measurement error.	AVE > .50	Fornell & Larcker (1981) [70]
Outer loadings	The results of regressions of an indicator variable on its own corresponding construct.	$\sqrt{0.50} = .708$	Hair et al. (2017) [83, p. 113]
Discriminant validity			
Cross-loadings	The correlation between items and every construct.	Variables should load higher on their own factor than on other factors.	Chin (1998) [41, p. 321]
Fornell-Larcker-Criterion	Correlations between the construct and other constructs should be smaller than the AVE of the construct.		Fornell & Larcker (1981) [70]
Heterotrait-monotrait ratio (HTMT)	"The average of the heterotrait-heteromethod correlations (i.e., the correlations of indicators across constructs measuring different phenomena), relative to the average of the monotrait-heteromethod correlations (i.e., the correlations of indicators within the same construct)." [86, p. 121]	Values in HTMT matrix < 0.85	Henseler, Ringle, & Sarstedt (2015) [86, p.129]

Evaluating Significant Effects via Bootstrapping. In a next step, the significance level of the estimated coefficients needs to be checked. In the context of PLS-SEM, parametric tests cannot be applied to determine significance due to the assumption of not normally distributed data. Instead, a non-parametric method must be used for the significance test of coefficients in PLS-SEM, i.e., bootstrapping [82, p. 130 ff.]. With the help of the bootstrapping algorithm, a large number of subsamples are drawn from the original data. Since the subsamples are drawn again and again, they are overlapping (i.e., "drawing without putting back" or "random sampling with replacement"). Thereby, each subsample has the same number of observations as the original total sample. The number of subsamples drawn should be higher than the number of bootstrapped cases (i.e., observations in the total sample). Generally, $n \geq 5{,}000$ subsamples are recommended as a rule of thumb [82, p. 163]. Finally, the estimates of the coefficients yield a distribution from which the standard error *SE* and the standard deviation *SD* can be determined. Subsequently, *t*-tests can be used to determine significances.

Evaluating the Quality of the Model. The last step of the regular PLS-SEM analysis is the investigation of the quality of the model. Table 5.4 summarizes the criteria that need to be applied in this step.

Table 5.4 Overview of Quality Criteria in the Context of PLS-SEM (own illustration).

Criteria	Definition	Convention	Source
Adjusted R^2	The amount of variance of the dependent variable that is predictable on the basis of the independent variable	> 0 no concrete convention	Hair et al. (2014) [82, p. 175]
Q^2	Measure for a model's predictive relevance: This criterion indicates to what extent the empirical data can be mapped by the model.	> 0	Hair et al. (2014) [82, p. 178]
f^2	„The change in the R^2 value when a specified exogenous construct is omitted from the model" [82, p. 177]	≤ 0.02 small ≥ 0.15 medium ≥ 0.35 large	Cohen (1992) [47]

Advanced PLS-SEM Analyses: Mediator Analysis. Finally, advanced PLS-SEM analyses may be applied. Since mediator analysis will be applied in Chapter 5.3.4, the mediation analysis procedure will be outlined briefly in this section. Here, the first step is to integrate the potential mediator into the model and analyze the significance level of the indirect effects. A mediation is identified by a significant indirect effect. The second step is to identify whether the mediation is complete (i.e., the direct effect gets non-significant by integrating the mediator into the model) or partial (i.e., both, direct and indirect effects are significant). The third step is to identify whether a partial mediation is complementary (i.e., direct and indirect effect have the same direction) or competitive (i.e., indirect and direct effect differ in terms of their direction) [82, p. 219 ff.].

In conclusion, the PLS-SEM was identified as the suitable method for the purpose of this thesis. Figure 5.3 summarizes the different steps of applying PLS-SEM systematically. The paragraphs above described the theory underlying PLS-SEM in detail, including the methods to estimate and evaluate the model. In the following, Chapter 5.1.4 and Chapter 5.2 will concentrate on step two of the systematic application of PLS-SEM (see Figure 5.3), namely the data collection and examination.

5.1.4 Overall Approach and Goals of the User Study

This section summarizes the overall approach and the goals of the user study elaborated in Chapters 5.1.1 to 5.1.3. Chapter 5 focuses on the technology acceptance of pre-trip ISs. Thereby, Chapter 5 relies on the pre-trip prototype described in Chapter 4 and aims to evaluate the pre-trip prototype with regard to its technology acceptance. Thereby, the overall goal of Chapter 5 is to achieve a deeper understanding of factors that motivate travelers to use pre-trip ISs. In order to reach this goal, a user study and an evaluation (n = 548) of the pre-trip prototype (see Chapter 4) was conducted. The design of the user study relies on state-of-the-art methods for modelling and evaluating technology acceptance. From the conceptual perspective, the user study relies on the constructs included in UTAUT2 (see Chapter 5.1.1) as well as further outcome variables of technology acceptance (i.e., satisfaction and loyalty: see Chapter 5.1.2). From the statistical perspective, the results of the user study are analyzed using PLS-SEM (see Chapter 5.1.3).

Concluding, this chapter aims to answer the second of the three research questions stated in the introduction of this thesis (see Chapter 1.1): Which factors motivate travelers to accept and use pre-trip ISs? This overall research question is addressed with the help of the following sub-questions which are covered in the hypotheses 1 to 13 listed above:

- Which factors predict the technology acceptance of pre-trip ISs?
- Which factors determine the travelers’ intention to use pre-trip ISs?
- Which factors determine the travelers’ satisfaction with pre-trip ISs?
- Which factors determine the travelers’ loyalty towards pre-trip ISs?

5.2 Method and Design of the User Study

In order to learn about the parameters that influence the travelers’ motivation to use pre-trip ISs, a user study in the BMW World in Munich (Germany) was conducted. This section describes the method and design of the user study. The core element of the user study was the presentation and evaluation of the pre-trip prototype described in Chapter 4. The user study can be divided into two main parts, namely (1) a presentation and exploration of the pre-trip prototype and (2) an online questionnaire that was answered on a tablet. The following paragraphs first concentrate on the overall procedure of the user study (see Chapter 5.2.1). This includes an overview of all considered items and scales as well as their sources. After introducing the overall procedure of the user study, the following two sections concentrate on describing the sample of participants (see Chapter 5.2.2) and the applied data analysis (see Chapter 5.2.3).

5.2.1 Procedure

The quantitative study was carried out in cooperation with BMW in Munich, Germany. All participants were recruited in a showroom of BMW in Munich, i.e., the BMW World. The showroom is illustrated in Figure 4.1 in Chapter 4. The study started with a briefing about the procedure (i.e., 20 minutes presentation of prototype and 15 minutes questionnaire). Next, the pre-trip prototype described in Chapter 4 was presented to the participants (see Figure 4.2 to Figure 4.7). After the presentation, the participants were also asked to explore the prototype on their own. Later on, the participants filled out an online questionnaire on a tablet. Besides demographic variables and the participants' technological affinity, the questionnaire assessed components of UTAUT2 (i.e., effort expectancy, performance expectancy, social influence, price value, hedonic motivation, and behavioral intention; items from: [203]) as well as the participants' satisfaction with and loyalty towards the prototype (items from: [57]). All items were assessed on a 7-point Likert scale ranging from 1 = *not agree at all* to 7 = *agree totally*. Since the study includes a German sample, all items were translated to German according to an adaption of Brislin's translation model [104]. Table 5.5 summarizes all scales and items.

Table 5.5 Overview of Scales, Items and Sources (own illustration. Note: *For price value a reference price of 1000 Euro was set based on an internal BMW business case).

Scale	Item	Source
Performance expectancy	I find the prototype useful in my daily life.	Venkatesh, Thong, & Xu (2012) [203, p. 178]
	Using the prototype helps me accomplish things more quickly.	
	Using the prototype increases my productivity.	
Effort expectancy	Learning how to use the prototype is easy for me.	
	My interaction with the prototype is clear and understandable.	
	I find the prototype easy to use.	
	It is easy for me to become skillful at using the prototype.	
Social influence	People who are important to me think that I should use the prototype.	
	People who influence my behavior think that I should use the prototype.	
	People whose opinions that I value prefer that I use the prototype.	
Price value*	The prototype is reasonably priced.	
	The prototype is a good value for the money.	
	At the current price, the prototype provides a good value.	
Hedonic motivation	Using the prototype is fun.	
	Using the prototype is enjoyable.	
	Using the prototype is very entertaining.	
Behavioral intention	I intend to continue using the prototype in the future.	
	I will always try to use the prototype in my daily life.	
	I plan to continue to use the prototype frequently.	
Satisfaction	It was the right thing to use the prototype.	Ding, Hu, & Sheng (2011) [57, p. 513]
	I have truly enjoyed using the prototype.	
	My choice to use the prototype is a wise one.	
	I am satisfied with my usage of the prototype.	
Loyalty	I encourage friends to use the prototype.	
	I say positive things about the prototype to other people.	
	I will use the prototype in the next few years.	
	I would recommend this prototype to someone else.	

5.2.2 Participants

All participants (n = 548) were recruited in the BMW World in Munich, Germany. Informed consent was obtained and every participant took part voluntarily in the present study. The participants' age ranged between 18 and 58 years (M = 26.60, SD = 7.60). Among the participants, n = 302 were male (55.11%), n = 242 were female (44.16%) and four participants (0.73%) did not give details about their gender. With regard to their occupation, 65.33% of the participants were working professionals (n = 358), 30.11% were students (n = 165) and 4.56% (n = 25) were in other work situations (e.g., trainee, freelancer). Except for one participant, all other participants owned a smartphone, which they use on a daily basis.

Table 5.6 Demographic Characteristics of the Sample of the User Study (own illustration).

	n	%			n	%
Participants	548	100				
Gender				**Car ownership**		
Male	302	55.11		Yes	443	80.84
Female	242	44.16		No	105	19.16
No details	4	0.73				
Occupation status				**Car brand**		
Working professionals	358	65.33		BMW	138	25.18
Students	165	30.11		VW	94	17.15
In education (Pupil, Trainee)	15	2.74		Audi	37	6.75
Other	7	1.28		Opel	25	4.56
Unemployed	3	0.55		Seat	23	4.20
Daily smartphone usage				Ford	21	3.83
Not at all	1	0.18		Mercedes	20	3.65
Less than 1 hour	27	4.93		Skoda	12	2.19
1 - 2 hours	136	24.82		Toyota	8	1.46
2 - 4 hours	223	40.69		Renault	7	1.28
4 - 6 hours	102	18.61		Peugeot	5	0.91
More than 6 hours	59	10.77		Other	53	7.30
	Min	**Max**		**Mean**	**SD**	
Age	18	58		26.60	7.60	

5.2.3 Data Analysis

This section focuses on the tools and methods used for the data analysis. The data was collected with the help of the online survey tool LimeSurvey [119]. After the data collection, the raw data was exported from LimeSurvey and Microsoft Excel (2016) was used for preparatory analysis. Afterwards, IBM SPSS Statistics 24 (2016) and SmartPLS 3 (2017) were used for higher level analysis. Structured equation modelling (SEM) via partial least squares (PLS) was used for the data analysis, because this method is acknowledged and commonly used for modelling and testing technology acceptance and use [e.g., 122,202,203]. SmartPLS 3 is a software that is developed specifically for all PLS-SEM analyses. With the help of SmartPLS 3, the measurement model was calculated in order to assess the quality of the model (i.e., reliability and validity). Then various structural models and mediation analyses were calculated and tested following acknowledged guidelines for PLS [82,83]. The mediation analysis was also calculated based on the guidelines of Hair et al. [82, p. 219 ff.]. The significance level of deductive statistical procedures was defined as $\alpha = .05$. In cases in which other significance levels were used, they are listed explicitly in the results section. The theory of the applied data analysis has already been explained in detail in Chapter 5.1.3. Hence, the following paragraph directly starts with describing the result of the evaluation of the pre-trip prototype.

5.3 Results of the User Study

This chapter summarizes the results of the evaluation of the pre-trip prototype. As described above, the pre-trip prototype was evaluated with the help of a user study. The data collected in the user study way mainly analyzed using PLS-SEM with the help of the modelling software SmartPLS 3. The following paragraphs will first describe the results concerning the measurement model. These results are used as indicators for the model's quality in terms of reliability and validity. Next, the results of the structural model will be summarized, i.e., the results concerning the prediction of the participants' intention to use the pre-trip prototype. These results reveal to which extent the participants actually intend to use the pre-trip prototype and which characteristics of the prototype influence the participants' behavioral intention. Later on, the extended structural model will be presented. The extended model contains the prediction of the participants' behavioral intention as well as the prediction of their satisfaction with and loyalty towards the pre-trip prototype. Finally, the results regarding the mediation analysis will be summarized. The mediation analysis concentrates on the question to which extent the effects of the UTAUT2 components (i.e., performance expectancy, effort expectancy, social influence, hedonic motivation, and price value) on the participants' behavioral intention are mediated by the participants' overall satisfaction with the pre-trip prototype. The moderators age, gender and experience (see Figure 5.1) were excluded from the results section because no moderating effects had been identified.

5.3.1 Measurement Model

This section presents the results of the measurement model, i.e., the results on item-level in contrast to the results on construct-level which will be presented in Chapter 5.3.2 and Chapter 5.3.3. The first step of the analysis was to check the quality criteria of the model. For all constructs, Cronbach's alpha and the composite reliability (see Table 5.7) were greater than the convention of $\alpha > .70$. This means that the internal consistency of the constructs is ensured [83, p. 111]. The AVE (see Table 5.7) was greater than the convention of AVE > .50 [83, p. 114] for all constructs. Moreover, Table 5.8 shows that the outer loadings (marked bold in Table 5.8) of all constructs were greater than the convention of $\sqrt{0.50} = .708$ [83, p. 113]. This means that more than half of the variance observed in the items can be explained by the constructs. Hence, the convergent validity is ensured [83, p. 114]. Furthermore, the discriminant validity was checked with the help of cross-loadings, the Fornell-Larcker-Criterion and the heterotrait-monotrait ratio (HTMT). Table 5.8 shows the fulfilment of the first requirement for discriminant validity, namely that for all constructs the outer loadings are higher than the cross loadings with other constructs [41, p. 321]. Additionally, Table 5.9 illustrates that the second requirement for discriminant validity is fulfilled, i.e., the square root of the AVE of every single construct (see diagonal line in Table 5.9) is higher than the correlations of the construct with other constructs (i.e., the Fornell-Larcker-Criterion: [70]). Finally, Table 5.10 supports the third criterion for discriminant validity for most constructs, namely that the heterotrait-monotrait ratio does not exceed the value of .85 [86, p.129]. The HTMT-correlation of hedonic motivation and satisfaction, however, exceeds the conservative convention of .85. Nevertheless, this HTMT-correlation does not exceed the more liberal convention of .90. Therefore, an acceptable discriminant validity can still be assumed with regard to hedonic motivation and satisfaction [86, p. 129]. The HTMT-correlations of behavioral intention and satisfaction, behavioral intention and loyalty and loyalty and satisfaction, however, also exceeds the liberal convention of .90. Since eliminating single items did not result in a significant reduction of these high HTMT-correlations and the other two requirements of discriminant validity were fulfilled (i.e., comparison of outer loadings and cross-loadings and the Fornell-Larcker-Criterion), all items were included in the further analysis.

Table 5.7 Mean, Standard Deviation, Cronbach's Alpha, Composite Reliability and AVE for all Constructs (own illustration).

Construct	**Mean**	**SD**	**Cronbach's alpha**	**Composite reliability**	**AVE**
Effort expectancy	5.63	0.85	0.77	0.85	0.58
Hedonic motivation	5.36	1.14	0.87	0.92	0.79
Performance expectancy	4.75	1.33	0.87	0.92	0.79
Price value	5.06	1.45	0.95	0.97	0.91
Social influence	3.69	1.40	0.93	0.95	0.87
Behavioral intention	4.84	1.41	0.94	0.96	0.89
Loyalty	5.02	1.24	0.92	0.95	0.81
Satisfaction	4.89	1.17	0.90	0.93	0.77

Table 5.8 Loadings and Cross-Loadings for all Constructs (own illustration: EE = Effort Expectancy, HM = Hedonic Motivation, PE = Performance Expectancy, PV = Price Value, SI = Social Influence, BI = Behavioral Intention, SAT = Satisfaction, LOY = Loyalty).

Item	EE	HM	PE	PV	SI	BI	LOY	SAT
EE[1]	**0.76**	0.42	0.51	0.23	0.32	0.48	0.42	0.48
EE[2]	**0.79**	0.38	0.36	0.18	0.25	0.39	0.35	0.40
EE[3]	**0.80**	0.32	0.31	0.17	0.19	0.37	0.36	0.37
EE[4]	**0.73**	0.26	0.23	0.19	0.13	0.29	0.27	0.30
HM[1]	0.46	**0.93**	0.65	0.41	0.40	0.72	0.72	0.74
HM[2]	0.43	**0.92**	0.64	0.33	0.43	0.73	0.69	0.74
HM[3]	0.32	**0.82**	0.43	0.34	0.30	0.51	0.50	0.53
PE[1]	0.48	0.66	**0.89**	0.28	0.42	0.77	0.74	0.73
PE[2]	0.39	0.50	**0.89**	0.27	0.45	0.58	0.55	0.60
PE[3]	0.40	0.55	**0.89**	0.22	0.48	0.62	0.58	0.63
PV[1]	0.21	0.32	0.21	**0.93**	0.17	0.27	0.31	0.33
PV[2]	0.25	0.40	0.28	**0.97**	0.20	0.36	0.39	0.40
PV[3]	0.26	0.43	0.32	**0.96**	0.24	0.37	0.42	0.43
SI[1]	0.28	0.40	0.49	0.22	**0.93**	0.44	0.44	0.50
SI[3]	0.30	0.40	0.46	0.20	**0.95**	0.43	0.46	0.51
SI[2]	0.28	0.40	0.46	0.19	**0.93**	0.46	0.48	0.50
BI[1]	0.47	0.70	0.71	0.35	0.44	**0.93**	0.80	0.79
BI[2]	0.46	0.69	0.71	0.31	0.45	**0.95**	0.77	0.79
BI[3]	0.50	0.71	0.70	0.33	0.44	**0.94**	0.80	0.79
LOY[1]	0.42	0.65	0.67	0.33	0.52	0.72	**0.89**	0.76
LOY[2]	0.44	0.65	0.60	0.36	0.38	0.71	**0.90**	0.76
LOY[3]	0.45	0.63	0.64	0.32	0.44	0.82	**0.88**	0.78
LOY[4]	0.38	0.67	0.64	0.42	0.43	0.75	**0.94**	0.80
SAT[1]	0.46	0.65	0.69	0.32	0.51	0.80	0.78	**0.90**
SAT[2]	0.46	0.79	0.63	0.39	0.48	0.73	0.73	**0.87**
SAT[3]	0.40	0.61	0.68	0.34	0.51	0.72	0.74	**0.88**
SAT[4]	0.48	0.63	0.59	0.40	0.38	0.69	0.76	**0.84**

Table 5.9 Fornell-Larcker-Criterion for all Constructs (own illustration: EE = Effort Expectancy, HM = Hedonic Motivation, PE = Performance Expectancy, PV = Price Value, SI = Social Influence, BI = Behavioral Intention, SAT = Satisfaction, LOY = Loyalty).

Construct	EE	HM	PE	PV	SI	BI	LOY	SAT
Effort expectancy	0.77							
Hedonic motivation	0.46	0.89						
Performance expectancy	0.48	0.65	0.89					
Price value	0.25	0.40	0.29	0.95				
Social influence	0.31	0.43	0.51	0.22	0.93			
Behavioral intention	0.51	0.74	0.75	0.35	0.47	0.94		
Loyalty	0.47	0.72	0.71	0.39	0.49	0.84	0.90	
Satisfaction	0.51	0.77	0.74	0.41	0.54	0.84	0.86	0.88

Table 5.10 HTMT-Criterion for all Constructs (own illustration: EE = Effort Expectancy, HM = Hedonic Motivation, PE = Performance Expectancy, PV = Price Value, SI = Social Influence, BI = Behavioral Intention, LOY = Loyalty).

Construct	**EE**	**HM**	**PE**	**PV**	**SI**	**BI**	**LOY**
Effort expectancy							
Hedonic motivation	0.54						
Performance expectancy	0.55	0.73					
Price value	0.29	0.44	0.31				
Social influence	0.34	0.47	0.57	0.23			
Behavioral intention	0.58	0.82	0.82	0.37	0.51		
Loyalty	0.54	0.80	0.78	0.42	0.53	**0.90**	
Satisfaction	0.60	**0.86**	0.83	0.44	0.59	**0.92**	**0.94**

5.3.2 Structural Model

This section presents the results on the structural model, i.e., the baseline model containing UTAUT2 components without any extensions. Figure 5.4 illustrates the first structural model. Table 5.11 lists all belonging path coefficients with their *t*-Statistics, *p*-values and effects sizes. Effect sizes are interpreted according to the convention of Cohen [47] for multiple partial correlations (i.e., ≥ .02 = small, ≥ .15 = medium, ≥ .35 = large). Supporting hypotheses 1 and 4, performance expectancy and hedonic motivation had medium significant positive effects on behavioral intention. Among the five predictors included in the model, performance expectancy (β = .41) and hedonic motivation (β = .39) had the highest path coefficients. Moreover, supporting hypothesis 2, effort expectancy had a small significant positive effect on behavioral intention. The effect size of the effect of effort expectancy is, however, just above the critical value of f^2 = .02. Contrary to hypothesis 3 and 5, social influence and price value did not show significant effects on behavioral intention. In sum, the components of UTAUT2 explain 69.50% of the variance in behavioral intention (see Table 5.12), which can be seen as a high amount of explained variance. Moreover, Stone-Geisser's Q^2 (see Table 5.12) indicates that the empirical data can be depicted well by the model. Hence, the model has predictive power [41].

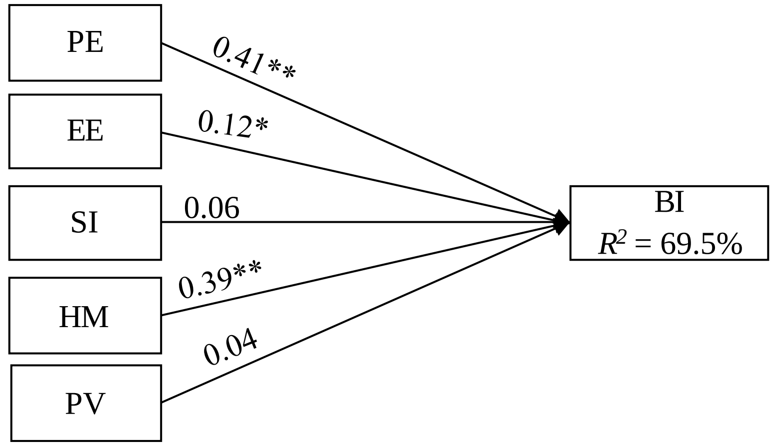


Figure 5.4 Model 1: Baseline Model (own illustration: EE = Effort Expectancy, HM = Hedonic Motivation, PE = Performance Expectancy, PV = Price Value, SI = Social Influence, BI = Behavioral Intention. *p < .01, **p <. 001).

Table 5.11 Standardized Path Coefficients and Effect Sizes of Model 1 (own illustration: EE = Effort Expectancy, HM = Hedonic Motivation, PE = Performance Expectancy, PV = Price Value, SI = Social Influence, BI = Behavioral Intention).

Path	Path coefficient	*t*-statistic	*p*-value	Effect size f^2
EE → BI	0.12	3.11	.002	0.02
HM → BI	0.39	10.59	.001	0.24
PE → BI	0.41	11.76	.001	0.25
PV → BI	0.04	1.32	.188	0.00
SI → BI	0.06	1.92	.055	0.01

Table 5.12 Overview of Explained Variances for both Models (own illustration).

Construct	Model	Adjusted R^2	Q^2
Behavioral intention	Model 1	0.695	0.573
Loyalty	Model 2	0.781	0.594
Behavioral intention	Model 2	0.756	0.633
Satisfaction	Model 2	0.720	0.519
ΔR^2 Behavioral intention		0.07	

5.3.3 Extended Structural Model

This section presents the results on the extended structural model, i.e., UTAUT2 components combined with satisfaction and loyalty. Figure 5.5 illustrates the extended structural model. Table 5.13 lists all belonging path coefficients with their *t*-statistics, *p*-values and effects sizes. With regard to the prediction of behavioral intention, satisfaction had a medium positive significant effect on behavioral intention. This supports hypothesis 11. Moreover, supporting hypothesis 1 and 4, performance expectancy and hedonic motivation had a positive significant effect on behavioral intention. Similar to model one, performance expectancy (β = .23) and hedonic motivation (β = .19) had the highest path coefficients compared to the other predictors of behavioral intention. These effects were, however, only small and ranged from f^2 = .06 (i.e., hedonic motivation) to f^2 = .09 (i.e., performance expectancy). Contrary to hypotheses 2, 3 and 5, effort expectancy, price value, and social influence did not have any significant effects on behavioral intention in the extended model.

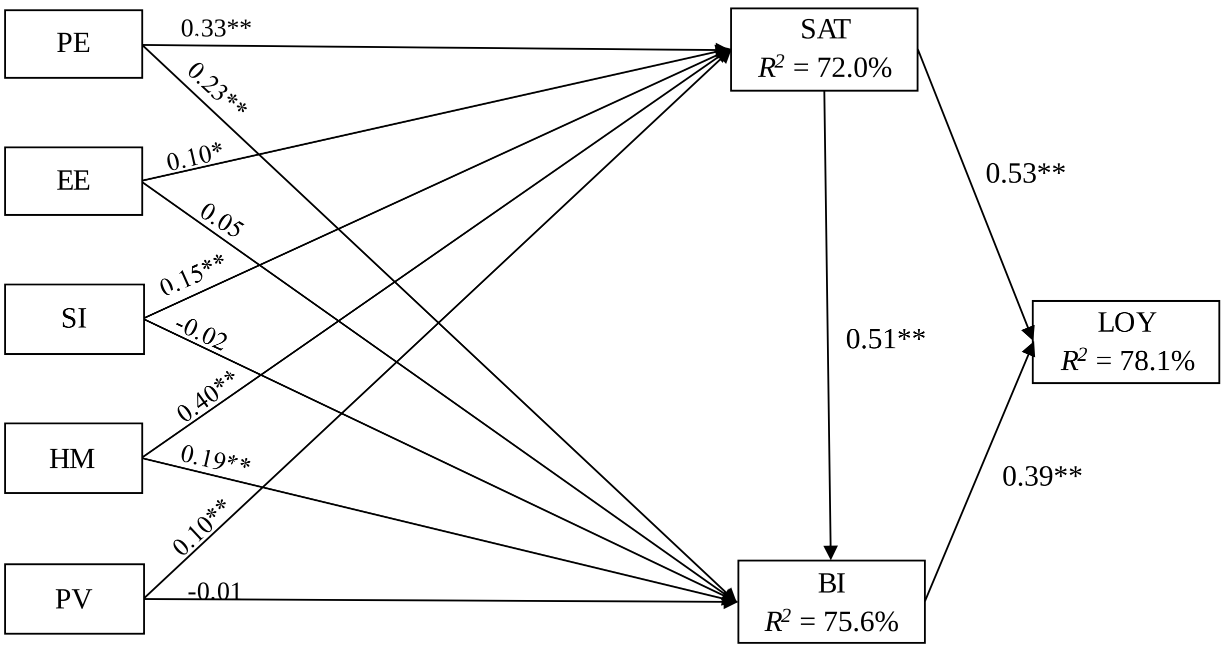


Figure 5.5 Model 2: Extended Model (own illustration: EE = Effort Expectancy, HM = Hedonic Motivation, PE = Performance Expectancy, PV = Price Value, SI = Social Influence, BI = Behavioral Intention, SAT = Satisfaction, LOY = Loyalty. *p < .01, **p <. 001).

Regarding the prediction of satisfaction, performance expectancy and hedonic motivation had a medium positive significant effect on satisfaction. This supports hypotheses 7 and 10. Moreover, supporting hypothesis 8, 9 and 11, effort expectancy, social influence, and price value had small significant effects on satisfaction. In this case, the effect sizes are, however, only small and range from f^2 = .03 (i.e., effort expectancy and price value) to f^2 = .06 (i.e., social influence). Concerning the prediction of loyalty, hypotheses 12 and 13 were supported: Satisfaction (β = .53) had a large positive significant effect on loyalty and behavioral intention (β = .39) had a medium positive effect on loyalty.

Summarizing, the extended model explains 75.6% of the variance in behavioral intention, 72.0% of the variance in satisfaction and 78.1% of the variance in loyalty (see Table 5.12). All three amounts of explained variance reflect a high amount of explained variance [82, p. 175]. The extension of the predictors of behavioral intention by satisfaction resulted in an incremental increase in the amount of explained variance in behavioral intention of 7%. Moreover, Stone-Geisser's Q^2 (see Table 5.12) indicates that the empirical data can be depicted well by the model for all three constructs (i.e., behavioral intention, satisfaction, and loyalty). Hence, all three models have predictive power [41]

Table 5.13 Standardized Path Coefficients and Effect Sizes of Model 2 (own illustration: EE = Effort Expectancy, HM = Hedonic Motivation, PE = Performance Expectancy, PV = Price Value, SI = Social Influence, BI = Behavioral Intention, SAT = Satisfaction, LOY = Loyalty).

Path	Path coefficient	*t*-statistic	*p*-value	Effect size f^2
EE → BI	0.05	1.81	.071	0.01
EE → SAT	0.10	3.02	.003	0.03
HM→ BI	0.19	4.68	.001	0.06
HM → SAT	0.40	10.59	.001	0.29
PE → BI	0.23	6.37	.001	0.09
PE → SAT	0.33	9.31	.001	0.19
PV → BI	-0.01	0.48	.633	0.00
PV→ SAT	0.10	3.61	.001	0.03
SI → BI	-0.02	0.60	.550	0.00
SI → SAT	0.15	5.07	.001	0.06
BI → LOY	0.39	8.92	.001	0.20
SAT → BI	0.51	11.11	.001	0.20
SAT→ LOY	0.53	12.54	.001	0.38

5.3.4 Mediation Analysis

In order to analyze potential mediators, the indirect effects of effort expectancy, performance expectancy, hedonic motivation, price value, and social influence through satisfaction on behavioral intention were calculated. Table 5.14 shows the path coefficients, *t*-statistics, and *p*-values for the five indirect effects. All five indirect effects were significant. Consequently, all five effects on behavioral intention are mediated by satisfaction. The effects of effort expectancy, price value and social influence were completely mediated by satisfaction. Regarding effort expectancy, the complete mediation was indicated by the existence of a significant positive effect in model one, a missing effect in the extended model and a significant indirect effect. Concerning price value and social influence, both predictors did not have a significant effect on behavioral intention in model one and in the extended model. The indirect effect is, however, significant, which shows a complete mediation.

The extension of model one through integrating satisfaction and loyalty into the model resulted in reduced but still significant positive direct effects of performance expectancy and hedonic motivation on behavioral intention. Since the direction of the effect (i.e., positive or negative) is positive in both models and the indirect effect is significant, the effects of performance expectancy and hedonic motivation on behavioral intention are complementarily mediated by satisfaction.

Table 5.14 Indirect Effects via Satisfaction in the Extended Model (own illustration: EE = Effort Expectancy, HM = Hedonic Motivation, PE = Performance Expectancy, PV = Price Value, SI = Social Influence, BI = Behavioral Intention, LO = Loyalty, SA = Satisfaction).

Path	*β*	*t*-statistic	*p*-value	Type of mediation
EE → SAT → BI	0.05	2.96	.001	complete
HM → SAT → BI	0.20	6.92	.001	partial (complementary)
PE → SAT → BI	0.17	7.69	.001	partial (complementary)
PV → SAT → BI	0.05	3.30	.001	complete
SI → SAT → BI	0.08	4.93	.001	complete

5.4 Discussion of Results

This section discusses the results of the user study described in Chapter 5.3. The following paragraphs will discuss the core findings of the user study with respect to answering research question two: Which factors motivate travelers to accept and use pre-trip ISs? After discussing the core findings of the user study (see Chapter 5.4.1), possible limitations of the study will be discussed and ideas for future research on the acceptance and use of pre-trip ISs will be elaborated (see Chapter 5.4.2). Finally, this chapter ends with a conclusion on the theoretical and practical implications of the results of the user study (see Chapter 5.4.3).

5.4.1 Core Findings

The aim of the user study presented in this chapter was to investigate the determinants of technology acceptance and use in the context of pre-trip ISs. In order to model the predictors and outcomes of technology acceptance and use, this thesis uses a state-of-the-art conceptual model for technology acceptance from the field of IS, namely the UTAUT2 (see Chapter 5.1.1), and state-of-the-art modelling procedures, namely PLS-SEM (see Chapter 5.1.3). With the help of a user study in the BMW World in Munich (Germany) the determinants of the travelers' behavioral intention, satisfaction and loyalty concerning a pre-trip prototype were assessed (see Chapter 5.2). The user study contained a presentation and exploration of the pre-trip prototype (see Chapter 4) and a subsequent online questionnaire on a tablet.

Similar to other studies [114], the present results show that the antecedents of different measures of technology acceptance and stages of technology acceptance differ. Precisely, performance expectancy and hedonic motivation were the main antecedents of both included measures, namely satisfaction and loyalty. While the travelers' effort expectancy played an additional role for the travelers' behavioral intention and their satisfaction, the travelers' social influence and their perceived price value only predicted the travelers' satisfaction. Furthermore, the present study replicated the positive effect of satisfaction on behavioral intention as indicated in previous research [26,121] in the context of pre-trip ISs. Finally, the present study supported the hypotheses that satisfaction and behavioral intention are important antecedents of the travelers' loyalty in terms of recommending pre-trip ISs. Table 5.15 summarizes the results of the hypothesis testing.

Table 5.15 Summary of Tested Hypotheses (own illustration).

Hypotheses		Hypotheses supported?	
H1: Performance expectancy	→ Behavioral intention	Yes	UTAUT2
H2: Effort expectancy	→ Behavioral intention	Yes	
H3: Social influence	→ Behavioral intention	No	
H4: Hedonic motivation	→ Behavioral intention	Yes	
H5: Price value	→ Behavioral intention	No	
H6: Satisfaction	→ Behavioral intention	Yes	Extension of UTAUT2
H7: Performance expectancy	→ Satisfaction	Yes	
H8: Effort expectancy	→ Satisfaction	Yes	
H9: Social influence	→ Satisfaction	Yes	
H10: Hedonic Motivation	→ Satisfaction	Yes	
H11: Price value	→ Satisfaction	Yes	
H12: Satisfaction	→ Loyalty	Yes	
H13: Behavioral intention	→ Loyalty	Yes	

UTAUT2 in the Context of Pre-trip ISs. In sum, the user study showed that performance expectancy and hedonic motivation were the most important predictors for the travelers' acceptance and use of pre-trip ISs. This supports hypotheses 1 and 4 and indicates that travelers are more likely to use pre-trip ISs that provide savings in terms of effort and time. For the acceptance of pre-trip ISs, it is important that the technology supports the travelers in reaching their mobility goals effectively. At the same time, travelers expect to be hedonically stimulated through the interaction with the pre-trip IS. Similar to a previous study [125], this highlights the importance of the interplay of pragmatic and hedonic qualities for accepting ITISs. According to acknowledged distinctions of pragmatic and hedonic qualities [e.g., 42,84], performance expectancy can be categorized as a pragmatic quality and hedonic motivation can be categorized as a hedonic quality. Consequently, in accordance with previous research, the present findings show that the intention to use pre-trip ISs is based on a smooth interplay of pragmatic and hedonic quality. Moreover, similar to previous studies in the context of other technologies [7,87,133] the present findings highlight the relevance of performance expectancy and hedonic motivation among the UTAUT2 predictors.

In contrast to the large effect of performance expectancy and hedonic motivation, effort expectancy only had a relatively small effect on the travelers' intention to use pre-trip ISs (see Figure 5.4). This relationship is, however, completely mediated by satisfaction, i.e., integrating satisfaction into the model results in a significant direct effect of effort expectancy on satisfaction and a non-significant effect of effort expectancy on behavioral intention (see Figure 5.5). Nevertheless, this result supports hypothesis 2. The small connection between the travelers' effort expectancy and their behavioral intention in this context can be explained in multiple ways. First of all, the descriptive statistics show that effort expectancy has the highest mean and the lowest standard deviation compared to all other predictors ($M = 5.63$, $SD = 0.85$). This indicates that the travelers' expected very few efforts in order to use the pre-trip prototype. They evaluated that it is easy for them to use the pre-trip prototype and they have a clear and understandable interaction with the pre-trip prototype. This might be attributed, for example, to a high usability of the pre-trip prototype or a high digital affinity of the participants. Since a high complexity of the system is, however, a common criticism [95, p. 359] with regard to smart technology, the connection of effort expectancy and behavioral intention should be examined in more detail in future studies with available pre-trip ISs.

Social influence and price value did not show any significant direct effects on the travelers' intention to use the pre-trip ISs (see Figure 5.4). Nevertheless, social influence and price value showed significant direct effects on the travelers' satisfaction with the pre-trip prototype, which in turns affects their behavioral intention largely (see Figure 5.5). Due to the non-significant direct effects, hypotheses 3 and 5 were not supported in this study.

With regard to social influence, this means that the participants' intention to use the pre-trip prototype is not affected by the attitudes and opinions of other people regarding the use of pre-trip ISs. Previous research has identified a high context-dependence of social influence. Recent studies provided examples who replicated the positive influence of social influence on technology acceptance [142,166] as introduced by Venkatesh, et al. [203] and examples that did not find any significant connections between social influence and behavioral intention [5,87]. The non-significant effect in the present study can also be explained based on the context. Here, a smart mirror prototype was examined which will only be used at home and will therefore only be visible for a very restricted group of people. Social influence might, however, be of higher importance for technology acceptance in contexts in which more people can see whether a technology is used or not (e.g., mobile internet). Furthermore, the participants might have very few social contacts that actually talk about using pre-trip ISs and share their opinions about pre-trip ISs with them (e.g. the opinion that it is important and necessary to use them). Therefore, social influence might gain influence on the intention to use pre-trip ISs with a growing market penetration.

A possible explanation of the non-significant effect concerning price value can be found in the descriptive statistics. With a mean of 5.06 (SD = 1.45) the participants' report that the pre-trip prototype was reasonably priced and the participants' perceived a good value for the price anchor of 1000 Euro used in the items for price value. Compared to previous findings, the non-significant effect of price value is not astonishingly. For example, Lisson et al. [125] only found small to moderate effects of price value on behavioral intention in the context of ITISs. The authors argued that ITISs are mostly available for free which represents a reasonably positive price value for the traveler. Thus, the influence of the price on the usage behavior is relatively small or nonexistent.

Summarizing, the present study showed that the UTAUT2 can be applied to the context of pre-trip ISs within the field of transportation research. Within this context, especially the travelers' performance expectancy and their hedonic motivation are important predictors for their intention to use pre-trip ISs. Moreover, effort expectancy also affects the travelers' behavioral intention. Perceived social influences and the technologies' price value did not show significant effects in the present study. Social influence and price value should, however, be considered as important predictors of technology acceptance in the context of pre-trip ISs because both constructs significantly influence the travelers' satisfaction with the pre-trip prototype. The results of satisfaction will be discussed in more details in the following paragraphs.

Satisfaction and Loyalty in the Context of Pre-trip ISs. In a further step, the original UTAUT2 was extended by the outcome variables satisfaction and loyalty. Table 5.15

summarizes the hypotheses concerning this extension and illustrates that all hypotheses regarding satisfaction and loyalty (i.e., hypotheses 6 - 13) were supported. Similar to the original model described above, performance expectancy and hedonic motivation were identified as the two main predictors for the satisfaction with pre-trip ISs and the intention to use them. Here, performance expectancy and hedonic motivation had the highest effects on behavioral intention and satisfaction compared to the other UTAUT2 predictors. Moreover, the effects of performance expectancy and hedonic motivation on behavioral intention were partially mediated by satisfaction. The findings that travelers are more satisfied with using pre-trip ISs that (1) enhances their perception of performance and productivity and (2) triggers their experience of enjoyment and hedonic motivation are in line with previous studies. For example, recent studies identified positive effects of usability on satisfaction [69], usefulness on behavioral intention and attitude [215] and perceived enjoyment on attitude and behavioral intention [56].

In contrast to performance expectancy and hedonic motivation, effort expectancy, price value, and social influence only showed non-significant effects on behavioral intention but significant effects on satisfaction. The effects on satisfaction were, however, smaller than the effects of performance expectancy and hedonic motivation on satisfaction. Moreover, the effects of effort expectancy, price value and social influence on behavioral intention were completely mediated by satisfaction. Concerning effort expectancy, these findings show that it is important that travelers experience their interaction with pre-trip ISs as easy, clear and understandable because this experience enhances their satisfaction with the interaction that will, in turn, influence their intention to keep on using the pre-trip IS. Because of the large influence of the travelers' satisfaction on their later behavioral intention, it is necessary to enable an intuitive interaction with the system right from the beginning. With regard to price value, these effects indicate that perceived price fairness [see 217, p. 1] enhances the travelers' satisfaction. Although the price value influences the travelers' satisfaction, later adoption and behavioral intention might, however, only be affected indirectly by the perceived price value [see 218, p. 25].

Furthermore, the indirect effect of social influence on behavioral intention through satisfaction might be explained based on the innovation-decision-making process [162, p. 163 ff.]. Here, the decision for using and adopting an innovation is a social process with different stages. After the first stage, in which the user only knows about the existence of the innovation (i.e., knowledge stage), the user needs to be convinced to use the innovation. A core component of this persuasion stage, is to build attitudes towards the innovation. Here, satisfaction can be seen as an attitude towards the innovation [31, p. 284] that is in turn influenced by the attitudes and opinions of other people regarding the use of pre-trip ISs (i.e., social influence). Through this effect, social influence also effects the travelers' behavioral intention to use pre-trip ISs indirectly. As already stated above, the effect of social influence in the context of pre-trip ISs is, however, only small. Nevertheless, this influence might grow with a growing spread of pre-trip ISs.

Moreover, the present study supports the assumption that user satisfaction is the most important predictor of behavioral intention [118, p. 2817]. Facing the large effect of satisfaction on behavioral intention and the different antecedents of satisfaction and behavioral intention or rather the many mediating effects in technology acceptance indicates that it is necessary to assess technology acceptance in multiple stages and with multiple outcome variables. Therefore, future technology acceptance models should not focus on one single measure of technology acceptance (e.g., behavioral intention) but include multiple facets of technology acceptance (e.g., behavioral intention, satisfaction, and loyalty). This is in accordance with the finding that satisfaction and behavioral intention are important antecedents of the travelers' loyalty in terms of recommending pre-trip ISs. Thus, loyalty should be regarded as a further interesting facet of technology acceptance.

5.4.2 Limitations and Future Research

Although the core findings of the user study provide considerable insights into the determinants of the travelers' motivation to use pre-trip ISs, the results underlie some restrictions. First of all, the data analysis is based on the participants' stated preferences and their conscious self-evaluation. Regardless of the quality of the research and survey design, stated preference data and self-evaluations may always be biased by barriers to human expression and social desirability. For example, participants might misreport supposed causal relationships because they simply lack cognitive access to their actual unconscious mental processes [107,138,139]. More specifically, participants may be unaware of the cues (i.e., stimuli used to prompt subsequent mental processes or actions) as well as the cues' integration and weighting into the participants' decision making process [107,138]. In order to avoid these limitations, future research should analyze the motivators for using pre-trip ISs in experimental settings. Laboratory as well as field experiments could reduce the potential bias of social desirability and unconscious mental process and provide insights into causal relationships.

Furthermore, the present study used stated preference data that was gathered based on a single interaction with a pre-trip prototype. Future research should extend these results by longitudinal studies analyzing revealed preference data. For example, longitudinal field experiments which use integrated user tracking in pre-trip ISs would provide interesting insights into the long-term motivators to use pre-trip ISs and the long-term weighting of the different predictors that form the mobility decision-making process. Since technology acceptance and user experiences are highly sensitive to the context in which a technology is used [116,202], it is necessary to double-check the external validity of the findings in a future field study. Additionally, technology acceptance and user experience are dynamic constructs [116] which might show changes over time [106,113]. For example, previous research has shown that the antecedents of adoption intention differ from the antecedents of continuous usage [114]. Therefore, future research should validate the present results in longitudinal field studies.

Another limitation of the present study concerns the characteristics of the present sample. The participants for the present study were recruited in the BMW World in Munich (Germany). Since the sample only considers German native speakers and no international visitors, the results are only representative for a German urban sample. Since the mobility infrastructure and thus the mobility behavior differs between urban and non-urban areas as well as different cities and different countries, future studies should investigate to which extent geographic variables moderate the relationships between the determinants identified in the present study (e.g., performance expectancy and hedonic motivation) and the intention to use pre-trip ISs.

Finally, future research should investigate how the UTAUT2 might be transferred more specifically to the field of transportation research and intelligent traveler ISs. The present thesis applied the UTAUT2 to the context of pre-trip ISs and extended the original UTAUT2 by more outcome variables of technology acceptance, namely satisfaction and loyalty. However, the present thesis did not include more predictors for behavioral intention, satisfaction and loyalty into the model that are not originally integrated into the UTAUT2. With the original UTAUT2 predictors that are applicable in the context of innovations that are not currently available on the market (i.e., performance expectancy, effort expectancy, social influence, price value, and hedonic motivation) the present study was able to explain 72% of the variance of the participants' satisfaction, 75.6% of their behavioral intention and 78.1% of their loyalty towards the pre-trip IS. Although these are high amounts of explained variance, future studies might consider the influence of more mobility-specific predictors like time and costs. For example, first tries of integrating mobility-specific predictors into the UTAUT2 framework were applied by Lisson et al. [125]. However, in their study mobility-specific predictors did not show significant effects on the travelers' usage intention [125, p. 98]. Nevertheless, future research should analyze these connections in greater depth.

In sum, the insights of the PLS-SEM analysis reported above provide considerable insights into the determinants of the travelers' motivation to use pre-trip ISs. Future research may extend these findings with the help of experimental studies, longitudinal studies, revealed preference data, multi-regional and multi-national surveys as well as additional possible mobility-specific determinants of technology acceptance.

5.4.3 Implications and Conclusion

In conclusion, the presented results have practical and theoretical implications. From a theoretical perspective, the findings help to understand the drivers of the travelers' satisfaction, loyalty and behavioral intention in the context of pre-trip ISs more accurately. For analyzing these connections this thesis draws upon the UTAUT2, which builds on well-established research from the field of technology acceptance and has already proved itself as a useful model for technology acceptance for a wide range of different consumer products [203,204]. The present study extends existing research by the application of UTAUT2 to the context of pre-trip ISs within the field of transportation research. Since this thesis explores the generalizability of UTAUT2 in a new context (i.e., pre-trip ISs), this is a theoretical contribution [8]. Moreover, the present research provides a contribution to IS theory by extending UTAUT2 by the relationship between the UTAUT2 components and satisfaction and the relationship between satisfaction, behavioral intention, and loyalty. Since this thesis includes new constructs into a well-established theory (i.e., UTAUT2) and examines the changes within the modified framework (see Figure 5.2 and Figure 5.5), this is also a theoretical contribution [8]. By extending the UTAUT2 by satisfaction, this thesis contributes to the criticism of Kupfer et al. [114] who argued that technology acceptance should be assessed in more facets than only behavioral intention. By extending the UTAUT2 by loyalty, this thesis contributes to the recommendations of future research directions of Venkatesh et al. [204], who argued that it is worthy to investigate the impact of technology use on further consumer outcomes such as brand loyalty.

The context-specific application and the extension of UTAUT2 help transportation research to better understand technology acceptance with its antecedents and effects in the context of pre-trip ISs. The specified model shows a good fit in predicting the travelers' satisfaction, behavioral intention, and loyalty in the context of pre-trip ISs. Especially performance expectancy and hedonic motivation were identified as important antecedents that should also be studied in future transportation research. The original baseline model already provides considerable insights into the technology acceptance of pre-trip ISs. The inclusion of satisfaction and loyalty as further measures of technology acceptance, however, provides even further relationships within the technology acceptance framework.

From a practical perspective, these results inform practitioners about the components that are especially important for designing pre-trip ISs that fulfil the travelers' pragmatic and hedonic needs and thus enhances their usage intention, satisfaction and loyalty towards pre-trip ISs. The presented results can be used in four main stages of the development of pre-trip ISs, namely for (1) the brand and product strategy, (2) pre-development phases, (3) development phases, and (4) for the continuous monitoring and controlling of running systems. The model and especially the constructs performance expectancy and hedonic motivation can serve as strategic requirements for traffic engineers. The further development of pre-trip ISs should especially concentrate on features that trigger the travelers' performance expectancy and hedonic motivation. The present findings illustrate that the travelers' performance expectancy as well as their hedonic motivation are the two most important drivers of their satisfaction and usage intention which in turn affects their loyalty. Hence, focusing on these characteristics could enhance the spreading and usage of pre-trip ISs, which has in turn the potential to cause a rethinking of modal decisions and behavioral changes that reduce urban traffic. Therefore, the model presented in this chapter provides a basis for strategic criteria as well as criteria for concepts and releases of pre-trip ISs. Moreover, the model can be used as an evaluation method for iteratively monitoring and controlling the technology acceptance and user experience of pre-trip ISs. Figure 5.6 summarizes the four main phases in which the insights presented in this chapter can be applied as criteria, goals and key performance indicators (KPIs).

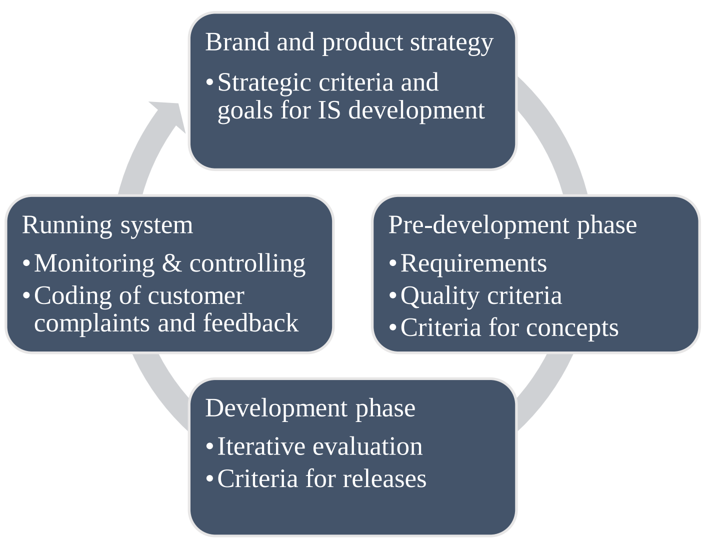


Figure 5.6 Summary of Practical Implications (own illustration).

6 Discrete Choice Models in the Context of Pre-trip Information Systems

This thesis follows the overall goal to motivate travelers to rethink their mobility habits and modal decisions with the help of user-centered pre-trip ISs. Here, pre-trip ISs are regarded as a mean to counteract the rising "Carmageddon" [16] by achieving changes on the individual behavioral level of travelers. Therefore, the former chapters have elaborated the pragmatic and hedonic needs of travelers regarding pre-trip ISs and have summarized these requirements into a pre-trip prototype and a technology acceptance model for pre-trip ISs.

Following the previous chapters, now the present chapter goes one step deeper into the individual decision-making process of travelers. In the context of pre-trip ISs, the algorithm integrated in a pre-trip IS is meant to support the travelers' modal decisions. Depending on the desired level of autonomy by the user, the algorithm may even replace the travelers' own decision-making process by simply suggesting a modal decision proactively without suggesting two or more modal alternatives and leaving the final decision to the user. Hence, in order to motivate travelers to rethink their modal decisions based on pre-trip ISs, the algorithm integrated in pre-trip ISs need to be based on the patterns of the decision-making process of the individual. Consequently, the basis for designing a user-centered pre-trip algorithm is to understand the factors that determine the travelers' individual mobility decisions. Therefore, this chapter focuses on discrete choice models in the context of pre-trip ISs. Thereby, this chapter aims to answer the third of the three research questions introduced at the beginning of this thesis (see Chapter 1.1):

- Research Question 3: Which factors should be included in pre-trip information systems in order to support modal choices of travelers?

As explained in detail in Chapter 2.1.2 and Chapter 2.2.2, state-of-the-art discrete choice models mainly combine eight different groups of parameters, namely (1) sociodemographic parameters of the traveler, (2) mobility habits of the traveler, (3) mobility-centered attitudes of the traveler, (4) infrastructure-related parameters, (5) quantitative and (6) qualitative characteristics of the mode of transport, (7) characteristics of the trip, and (8) side conditions of travelling. The literature review presented at the beginning of this thesis, has also highlighted that discrete choice models in terms of logit or probit models are the state-of-the-art methods for modelling modal choices. Besides this well-established framework of discrete choice models, the literature review has also emphasized that the research field of mode choice modelling still leaves some questions of detail unanswered. Subsequently, Chapter 2.2.2 has ended with a summary of identified research gaps concerning modal choices in the context of current and future ODM services. Here, especially the distinction of carpooling as a passenger and carpooling as a driver, carpooling during commuting and carpooling during leisure time as well as the willingness for ridepooling were identified as not fully developed areas of research. Therefore, this chapter especially concentrates on discrete choice models in the context of carpooling and ridepooling. Moreover, the developed discrete choice models will be discussed with regard to their implications for potential algorithms in pre-trip ISs.

In order to answer research question three, this chapter focuses on the prediction of modal choices of travelers in a present and future scenario. Since mode choice models and the willingness to share rides will change in the era of autonomous vehicles and future on-demand mobility services (see Chapter 2.2.2), this thesis will regard both, a present and future scenario. The present and future scenario differ in the considered means of transport, namely (1) private car, public transport, and carpooling in the present scenario and (2) public transport, robo-taxis, and shared robo-taxis or rather ridepooling in the future scenario. In order to cover different mobility contexts, two contextual factors are considered in the present and future scenario (i.e., trip purpose and time pressure). Since recent research has shown that mode choice models differ depending on the trip purpose and temporal factors (see Chapter 2.1.2 and 2.2.2), this chapter distinguishes the following four scenarios, each in the present and the future scenario (i.e., eight scenarios in total):

Table 6.1 Overview of Scenarios Considered in Chapter 6 (own illustration).

<table>
<tr><th colspan="2" rowspan="2"></th><th colspan="2">Trip purpose</th></tr>
<tr><th>Commuting</th><th>Leisure time trip</th></tr>
<tr><th rowspan="2">Time pressure</th><th>Low</th><td>Scenario 1</td><td>Scenario 3</td></tr>
<tr><th>High</th><td>Scenario 2</td><td>Scenario 4</td></tr>
</table>

These scenarios are analyzed in two user studies ($n_{present}$ = 610; n_{future} = 579). The user studies mainly consist of choice-based conjoint analyses (see Chapter 6.2.3). Besides some descriptive and qualitative analysis, the results of the user studies are mainly used to estimate discrete choice models (see Chapter 6.1.2). The discrete choice models are used to draw conclusions on the factors that determine the travelers' modal decisions in different contexts (i.e., the different scenarios listed in Table 6.1). Thereby, this chapter especially concentrates on the factors that predict the travelers' willingness for sharing trips in terms of carpooling and ridepooling.

Concluding, this chapter aims to answer the third of the three research questions introduced at the beginning of this thesis (see Chapter 1.1): Which factors should be included in pre-trip information systems in order to support modal choices of travelers? This overall research question is addressed with the help of the following sub-question for the present scenario:

- **RQ 3a**: Which factors predict the travelers' willingness for carpooling in a present scenario?

Regarding the future scenario, the overall research question is addressed with the help of the following sub-question:

- **RQ 3b**: Which factors predict the travelers' willingness for ridepooling in a future scenario?

This chapter proceeds as follows: Chapter 6.1 starts with an introduction to the state-of-the-art methods used for modelling modal choices of travelers. This includes a short review of data sources for modelling modal choices in Chapter 6.1.1. Here, the difference between revealed and stated preference data is summarized and stated preference data is selected as the appropriate data source for the present thesis. Next, a literature review on discrete choice modelling procedures is presented in Chapter 6.1.2. This chapter summarizes the theory on discrete choice modelling and the mathematical background of the single modelling procedures, namely multinomial logit models, probit models, latent class models, nested logit models, and mixed multinomial logit models. Based on the literature review, the appropriate modelling procedure for the present thesis is determined, namely the estimation of nested and mixed multinomial logit models.

In the following, the Chapter first concentrates on the present scenario and afterwards on the future scenario. This includes the method and design section (see Chapter 6.2) as well as the results section (see Chapter 6.3) of the present scenario. In the method and design section (see Chapter 6.2), it will be explained in detail, which material and variables were used in the present scenario. Since both, the present and future scenario, mainly consisted of a choice-based conjoint analysis, Chapter 6.2.3 provides a methodological literature review on choice-based conjoint analysis and its different methodological designs. Here, the alternative-specific choice-based conjoint analysis (AS-CBC) is selected as the most suitable approach for the present thesis. Furthermore, the method and design section includes a description of the sample of participants of the present scenario (see Chapter 6.2.4) and the applied data analysis (see Chapter 6.2.5).

Before discussing the results of the present scenario, the method and design (see Chapter 6.4) as well as the results (see Chapter 6.5) of the future scenario are presented. The structure of these two chapters is similar to the structure of the method and design as well as the results section of the present scenario.

After describing both, the present and future scenario in detail, all results of Chapter 6 are discussed in a combined discussion of the present and future scenario in Chapter 6.6. As in earlier chapters, this includes a summary of the core findings (see Chapter 6.6.1), an elaboration of the limitation of the studies and ideas for future research (see Chapter 6.6.2), and a conclusion (see Chapter 6.6.3).

6.1 Methods for Modelling Modal Choices

The following sections concentrate on state-of-the-art methods for modelling modal choices in the field of transportation and traffic engineering. This includes a description of the two main types of data sources used for modelling modal choices, namely stated and revealed preference data. Since stated and revealed preference studies on modal choices were already reviewed at the beginning of this thesis (see Chapter 2.1.2), this section will concentrate on the theory of the applied statistical models and avoid reviewing the conceptual side of the models. A literature review on concrete model parameters and model content can be found in Chapters 2.1.2 and 2.2.2. Moreover, different approaches of discrete choice modelling will be described and distinguished from each other. This includes multinomial logit models as well as nested logit models and mixed multinomial logit models. Besides logit models, latent class models and probit models will be described. Finally, the selection of a suitable modelling technique will be explained.

6.1.1 Data Sources for Modelling Modal Choices

This section provides an overview of the different data sources that are used for modelling modal choices in the context of transportation and traffic engineering. As described in Chapter 2.1.2, stochastic models that aim to predict the travelers' modal choices mainly rely on two main data sources, namely (1) stated preference data and (2) revealed preference data [58]. Stated preference data contains hypothetical mode choices of travelers assessed with the help of surveys. The practical limitation of stated preference data is the lack of actually observed modal choices and travel behavior. Nevertheless, the great advantage of stated preference methods is that a wide range of different conditions and scenarios can be tested, including future scenarios with means of transport that are not currently available on the transportation market (e.g., AVs, SAVs, and urban ropeways). In order to derive valid conclusions from stated preference data, it is important to question a large sample of representative participants. Although strict conventions for the optimal sample sizes are not provided in the context of discrete choice modelling, an a priori efficiency testing should be used to identify the optimal sample size [58, p. 261]. More details on a priori efficiency testing will be provided in Chapter 6.2.3.

Contrary to stated preference data, revealed preference data contains observed choices and decisions from the travelers' actual mobility behavior. However, revealed preference data also underlies practical limitations such as high survey costs and the difficulty to assess latent variables (e.g., quality and convenience of different modes). Moreover, future scenarios with currently unavailable means of transport such as SAVs cannot be tested using revealed preference data [58].

The following analyses concentrate on stated preference data. The reason for using stated preference data in this thesis is twofold: First, this thesis focuses on both, the analysis of modal decisions in a present and a future scenario. Future mobility options can only be analyzed using stated preference data. Secondly, the present research project does not have access to actual data from a carpooling provider. Consequently, stated preference data needs to be assessed for the subsequent analysis.

In sum, using stated preference data is a frequently applied method for modelling modal choices in the context of transportation and traffic engineering. Therefore, this thesis focuses on the analysis of stated preference data in order to analyze modal decisions in a present and future mobility scenario. A detailed description of how to generate valid stated preference data with the help of choice-based conjoint designs will be provided in Chapter 6.2.3. The concrete modelling procedure including different kinds of discrete choice models will be described in the following paragraphs.

6.1.2 Discrete Choice Modelling

This chapter provides a detailed overview of discrete choice modelling. Generally, discrete choice models consider scenarios in which travelers have to select one option from a finite set of modal alternatives. The estimation of discrete choice models is based on the assumption that "the probability of individuals choosing a given option is a function of their socioeconomic characteristics and the relative attractiveness of the option" [58, p. 227]. Hence, socioeconomic variables and variables representing the attractiveness of a modal alternative are used to predict the probability of a modal decision. After introducing the mathematical foundation of discrete choice modelling (i.e., random utility theory), the following paragraphs discuss the different kinds of discrete choice models (i.e., probit, latent class, multinomial logit, nested logit, and mixed logit models). Finally, the nested logit and the mixed multinomial logit model are selected as the suitable modelling techniques for the purpose of the present thesis.

Mathematical Foundation. Discrete choice modelling mainly relies on random utility theory [58, p. 230 ff.]. In the context of transportation research, random utility theory postulates that among a set of modal alternatives $\boldsymbol{A} = \{A_1, \ldots, A_j, \ldots, A_N\}$, a traveler q will choose the alternative A_i with the highest perceived utility U_{iq} [194, p. 300]:

$$P_q(i) = P\left(U_{iq} > U_{jq}, j, i \in A_q, j \neq i\right) \tag{6.1}$$

Thereby, each perceived utility U_{jq} of a certain alternative is a sum of the observable attractiveness of its attributes and attribute levels (for attributes and attributes levels see Chapter 6.2.3). Hence, each perceived utility U_{jq} is a relative score, i.e., a relative perceived utility of one alternative compared to other alternatives. Each perceived utility U_{jq} can be separated into two components, namely a measurable component V_{jq} and a random component ε_{jq} [58, p. 230]:

$$U_{jq} = V_{jq} + \varepsilon_{jq} \tag{6.2}$$

Thereby, the measurable component V_{jq} of a certain alternative A_j is defined as a weighted linear combination of its attributes [194, p. 300]:

$$V_{jq} = \beta_0 + \beta_1 X_{jq}^1 + \beta_2 X_{jq}^2 + \cdots + \beta_R X_{jq}^R \tag{6.3}$$

Hence, U_{jq} can also be expressed as:

$$U_{jq} = \beta_0 + \beta_1 X_{jq}^1 + \beta_2 X_{jq}^2 + \cdots + \beta_R X_{jq}^R + \varepsilon_{jq} \tag{6.4}$$

In order to predict the probability that a modal alternative will actually be chosen, the alternative's utility must be compared with the utilities of other alternatives and transformed into a probability value (i.e., ranging between 0 and 1). This mathematical transformation is handled with the help of logit or probit models [58, p. 228 ff.]. This will be described in more detail in the following paragraphs. The models mainly differ concerning their assumptions of the distribution of the stochastic residuals ε of equation 6.2.

Multinomial Logit Model (MNL). Within the MNL model, ε is associated with an Extreme Value Type I (EV1) distribution which is also called Gumbel or Weibull distribution. This distribution is the basis of the whole logit model family [58, p. 50]. The EV1 distribution can be expressed as $\varepsilon \sim \text{EV1}(\eta, \lambda)$. Here, the probability of choosing an alternative i is the ratio of the utility of an alternative i and the utilities of all other available alternatives j [58, p. 232]:

$$P_{iq} = \frac{\exp(\beta\, V_{iq})}{\sum_{A_j \in A(q)} \exp(\beta\, V_{jq})} \tag{6.5}$$

The MNL underlies two restrictions, namely (1) the assumption that the different alternatives are independent (i.e., independence of irrelevant alternatives: IIA-assumption) and identically distributed and (2) the restriction that the model does not include latent heterogeneity. The IIA-assumption can be tested with the Hausman and McFadden Test [85]. "The basic idea for the test […] is to test the reverse implication of the independence from irrelevant alternatives property" [85, p. 1219]. The test "compares the estimates $\widehat{\beta^f}$, which are consistent and efficient if the null hypothesis is true [i.e., the IIA holds], to the consistent but inefficient estimates $\widehat{\beta^r}$ " [40, p. 589]. The test is defined as followed [40, p. 589]:

$$HM = \left(\widehat{\beta^r} - \widehat{\beta^f}\right)'\left[\widehat{Var}(\widehat{\beta^r}) - \widehat{Var}(\widehat{\beta^f})\right]^{-1}\left(\widehat{\beta^r} - \widehat{\beta^f}\right) \tag{6.6}$$

- Estimated covariance matrices: $\widehat{Var}(\widehat{\beta^r}) - \widehat{Var}(\widehat{\beta^f})$
- If IIA holds, *HM* follows a χ^2-distribution with (*df* = rows in $\widehat{\beta^r}$)

Hausman and McFadden have commented that the test statistic can be negative "due to lack of positive semidefiniteness in finite sample applications" [85, p. 1226]. The authors concluded that in the case of a negative test statistic, the IIA holds [85]. The Hausman and McFadden Test will be applied in the upcoming data analysis in order to test the IIA-assumption and the described decision rules will be used. These restrictions of the MNL can be lifted with the help of the probit model, the nested logit model (NL), the latent class model (LCM) or the mixed multinomial logit model (MMNL) which will be described in the following.

Probit Model. Within the binary or multinomial probit model, ε is associated with a multivariate normal distribution with mean zero and heteroscedasticity (i.e., the variances of the stochastic residuals may differ and the error terms may be correlated). These assumptions generalize the model but also enhance the complexity to solve it numerically for more than two alternatives (i.e., above the binary case). Beyond the binary case, advanced mathematical approximations or simulations are needed to solve the model [58, p. 248]. Since this thesis goes beyond the binary case and regards more than two alternative modes, the probit model was excluded from further analysis.

Nested Logit Model (NL). The nested logit model (NL) is based on a generalized extreme value distribution. The NL model can be applied whenever the IIA-assumption is violated and thus the different alternatives are correlated with each other. In this case, the different alternatives can be divided in subsets and the decision tree contains multiple decision levels [194, p. 304 ff.]. Figure 6.1 illustrates the difference between the decision tree in the context of a MNL and a NL. In the NL model, the probability of choosing an alternative can be divided in two components, namely (1) the probability P_{iqIK} that an alternative i will be chosen from the set of all alternatives in nest K and (2) the probability P_{qK} that an alternative from nest K will be chosen. Combined, the choice probability can be expressed as follows with λ representing the independence between the different alternatives within a nest k (the larger λ, the more independent) [194, p. 304 ff.]:

$$P_q(i) = P_{iqIK} \cdot P_{qK} = \frac{e^{\frac{V_{qi}}{\lambda_k}} (\sum_j e^{\frac{V_{qj}}{\lambda_k}})^{\lambda_k - 1}}{\sum_l (\sum_j e^{\frac{V_{qj}}{\lambda_l}})^{\lambda_l}} \tag{6.7}$$

Thereby, the IIA-assumption applies for all alternatives within a certain nest, but does not apply for alternatives of different nests. Since the different alternatives in the present and future scenario considered in this thesis may be correlated (see Figure 6.1), the nested logit model was applied in the upcoming modelling procedure.

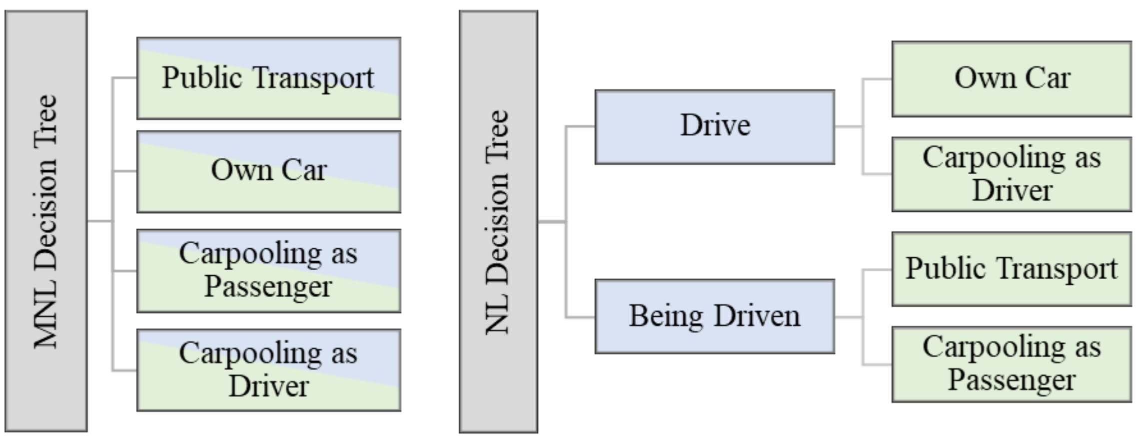


Figure 6.1 Examples of Decision Trees in the Context of MNL and NL Models (own illustration).

Latent Class Model (LCM). A special kind of MNL model is the latent class model (LCM). The LCM considers possible heterogeneity between the travelers and regards distinct segments (i.e., latent classes) within one population [58, p. 251]. Thereby, the weights β_R of the attributes X_{jn} of one alternative j are estimated class-specific for a certain class k [194, p. 305 ff.]:

$$U_{jkq} = \beta_{0k} + \beta_{1k} X_{jq}^1 + \beta_{2k} X_{jq}^2 + \cdots + \beta_{Rk} X_{jq}^R + \varepsilon_{jkq} \tag{6.8}$$

The probability of choosing a certain alternative within one class can be expressed as the normal MNL model described above. Since this thesis does not aim to analyze different classes but more or less homogenous samples, the latent class model was not chosen for further analysis. A detailed comparison of the latent class model and the mixed logit model in the context of transport mode choice data can be found in [181].

Mixed Multinomial Logit Model (MMNL). Another special kind of MNL model is the MMNL model. The MMNL allows a flexible modelling that considers latent heterogeneity and lifts the assumption of the MNL that the different alternatives are independent. Similar to the LCM, the MMNL estimates more specific parameters. Instead of class-specific parameters, the MMNL contains person-specific parameters β_q. Thereby, the conditional probabilities are calculated based on a distribution function of β: $f(\beta \mid \mu, \sigma)$. The mixed logit probability takes the following form [58, p. 250 ff.]:

$$P_{qi} = \int L_{qi}(\beta)\, f(\beta) d\beta \tag{6.9}$$

In which $L_{qi}(\beta)$ can be expressed as:

$$L_{qi}(\beta) = \frac{e^{V_{qi}(\beta)}}{\sum_{j=1}^{J} e^{V_{qj}(\beta)}} \tag{6.10}$$

In sum, the "mixed logit probability is a weighted average of the logit formula evaluated at different values of β, with the weights given by density $f(\beta)$. In the statistics literature, the weighted average of several functions is called a mixed function, and the density that provides the weights is called the mixing distribution. Mixed logit is a mixture of the logit function evaluated at different β's with $f(\beta)$ as the mixing distribution" [195, p. 154]. Since the MMNL model allows flexible modelling in the context of more than two alternatives and since the MMNL is the "most popular practical discrete choice model" [58, p. 232], the MMNL was chosen as a suitable model for the present research purpose. The concrete parameter estimation in the context of MMNL modelling is run through a Simulated-Maximum-Likelihood (SML) estimation or the Hierarchical-Bayes (HB) estimation [194, p. 307]**.**

In conclusion, the NL and the MMNL model were identified as the most suitable discrete choice models for the purpose of this thesis. Figure 6.2 and Table 6.2 summarize the characteristics, advantages, and disadvantages of the different discrete choice models described above. The following Chapter 6.2 will describe the method and design of the first of the two studies presented in Chapter 6, namely the present scenario. This includes a detailed description of the applied data analysis in Chapter 6.2.5. Hence, the concrete application of the nested and mixed multinomial logit model in the present thesis will be described in more detail in the following paragraphs.

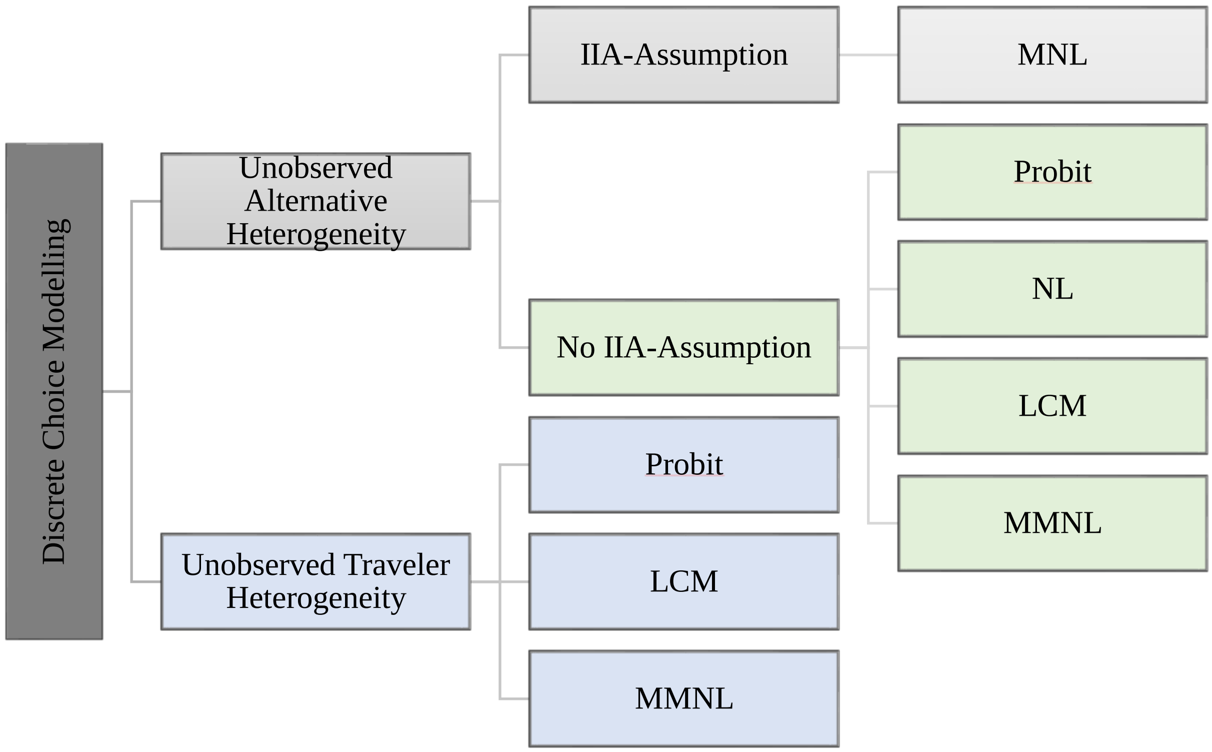


Figure 6.2 Different Approaches of Discrete Choice Modelling (Adapted from [195, p. 303]).

Table 6.2 Summary and Comparison of the Different Discrete Choice Models (Selected models are highlighted in blue; own illustration).

Model	Characteristics	Advantage	Disadvantage
Multinomial Logit Model	• EV1-distribution • The probability of choosing an alternative *i* is the ratio of the utility of alternative *i* and the utilities of all other available alternatives.	• Applicable for an unlimited number of alternatives • Clearly solvable	• The MNL underlies two restrictions, namely (1) the assumption that the different alternatives are independent and identically distributed and (2) the restriction that it does not include latent heterogeneity. • **IIA-assumption**
Probit Model	• Requires normal distribution of ε • Allows heteroscedasticity	• Distribution of the utility of each alternative can be specified in detail. • Only ε has to follow a normal distribution. • **No IIA-assumption**	• Only applicable for binary cases. • Otherwise not clearly solvable
Latent Class Model	• The weights of the attributes of one alternative are estimated class-specific.	• Considers possible heterogeneity between the travelers and regards distinct segments (i.e., latent classes) within one population • **No IIA-assumption**	• Only applicable if the research project aims to analyze different classes within one population.
Mixed Multinomial Logit Model	• The weights of the attributes of one alternative are estimated person-specific.	• Allows flexible modelling, considers latent heterogeneity • **No IIA-assumption**	• No disadvantage in the present context. • Suitable model for the present purpose.
Nested Logit Model	• The different alternatives can be divided in subsets or nests and the decision tree contains multiple decision levels.	• Considers multiple levels of a decision tree • **No IIA-assumption**	• Does not account for latent individual heterogeneity. • Suitable model for the present purpose.

6.2 Method and Design of the Present Scenario

In order to learn about the parameters that influence the travelers' modal choices in a present scenario, an online survey was conducted. This section describes the method and design of the online survey. The survey can be divided in five main parts, namely (1) an introduction, (2) an assessment of the participants' mobility habits and pre-trip habits, (3) a choice-based conjoint (CBC) analysis, (4) an exploration of the participants' attitude towards carpooling and (5) a sociodemographic questionnaire.

The following paragraphs first concentrate on the survey design in general (see Chapter 6.2.1). This includes the assessment of factors influencing the travelers' modal decisions and willingness for carpooling in a present scenario depending on the route purpose (travelling to work, university or school vs. travelling during leisure time) and depending on the amount of experienced time pressure (high vs. low). Figure 6.3 summarizes the overall structure of the survey design.

After introducing the overall survey structure, the following two sections concentrate on specific parts of the survey. First, in Chapter 6.2.2 the items concerning the travelers' mobility habits and pre-trip habits as well as their attitude towards carpooling will be described. Next, Chapter 6.2.3 focuses in more detail on the method to assess the participants' modal decisions. Since the core element of the survey is the CBC analysis, this chapter will describe in detail which kind of CBC analysis was conducted. For the present study, an alternative-specific CBC (AS-CBC) design was chosen. Besides introducing the AS-CBC design, Chapter 6.2.3 also explains why the AS-CBC is the most suitable CBC design for the research objective of this thesis. Furthermore, Chapter 6.2.4 contains the description of the sample of participants. Before presenting the results of the survey, Chapter 6.2.5 will elaborate the theory of the applied data analysis. The main part of the data analysis contains discrete choice modelling with the help of nested and mixed multinomial logit models (MMNL). More details on discrete choice modelling can be found in Chapter 6.1.2.

6.2.1 Overall Survey Structure

Before concentrating on single parts, items, and methods included in the survey, this chapter introduces the overall survey structure. Generally, the survey differentiates between different scenarios of modal choices, namely two different route purposes (travelling to work, university or school vs. travelling during leisure time) and two different scenarios of experienced time pressure (high vs. low). Concerning the different conditions, the survey contained a mixed-subject design, i.e., using both between-subject and within-subject conditions. The conditions were assigned to a mixed-subject design in order to reduce the cognitive load of the participants. Answering all conditions within-subject would have resulted in a survey lasting too long to keep the participants' attention and motivation on a constantly high level. Therefore, in order to enhance the quality of the gathered data and to counteract possible frustrations of participants, the two different conditions of (1) high and (2) low time pressure were assigned between-subject whereas the conditions of (1) travelling to work, university or school and (2) travelling to leisure time activities were assigned within-subject. After the participants were assigned randomly to the condition with high or low time pressure, the survey can be divided in five main parts, including the following content:

1) The survey started with a welcome page with a short introduction to the topic of modal decisions and the two within-subject conditions (i.e., travelling to work, university or school vs. travelling during leisure time). Moreover, the welcome page included an explanation that the survey will last approximately 20 minutes and the participants were asked to answer honestly and intuitively. Additionally, an anonymous data analysis was guaranteed.
2) Afterwards, the participants' mobility habits and pre-trip habits were assessed. The related items will be described in Chapter 6.2.2.
3) Next, the core part of the survey started, namely the assessment of modal decisions with the help of choice sets. The calibration of the choice sets according to the actual mobility situation of the participant and the AS-CBC design of the choice sets will be described in detail in Chapter 6.2.3. As mentioned above, the two different conditions concerning the route purpose were assigned within-subject (i.e., travelling to work, university or school vs. travelling during leisure time). More specifically, each participant answered n = 8 choice sets regarding travelling to work, university or school and n = 8 choice sets regarding travelling during leisure time. In sum, n = 16 choice sets were answered by each participant.
4) After the choice sets, the survey contained a qualitative exploration of the participants' perceived advantages and disadvantages of carpooling.
5) Finally, the survey contained sociodemographic questions concerning the participants' gender, age, occupation status, income, living situation, place of residence, and education. Figure 6.3 summarizes the overall structure of the survey.

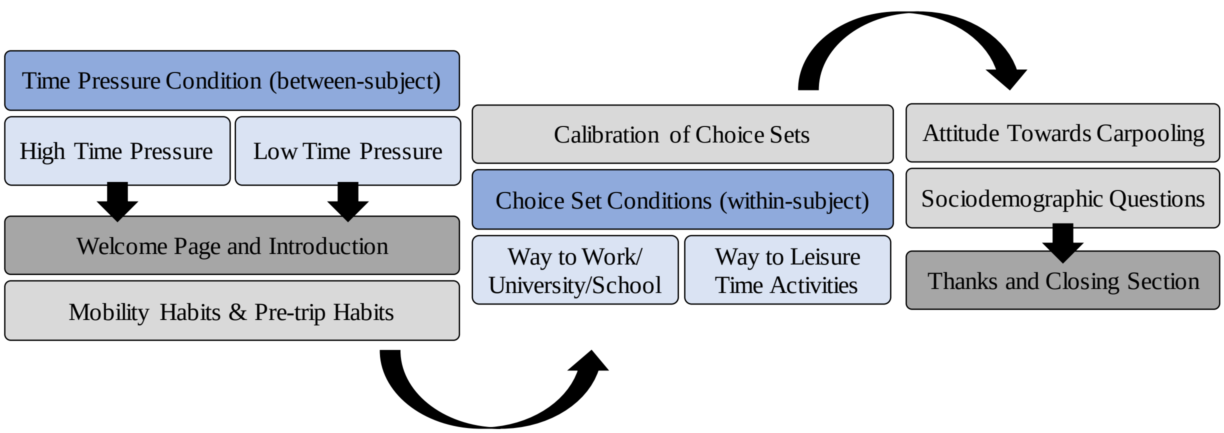


Figure 6.3 Overall Survey Structure of the Present Scenario (own illustration).

6.2.2 Mobility Habits, Pre-trip Habits and Attitudes Towards Carpooling

This chapter focuses on the assessment of the participants' mobility habits, pre-trip habits and their attitude towards carpooling. Mobility habits and pre-trip habits were assessed similarly to the assessment used in the pre-study (see Chapter 3.2). As defined in Chapter 3.2, referring to mobility habits, this thesis regards the travelers' everyday habits concerning the use of different means of transport. Referring to pre-trip habits, this thesis regards the travelers' habits concerning informing oneself about mobility options at home before upcoming trips including, for example, the type of information that is considered by the traveler. In the following, the items will be explained in detail. Table 6.3 summarizes the item content and answer options of the present scenario.

Mobility Habits. Since the modelling of modal choices considered in this chapter concentrates on actual mobility habits in a present scenario the survey assessed the participants' regular use of currently available means of transport, namely private car, carsharing, public transport, bike, and the use of carpooling as a driver and carpooling as a passenger. For each of the six modes, the survey contained an item that assessed the frequency with which the mode was used within the last three months (i.e., not at all, less than once a month, one to three times per month, one to three times per week, almost daily or daily). These modal habits were assessed with regard to commuting to work, university or school and with regard to travelling to leisure time activities. In order to put the participants' usage of public transport into a context, the participants' access to public transport was assessed. Here, the walking distance (in minutes) to the next public transport station from the participant's home was assessed.

Pre-trip Habits. Concerning pre-trip habits, similar to the pre-study, the survey assessed the frequency with which the participants inform themselves about their mobility options at home before an upcoming trip (i.e., never, once, at the beginning, regularly, in specific situations and always). Furthermore, the type of information considered pre-trip was assessed in the same way as in the pre-study (see Chapter 3.2.2) including for example the price and duration of the mobility option. The route purpose was distinguished in all items concerning the participants' pre-trip habits (i.e., travelling to work, university or school vs. travelling during leisure time).

Attitude towards Carpooling. Regarding the participants' attitude towards carpooling, the survey assessed with two open questions what the participants' like most and least about carpooling as a driver and passenger.

In sum, the survey focused on a present scenario of mobility behavior with mobility options that are currently available on the market. The paragraphs above have described in detail which items were used to assess the participants' mobility habits, pre-trip habits and their attitude towards carpooling (see Table 6.3). Furthermore, the survey contained a CBC analysis. The method and design of the CBC analysis will be explained in detail in the following section.

Table 6.3 List of Item Content and Answer Options of the Present Scenario (own illustration).

Item content	**Answer option**
Mobility habits	
Frequency of use of present means of transport within the last three months depending on the route purpose (commuting vs. leisure time): (1) private car, (2) carsharing, (3) public transport, (4) bike, and the use of (5) carpooling as a driver and (6) carpooling as a passenger	**Ordinal scales:** (1) not at all, (2) less than once a month, (3) one to three times per month, (4) one to three times per week, (5) almost daily or (6) daily
Access to public transport: walking distance (in minutes) to the next public transport station from the participant's home	**Metric scale** (in minutes)

Item content	Answer option
Pre-trip habits	
Pre-trip information frequency: depending on route purpose, i.e., (1) commuting, (2) purchases & finishes, (3) hobbies & leisure time activities, and (4) appointments such as meeting with friends	**Ordinal scales:** (1) never, (2) once, (3) at the beginning, (4) regularly, (5) in specific situations, and (6) always
Type of pre-trip information depending on the route purpose (commuting vs. leisure time): (1) the traffic situation, (2) weather on the route, (3) price of the mobility option, (4) duration, (5) complexity of a route, (6) alternative routes, (7) departure times, and (8) no information at all	**Multiple-choice items:** yes vs. no **+ open text**
Calibration of choice sets	
How long is your average journey: (1) from home to work, university or school? (2) from home to leisure time activities?	**Metric scale** (in km)
How long is your average travel time from home to work, university or school: (1) by car (2) by public transport?	**Metric scale** (in minutes)
How long is your average travel time from home to leisure time activities: (1) by car (2) by public transport?	**Metric scale** (in minutes)
Choice sets	
8 Choice Tasks regarding commuting **8 Choice Tasks** regarding leisure time activities	**Single-choice items**
Attitude towards carpooling	
Advantages and disadvantages of carpooling	**Open text**

6.2.3 Choice-Based Conjoint Analysis

This chapter concentrates on the core element of the survey, i.e., the CBC analysis. The following paragraphs will elaborate how the AS-CBC design applied in this survey looks like and why this is the most suitable method among the different CBC designs for the purpose of this thesis. Moreover, the determination of choice sets including the considered attributes and their levels will be illustrated. Additionally, the efficiency test that was made before starting the data collection will be reported and discussed.

Introduction to Conjoint Analysis. Generally, conjoint analysis is a multivariate method to analyze consumers' preferences and choices [15, p. 3-18]. Within the terminology of the conjoint analysis, it is important to distinguish attributes, attribute levels, and stimuli. Attributes are defined as characteristics of products or services, such as the price of a mobility option, whereas attribute levels define the concrete shaping of the attribute, such as a high price vs. a low price. Hence, each attribute has at least two levels or more. Taken together, different attributes shape one stimulus, such as one certain mobility option (e.g., public transport).

Consequently, the conjoint analysis does not focus on presenting single attributes of products or services but considers the different attributes together in one stimulus (i.e., a product or service). This characteristic has given the conjoint analysis its name, i.e., CONsider attributes JOINTly. Although the conjoint analysis considers multiple attributes combined in one product or service, the results of the conjoint analysis are meant to provide insights into the importance, utility or price value of single attributes for the consumers' preferences and choices. This is a great advantage of the conjoint analysis compared to other techniques such as the contingent valuation [58, p. 95]. Since this thesis aims to investigate the single factors influencing the travelers' modal decisions it is important to apply a method that allows conclusions about the weighting of single attributes such as the price of the mobility option or waiting time. Therefore, the conjoint analysis was chosen as the method of choice for answering research question three.

Within the field of conjoint analysis, different kinds of conjoint designs are distinguished [see 15]. The similarity of all conjoint designs is that attribute levels are varied systematically in order to regress them against empirical data. For example, in the traditional conjoint analysis (TCA), participants are asked to rate or rank different stimuli. Afterwards, the attribute levels are regressed against the empirical rating or ranking data and conclusions about the relative preference of the single attributes are drawn. However, due to shortcomings regarding the statistical methods and the unrealistic scenario of rating or ranking transport alternatives instead of simply choosing one mode, TCA has had limited acceptance in the field of transportation research [58, p. 95].

Therefore, this thesis applied a choice-based conjoint (CBC) design. Instead of asking participants to rate or rank stimuli, the CBC design asks participants to choose one stimulus out of two or more different stimuli (e.g., public transport vs. private car) presented next to each other in a choice set. Examples of choice sets will be presented below (see Figure 6.4). As explained in Chapter 2.1.2, data including hypothetical mode choices of travelers is referred to as stated preference data. The literature review presented above has highlighted that analyzing stated preference data is a well-accepted and frequently applied method in the field of transportation research. Applying a CBC design producing stated preference has huge methodological advantages compared to TCA. First, transportation research provides a set of econometric models that were specifically developed for analyzing discrete choice data, namely discrete choice models (see Chapter 6.1.2). Hence, the data analysis does not underlie any shortcomings regarding the statistical methods. More details on the theory of the applied data analysis will be presented in Chapter 6.2.5. Moreover, the CBC design forces the participant to react in the same way as it is common in a real-world scenario, i.e., via choosing one alternative for travelling. Measuring the same type of behavioral response in stated preference data as could be observed in revealed preference data has a higher methodological quality than a variation between the actual response and the measured response [58, p. 96].

Summarizing, within the wide field of conjoint design, this thesis applies a CBC design. The CBC design is used to produce stated preference data with the help of choice sets that were integrated in the online survey described above. Applying a CBC design and analyzing stated preference data is a common procedure in the context of analyzing modal choices in the field of transportation research. The specific determination of the choice sets and the selection of attributes and attribute levels will be described in the following.

Determination of Choice Sets. Next, this chapter concentrates on the specific determination of the choice sets presented in the online survey. Each choice set consisted of four different modal alternatives of which the participants were asked to choose one. Similar to other CBC studies in the field of transportation research (e.g., [77]), the choice sets did not include a "none" option. Consequently, the participants were forced to make a modal decision. The exclusion of the "none" option can be justified by the fact that in real life scenarios travelers would also be forced to make a decision. Only in very rare and specific cases, travelers might really cancel a trip due to the lack of suitable mobility options. As stated above, while designing CBC approaches it is important to ask the participants to react in the same ways as in the real-world scenario. Thus, omitting the "none" option again makes the design more realistic and thereby more valid [58, p. 96].

Since the present study investigates modal decisions in a present scenario the choice sets only included modal alternatives that are currently available on the transportation market (i.e., private car, public transport, and the use of carpooling as a driver and as a passenger). Each choice set consisted of four alternatives in which each mode was represented exactly once. Furthermore, in order to reduce the participants' cognitive load and make it easier for them to actually weight up the different mobility options, the modes as well as the attributes of each stimulus were presented in a fixed order. Presenting the attributes in a randomized order would have made it more difficult for the participants to consider the different alternatives. In choice sets in which attributes appear in a randomized order, the participants have to reorient themselves in every single choice set in order to retrieve all information correctly. This enhances the participants' cognitive load [77, p. 63].

As mentioned above (see Chapter 6.2.1), each participant answered n = 16 choice sets in total, of which n = 8 choice sets focused travelling to work, university or school and n = 8 choice sets focused travelling during leisure time. The route purpose condition was introduced at the beginning of the two different sets of choice sets with a short explanation. The total number of choice sets was determined based on similar CBC studies [72,77,200]. Moreover, methodological research has shown that participants are capable of answering up to n = 17 choice sets without losing statistical efficiency [21]. Hence, n = 16 choice sets in total should not reduce the statistical efficiency of the present design.

In sum, each participant answered n = 16 choice tasks which were presented without a "none" option and with four modes and different attributes in a fixed order. Which attributes and attribute levels were included in the choice sets, will be described in the following.

Selection of Attributes and Attribute Levels. The selection of attributes and attribute levels was based on the literature review presented in Chapter 2.1.2 and 2.2.2. Here, the present study especially relies on previous studies in the field of carpooling conducted in the Swiss transportation research group among Prof. Axhausen. Similar to previous studies [e.g., 136], an alternative-specific (AS-) CBC design was chosen. AS-CBC is an advanced type of CBC design in which the different alternatives can get their own unique set of attributes [168,169]. Thus, the advantage of the AS-CBC design is that it fits more complex combinations of alternatives. Especially in the context of means of transport, an AS-CBC is the suitable method because means of transport are associated with different sets of attributes and attribute levels [168,169]. Therefore, an AS-CBC design was chosen for the present study. Table 6.4 summarizes the attributes, attribute levels and individual references of the attributes for each considered mode (i.e., private car, carpooling as a driver, carpooling as a passenger, and public transport). The table illustrates that the attributes are selected specifically for each mode. Hence, not all attributes are considered in all modes. Instead, prohibitions were defined between specific modes and attributes (e.g., parking costs are prohibited in the context of public transport).

The selection of concrete attributes was also based on the literature review (see Chapter 2.1.2 and 2.2.2). For example, similar to Mühlethaler, Axhausen, Ciari, Tschannen-Süess and Gertsch-Jossi [136], the attributes price, travel time, parking costs and walking time were integrated into the CBC design considered in this chapter. In contrast to Mühlethaler et al. [136], different levels of type of passenger and risk of missing the passenger or lift in the choice sets regarding carpooling were not integrated into the CBC design. Since too many attributes enhance the complexity of the choice tasks, these attributes were omitted in order to enhance the efficiency of the design, reduce the participants' cognitive load and thereby reducing the risk of producing low-quality data [168, p. 2].

Instead of type of passenger and risk of missing the passenger or lift, the present study concentrated on the features of the car with which the carpooling is operated. For the alternative "carpooling as a passenger" three different levels of features were varied as attribute levels, i.e., (1) small car with standard features, (2) mid-range car with leather seats and screens inside and (3) upper-range car with massage seats and mobile tablets inside. The additional features of the car are less well studied compared to the type of passenger and the risk of missing the passenger or lift. Therefore, including additional features of the car as an attribute into the CBC design can provide additional insights into modal choices and pooling decisions. Moreover, the attribute additional features was included in the choice sets in order to make the results best comparable with the future ridepooling scenario that will be addressed in Chapter 6.4. In a future ridepooling scenario the additional features of the vehicle become more important than for example the risk of missing the lift because robo-taxis are expected to show a high reliability that is no longer dependent on the driver.

Moreover, in contrast to Mühlethaler et al. [136], different levels of transfers in the context of travelling with public transport were not integrated into the choice sets. Transfers were also omitted as an attribute in the choice sets in order to make the design leaner and reduce the participants' cognitive load. Additionally, contrary to Mühlethaler et al. [136], parking costs and waiting times were only presented in whole numbers without decimal numbers in order to reduce the participants' cognitive load. In addition, since the stated preference data was mostly collected in Munich (Germany) the waiting times were adapted to levels that fit the Munich public transport system (i.e., 3, 5, 7). Another change in the design compared to Mühlethaler et al. [136] was made regarding walking time. Since a qualitative pre-study of $n = 5$ has shown that 10 minutes walking time is perceived as an unrealistic long time, the maximum of walking time was set as 6 minutes instead of 10 minutes.

In conclusion, the four different modes were varied with the help of six different attributes with three attribute levels each (see Figure 6.4). More details on the calculation of specific attribute levels will be explained in the following paragraphs and summarized in Table 6.4.

Table 6.4 Attributes, Attribute Levels, and Individual Reference for Attribute Levels for the Present Scenario (own illustration).

Mode	Attribute	Individual reference	Attribute levels		
Private car	Price (€)	Distance*30ct	-10%	+10%	+50%
	Travel time (min.)	Actual time in car	-20%	1	+20%
	Parking costs (€)		2	4	6
	Walking time (min.)		0	3	6
	Waiting time		-	-	-
	Additional features		-	-	-
Pooling driver	Price (€)	Distance*0.50*30ct	-10%	+10%	+50%
	Travel time (min.)	Actual time in car + 5 min detour time	-20%	1	20%
	Parking costs (€)		2	4	6
	Walking time		0	3	6
	Waiting time		-	-	-
	Additional features		-	-	-
Pooling passenger	Price (€)	Distance*0.50*30ct	-10%	+10%	+50%
	Travel time (min.)	Actual time in car + 5 min detour time	-20%	1	20%
	Walking time (min.)		0	3	6
	Waiting time (min.)		3	5	7
	Additional features		Small	Mid-range	Upper-range
Public transport	Price (€)	Distance*0.50*30ct	-10%	+10%	+50%
	Travel time (min.)	Actual time in public transport	-20%	1	20%
	Walking time (min.)		0	3	6
	Waiting time (min.)		3	5	7
	Additional features		-	-	-

Efficient Choice Set Design. This paragraph concentrates on the efficient design of the attribute levels of the attributes price and travel time. Similar to previous studies [e.g., 72,97], the attribute levels of the attributes price and travel time were based on the participants' actual conditions. More specifically, the distance (in km) and travel duration (in minutes) from the participants' home to their office, university or school and from the participants' home to their regular leisure time activities were assessed in the choice set calibration before presenting the actual choice sets. Based on the participants' responses the attribute levels of price and travel time were calculated and presented in the choice sets. The formula-based choice set design again enhances the realism of the choice sets. Previous research has shown that efficient stated preference survey designs result in better *t*-statistics for the estimated parameters, better predictions and require fewer participants [163,164]. Therefore, formulas considering the participants' actual situation were integrated in the choice sets of the present study. Table 6.4 illustrates the formulas which were the basis for the presented attribute levels. Concerning the price of the public transport alternative, the attribute levels in the present study were based on previous studies of Frei, Hyland and Mahmassani [72]. Here, similar to the price for private car usage and pooling, a formula considering the participants' actual travel distance was implemented. Figure 6.4 illustrates the implementation of the different alternatives, attributes and levels into an exemplary choice set.

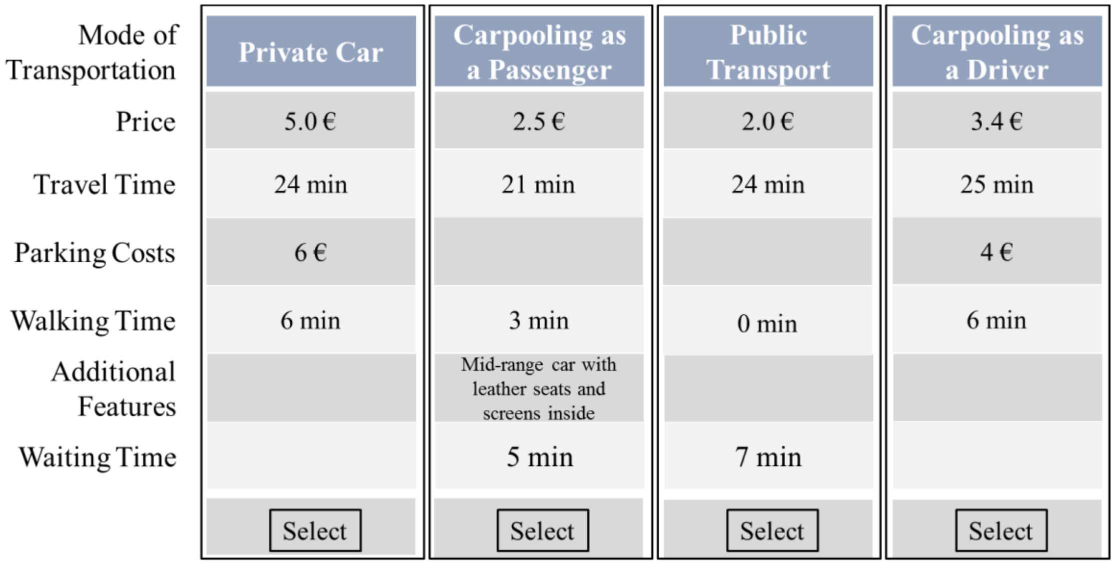


Figure 6.4 Exemplary Choice Set Presented in the Present Scenario (own illustration).

Efficiency Testing. After describing the selection of attributes and attribute levels, this paragraph focuses on the distribution of the choice sets between-subject and the testing of the efficiency of the survey design. Generally, a stated preference survey considering K different modes in each choice set that varies in S possible combinations of attributes and attribute levels results in $\frac{S!}{K!*(S-K)!}$ possible different choice sets [13]. Due to restrictions in the participants' cognitive load, each participant is only asked to answer $n = 16$ different choice sets in the present survey. Therefore, a randomized design was applied in order to present as many different choice sets as possible between-subject. For the randomization, a complete enumeration approach was applied because this approach is recommended in the context of an AS-CBC design [169]. The complete enumeration ensures that a lot of different possible choice sets with a high quality of information are presented to different participants [126]. Table 6.5 illustrates the efficiency test of the AS-CBC design calculated with complete enumeration as task generation method based on $n = 300$ versions with $n = 8$ choice sets in each version (i.e., 2,400 modal decisions in total). The efficiency testing was estimated with the help of Sawtooth. The results of the efficiency test comply with the conventions for standard errors for common attributes ≤ 0.05 and for alternative-specific attributes ≤ 0.10 [169]. In conclusion, the efficiency testing confirmed the goodness of the design of the present study and showed that a sample size of $n = 300$ participants represents an efficient sample size.

Table 6.5 Efficiency Test of the AS-CBC Design of the Present Scenario with Complete Enumeration as Task Generation Method (Based on 300 versions with 8 Choice Sets in each Version and 2400 Total Choice Tasks) (blue highlighting = alternative-specific attributes; own illustration).

Attribute	Attribute level	Standard error	Attribute	Attribute level	Standard error
Price car	-10%	0.068	**Parking costs**	2€	0.044
	+10%	0.068		4€	0.045
	+50%	0.069		6€	0.044
Price other modes	-10%	0.033	**Walking time**	0 Min	0.030
	+10%	0.033		3 Min	0.030
	+50%	0.033		6 Min	0.030
Travel time car	-20%	0.068	**Additional features**	Small	0.065
	Reference	0.069		Mid-range	0.066
	+20%	0.069		Upper-range	0.066
Travel time pooling	-20%	0.043	**Waiting time**	3 Min	0.043
	Reference	0.043		5 Min	0.043
	+20%	0.043		7 Min	0.043
Travel time public transport	-20%	0.067			
	Reference	0.066			
	+20%	0.067			

6.2.4 Participants

After the recruiting phase from December 2018 until January 2019, *n* = 691 participants answered the survey completely. The participants were recruited in the BMW World in Munich (Germany) and via e-mail and answered the survey in German. Informed consent was obtained and every participant took part voluntarily in the present study. Only full data sets were included in the analysis. In order to obtain a high-quality sample, conservative cut-off scores regarding the page times and the variance of the answers were set. These cut-off scores made sure that only participants who answered the survey conscientiously and did not just "click through" the survey were included in the further analysis. In sum, *n* = 76 (11%) were excluded from the analysis because they answered all choice tasks in less than 120 seconds and chose the same alternative in all choice tasks. Additionally, *n* = 4 participants (0.58%) were excluded because of lacking variance in their answers (i.e., SD = 0 on multiple survey pages), which indicates that they clicked through the survey. Furthermore, one participant (0.14%) was excluded from further analysis because of an outlier in his or her number of owned cars. An outlier was here defined as a number of owned cars > 10. Hence, further analysis was made with *n* = 610 participants ($n_{\text{high time pressure}} = 274$, $n_{\text{low time pressure}} = 336$). Since every participant answered *n* = 16 choice tasks, this equals a total number of *n* = 9,760 decisions ($n_{\text{high time pressure}}$ = 4,384, $n_{\text{low time pressure}}$ = 5,376).

Among these participants, the age ranged between 18 and 78 years (*M* = 31.80, *SD* = 12.48). Among the participants, *n* = 372 were male (60.98%), *n* = 231 were female (37.87%) and seven participants (1.15%) did not give details about their gender. With regard to their occupation status, most participants were students and working professionals, namely 58.69% were students (*n* = 358) and 27.54% of the participants were working professionals (*n* = 168). More details on the sample can be found in Table 6.6.

Table 6.6 Demographic Characteristics of the Sample of the Present Scenario (own illustration).

	n	%			n	%
Final sample of participants	610	100		**Place of residence**		
Sample high time pressure	274	44.92		Large city (> 500.000)	245	40.16
Sample low time pressure	336	55.08		Medium city (> 100.000 - 499.999)	70	11.48
Final sample of decisions	9760	100		Small city (20.000 - 99.999)	83	13.61
Decisions high time pressure	4384	44.92		Town (5.000 - 19.999)	80	13.11
Decisions low time pressure	5376	55.08		Village (< 5.000)	132	21.64
Gender				**Household situation**		
Male	372	60.98		Single	153	25.08
Female	231	37.87		Shared apartment	154	25.25
No Details	7	1.15		With partner	178	29.18
Occupation status				With partner and children	80	13.11
Students	358	58.69		Single parent	6	0.98
Working professionals	168	27.54		Other	39	6.39
PhD Students	26	4.26		**Education**		
Other	25	4.10		Secondary school	19	3.11
Retired	14	2.30		Junior high school	48	7.87
In education (apprentice)	13	2.13		High school	197	32.30
Unemployed	6	0.98		Apprenticeship	67	10.98
Net-Income (Euro/Month)				Master craftsman	19	3.11
≤ 1000	48	7.87		Bachelor	102	16.72
1001-2000	208	34.10		Master	128	20.98
2001-3000	189	30.98		PhD	13	2.13
3001- 4000	58	9.51		Other	17	2.79
≥ 4001	58	9.51		**Car class of private car**		
No Details	49	8.03		Small car	153	31.03
Car ownership				Mid-range car	297	60.24
Yes	493	80.82		Upper-range car	43	8.72
No	117	19.18				

	Min	Max		Mean	SD
Age	18	78		31.80	12.48
Access to PT (in minutes from home)	0.5	11		5.96	3.22
Actual commuting time PT	1	500		73.21	90.82
Actual commuting time car	1	500		48.17	67.03
Cars in household	0	10		1.93	1.41

6.2.5 Data Analysis

This chapter focuses on the tools used to analyze the collected data of the present scenario. The data was collected with the help of the online survey tool Sawtooth [170]. Sawtooth Software offers a software grant program for Masters and Ph.D. students [171]. This research project got accepted for the Sawtooth Software grant program and thus got access to Sawtooth Software which is embedded in Lighthouse Studio 9.6.1. Sawtooth Software and Lighthouse Studio 9.6.1 were used for the data collection because the software is able to apply the complete enumeration algorithm described in Chapter 6.2.3.

Furthermore, Microsoft Excel (2013) was used for preparatory analysis. This includes merging data sets and controlling values. RStudio Version 1.1.463 [165] relaying on R 3.5.2 [165] was used for higher level analysis. Within RStudio, the mlogit package [52] is a software that is developed specifically for the analysis of multinomial choice data such as mode choices in the context of transportation research. Mlogit contains advanced programs for estimating MNL, NL and MMNL models. The package is considered as a state-of-the-art software for estimating random utility discrete choice models by the maximum likelihood technique [52].

The data was mainly analyzed using descriptive statistics, discrete choice modelling, and qualitative clustering. The theory of the applied modelling procedure was already explained in detail in Chapter 6.1. Therefore, Figure 6.5 summarizes briefly the applied systematic procedure for discrete choice modelling. The present thesis tested different models iteratively in order to determine the most suitable discrete choice model with the highest quality. Furthermore, Table 6.7 provides an overview about the main quality criteria for discrete choice models, namely McFadden's R^2, the log-likelihood of a model and the likelihood ratio test as well as the inclusive value parameter in the context of nested logit models. According to state-of-the-art guidelines for discrete choice modelling [127], these quality criteria were applied in the present data analysis. Furthermore, qualitative data was analyzed according to the clustering procedure described in Chapter 3.3.1.

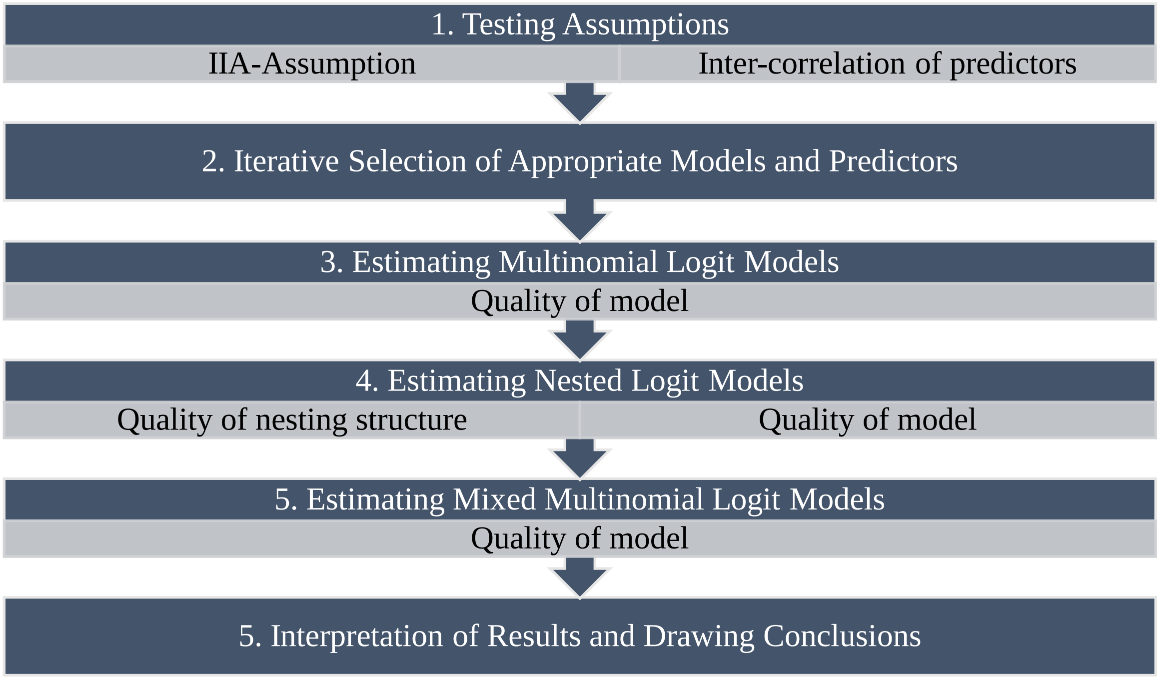


Figure 6.5 A Systematic Procedure for Discrete Choice Modelling (own illustration).

Table 6.7 Overview of Criteria for Model Quality in the Context of Discrete Choice Modelling (own illustration).

Criteria	Definition & convention	Source
Quality of logit models		
McFadden's *R^2*	McFadden's R^2 is a type of pseudo-R^2 that measures the goodness-of-fit of discrete choice models. It can be seen as a "likelihood-ratio index" [127, p. 54]. The values lie between 0 and 1. Higher values indicate relatively better overall model fit. Values between 0.2 and 0.4 express an extremely good model fit [127, p. 54].	Louviere, Hensher & Swait (2010) [127, p. 52 ff.]
Log-Likelihood and Likelihood ratio test	Analogous to the *F*-test in ordinary least square regression, the likelihood ration test can be used to compare a specified model with a null model or two nested specified models in the context of logit models. "The null hypothesis is that the probability P_i of an individual choosing alternative *i* is independent of the value of the parameters in the MNL function […]. If this hypothesis is retained, we infer that the utility parameters are zero" [127, p. 53].	

Criteria	Definition & convention	Source
Quality of nesting structure		
Inclusive value parameter (*IV*)	The *IV* is an index variable or "expected maximum utility, defined by a set of utility expressions associated with a portioned set of alternatives" [127, p. 144]. • 0 < *IV* < 1: tree-structure is consistent with utility maximization • *IV* = 1: MNL applies • *IV* > 1: tree-structure is not consistent with utility maximization Note: In the case of a "degenerated nest" (i.e., a nest containing only one alternative) the nest elasticity is difficult to interpret. Here, the parameter is "somewhat meaningless, as it is related to the degree of correlation of the alternatives within the nests and that there is only one alternative in this nest" [51, p. 36].	Louviere, Hensher & Swait (2010) [127, p. 144 ff.]

6.3 Results of the Present Scenario

This chapter summarizes the results of the present scenario. The results will be presented in the same order as the data for the different parts of the questionnaire was collected (see Figure 6.3). Hence, the following paragraphs will first describe the results concerning the participants' current mobility habits and pre-trip habits (see Chapter 6.3.1). These descriptive results are meant to get a deeper understanding of the sample and set the following discrete choice models into a more specific context. Next, in Chapter 6.3.2, the results of the main part of the survey will be reported, i.e., the results from the AS-CBC study. The CBC-data will be analyzed according to the procedure illustrated in Figure 6.5 which includes multinomial logit models, nested logit models and mixed multinomial logit models. Finally, in Chapter 6.3.3, the results regarding the participants' attitude towards carpooling will be outlined qualitatively.

6.3.1 Mobility Habits and Pre-trip Habits

In order to better understand the main results of the present scenario (i.e., the AS-CBC results), it is important to get an overview of the participants' current mobility habits, modal decisions, and pre-trip habits. Therefore, Figure 6.6 to Figure 6.9 summarize these insights descriptively. The following results on the participants' mobility habits and pre-trip habits will help to put the results regarding the AS-CBC analysis into a context. The results will only be described very briefly because the main focus of the results section is the discrete choice modelling presented in Chapter 6.3.2.

Figure 6.6 illustrates that most participants use their own car or public transport for commuting whereas carsharing (never: 90.33 %), carpooling as a driver (never: 71.80 %), and carpooling as a passenger (never: 73.44 %) is rarely used for commuting. Moreover, less than half of the participants (49.69%) use their bike for commuting from less than once per month up to daily. Compared to commuting, Figure 6.7 illustrates that carpooling as a driver (never: 61.97%) and carpooling as a passenger (never: 59.51%) is more frequently used for leisure time trips than for commuting. Similar to commuting, carsharing is also rarely used for leisure time trips (never: 90.49%). Own car and public transport remain as the two main modes of the present sample.

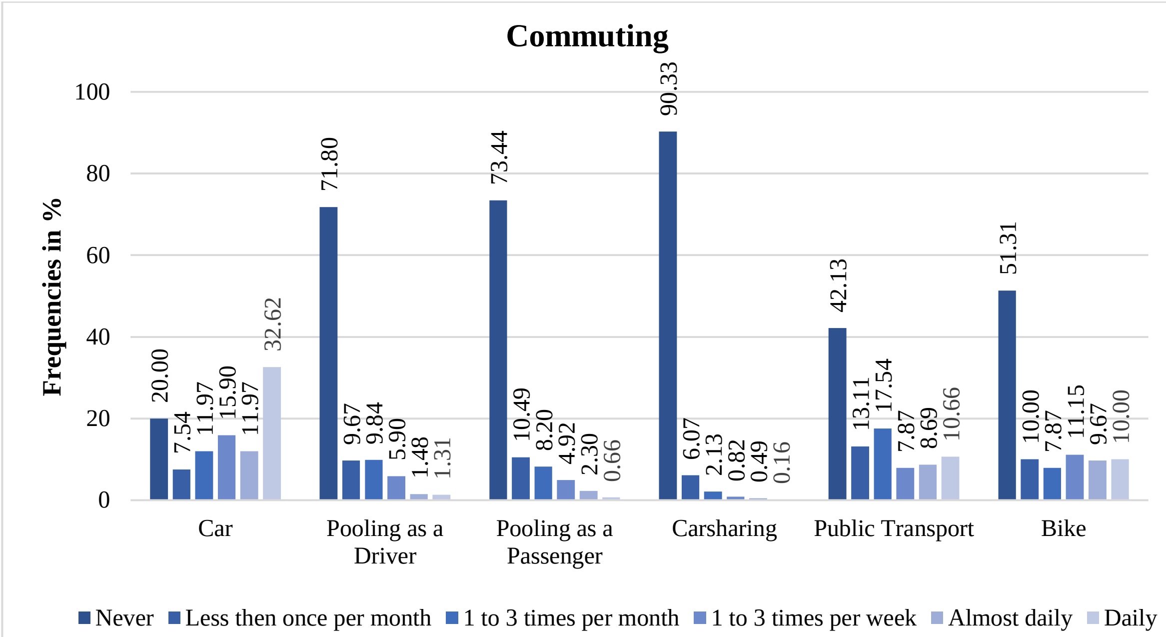


Figure 6.6 Current Mobility Habits of the Sample of the Present Scenario with regard to Commuting (own illustration).

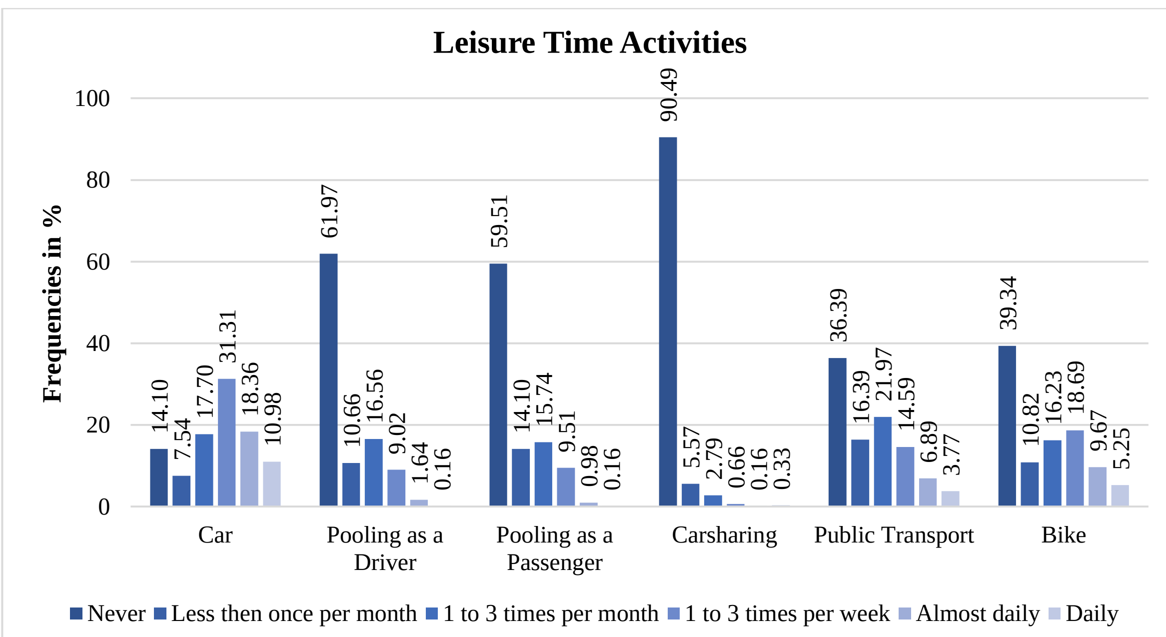


Figure 6.7 Current Mobility Habits of the Sample of the Present Scenario with regard to Leisure Time Trips (own illustration).

The participants' pre-trip habits are summarized in Figure 6.8 and Figure 6.9. Figure 6.8 illustrates that a high percentage of the participants never inform themselves about mobility-centered information before their trip (i.e., commuting: 25.08%, leisure time trips: 42.13%). Concerning leisure time trips, nearly half of the participants never inform themselves pre-trip (42.13%). Regarding the type of information that is collected pre-trip, Figure 6.9 visualizes that traffic, travel time and departure time are the top three information needs.

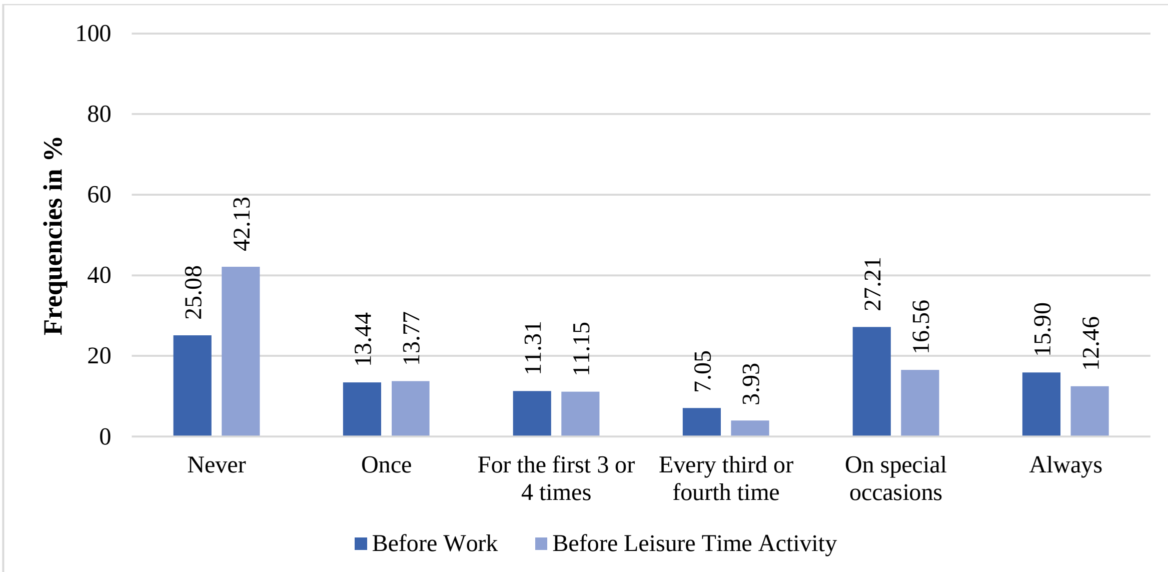


Figure 6.8 Frequency of Pre-trip Information Collection Depending on the Purpose of the Route (present scenario; own illustration).

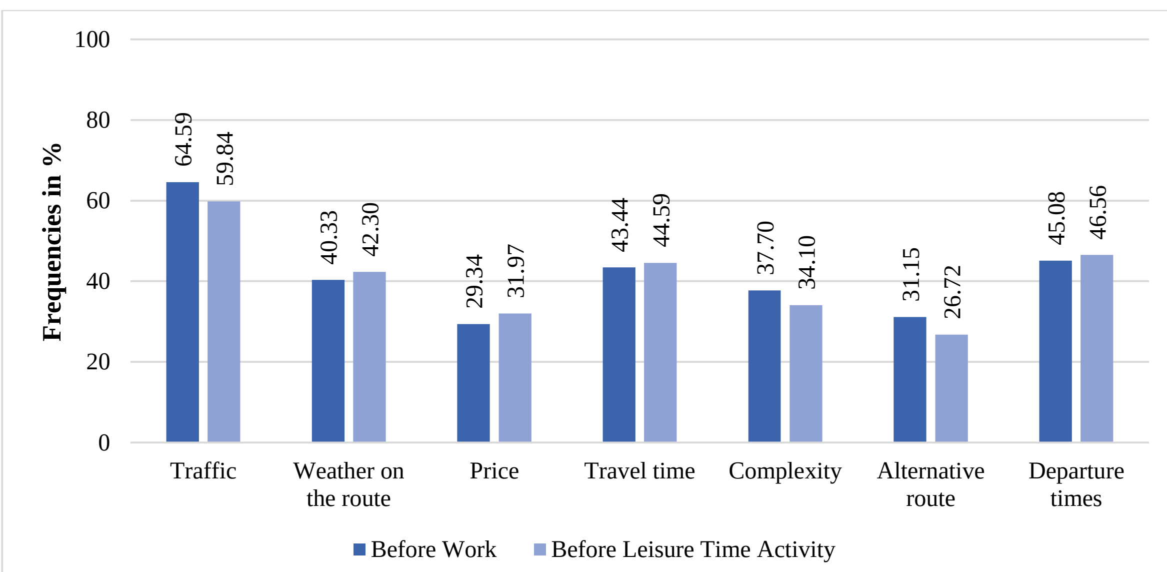


Figure 6.9 Type of Mobility-Centered Information that is Accessed Pre-trip by the Participants' of the Present Scenario (own illustration).

6.3.2 Discrete Choice Modelling

This section presents the core results of the present scenario, namely the discrete choice models. After presenting a descriptive overview of the modal decisions, the final selection of predictors will be reported. This also includes the reporting of inter-correlations between possible predictors and the subsequent decision of predictor inclusion or exclusion. Afterwards, the results of the test concerning the IIA-assumption will be described. Since the IIA-assumption does not hold for the present scenario, the MNL results are only reported briefly. Next, the nested model (NL) results will be described. Since, the nested models were not selected as the final models with the best model fit, the NL results are also only reported briefly. Finally, the mixed model (MMNL) results are presented in detail and chosen as the final models.

Descriptive Overview of Modal Decisions. Figure 6.10 illustrates the participants' modal decisions within the four different present scenarios descriptively (i.e., commuting and leisure time trips each with low and high time pressure). First of all, the diagram supports a simple assumption of the subsequent discrete choice models, namely that all four modes were selected in all four scenarios. Hence, there is no mode that was not selected at all or so rare that it cannot be included in the modelling procedure. Furthermore, the diagram highlights that the frequencies with which the modes were selected differ depending on the trip purpose and the time pressure condition. Own car is selected most frequently in the two conditions with high time pressure, followed by public transport, carpooling as a passenger, and carpooling as a driver. Regarding the two conditions with low time pressure, the differences between the frequencies of own car, public transport, and carpooling as a passenger are, however, less big. Carpooling as a driver is the least chosen alternative in all four scenarios.

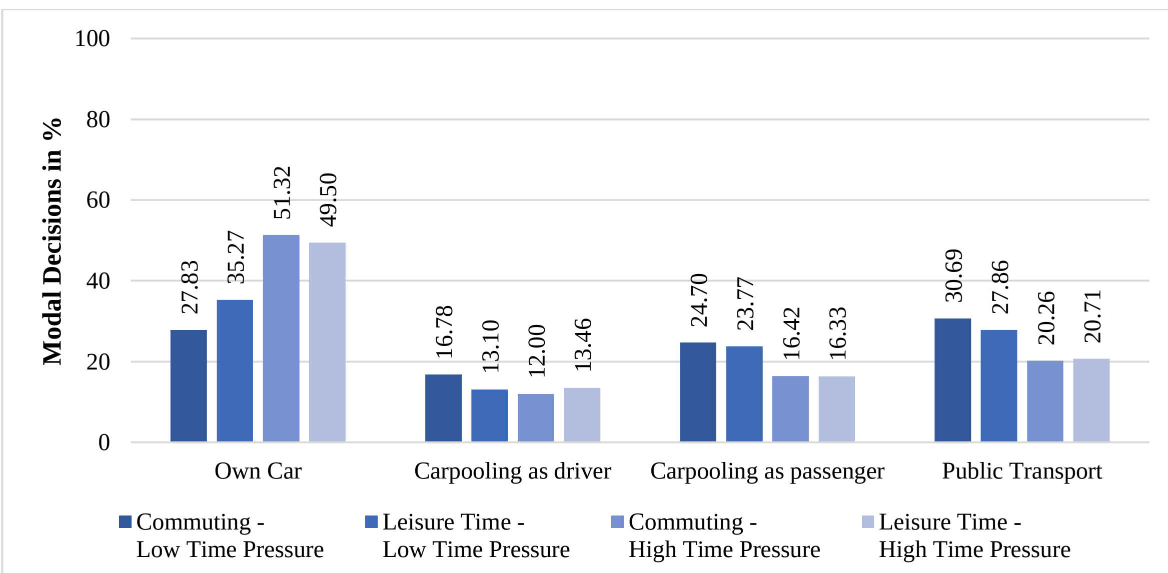


Figure 6.10 Overview of Modal Decisions in all Four Present Scenarios (n = 9760; own illustration).

Selection of Predictors. The overall selection of predictors was based on the literature review presented in Chapter 2.2. Based on previous choice models, individual-specific demographic variables (e.g., age and gender) and attitudes as well as alternative-specific variables (e.g., cost and time) were included. Table 6.8 summarizes the final selection of predictors included in all four discrete choice models of the present scenario.

The final set of predictors was identified in an iterative process including the testing of different models. Within this process, predictors with large inter-correlations (i.e., $r \geq .50$) were excluded from the models (see Table 6.8). For example, the actual commuting times in car and the actual commuting time in public transport were correlated significantly. Therefore, only the commuting time in car was integrated in the final models. Appendix C to Appendix F provide a detailed overview of the inter-correlation of all predictors considered in the present scenario and their significance.

In order to build an economic model with a manageable number of predictors, the participant's income was integrated as a metric predictor in the model. As illustrated in Table 6.6, income was assessed with the help of five categories. Hence, integrating income as an ordinal variable in the models would result in 4 predictors in the models (i.e., 5 categories -1 reference category). Integrating income as a metric predictor in the models, reduces the number of predictors because only one predictor has to be integrated. It is reasonable to consider income as (semi-)metric because the first four categories (i.e., ≤ 1000, 1001 – 2000, 2001 – 3000, and 3001 – 4000 Euro per month) have the same spacing between each other. Only the last category (i.e., ≥ 4000 Euro per month) differs from the other income categories in terms of spacing because it is infinite. However, only few participants of the present sample belong to the category with an income ≥ 4000 Euro. Summarizing, income was integrated as a (semi-)metric predictor in the model because the structure of the assessed income categories can be considered as (semi-)metric and the only biased category (i.e., ≥ 4000) is the smallest of all income categories in the present sample.

Regarding the participant's household situation, the six different categories listed in detail in Table 6.6 were reduced to two categories, i.e., (1) having children in contrast to not having children and (2) living alone in contrast to living together with someone such as roommates, a partner or a partner and children. An iterative testing of different predictors of the participant's household situation has shown that the integration of more levels of household situation does not improve the quality of the models significantly. Consequently, in order to avoid unnecessary complexity in the models, the other levels of household situation were excluded from the final models.

Similarly, the participant's frequency of pre-trip information collection was reduced to a binary predictor. Here, the six levels listed in detail in Table 6.3 were aggregated to one contrast, namely collecting pre-trip information always and regularly vs. less than regularly. Again, an iterative testing of the effects of more levels of pre-trip information collection has shown that the integration of more levels of pre-trip information collection does not improve the quality of the models significantly. Consequently, pre-trip information collection was integrated as a binary predictor into the final models.

Finally, all alternative-specific variables were integrated as ordinal predictors with three levels. More details on the selection of predictors are illustrated in Table 6.8.

Table 6.8 Selection of Predictors Included in the Present Scenario (own illustration).

Included predictors	**Scale**
Individual-specific	
Demographic	
Age	metric
Gender	binary (male vs. female)
Income	metric
Household situation	
• Kids	binary (yes vs. no)
• Single apartment	binary (yes vs. no)
Place of residence	ordinal with 5 levels (see Table 6.6)
Access to public transport	metric (in minutes from home)
Actual commuting time in car	metric (only in commuting scenarios)
Leisure time car	metric (only in leisure time trip scenarios)
Attitudes	
Frequency of pre-trip information collection	binary (always or regularly vs. not regularly)
Alternative-specific	
Cost	ordinal with 3 levels (see Table 6.4)
Travel time	ordinal with 3 levels (see Table 6.4)
Waiting time	ordinal with 3 levels (see Table 6.4)
Walking time	ordinal with 3 levels (see Table 6.4)
Parking costs	ordinal with 3 levels (see Table 6.4)
Features of car	ordinal with 3 levels (see Table 6.4)
Excluded predictors	**Reason**
Education	large inter-correlation with occupation status and income
Occupation status	large inter-correlation with education and income
Actual commuting time in public transport	large correlation with actual commuting time in car
More levels of household situation (e.g. single parent)	model economy

MNL Estimation and Test of IIA-assumption. Table 6.9 summarizes the results of the Hausman McFadden Test which tests the IIA-assumption. As described in Chapter 6.1.2, non-significant test results indicate that the IIA holds, whereas significant test results indicate that the IIA has to be rejected. According to Hausman and McFadden [85, p. 1226], this thesis applies the decision rule that negative estimates indicate that the IIA holds. In conclusion, the results highlight that the IIA-assumption has to be rejected in all four scenarios. Hence, Table 6.10 only briefly summarizes the key parameters of the multinomial logit models (MNL) for the four scenarios. Due to the unfulfilled IIA-assumption, the MNLs are, however, not selected as the final discrete choice model.

Table 6.9 Hausman McFadden Test Results (present scenario; own illustration).

	χ^2	*p-value*	*IIA*
Commuting - Low time pressure			
All alternatives vs. subset without pooling as driver	-67.23	1.00	accepted
All alternatives vs. subset without pooling as passenger	-55.05	1.00	accepted
All alternatives vs. subset without public transport	17.82	1.00	accepted
All alternatives vs. subset without own car	1179.70	<.001	rejected
Commuting - High time pressure			
All alternatives vs. subset without pooling as driver	37.25	1.00	accepted
All alternatives vs. subset without pooling as passenger	-20.57	1.00	accepted
All alternatives vs. subset without public transport	12.96	1.00	accepted
All alternatives vs. subset without own car	226.46	<.001	rejected
Leisure time - Low time pressure			
All alternatives vs. subset without pooling as driver	-101.38	1.00	accepted
All alternatives vs. subset without pooling as passenger	-0.96	1.00	accepted
All alternatives vs. subset without public transport	-55.97	1.00	accepted
All alternatives vs. subset without own car	146.69	<.01	rejected
Leisure time - High time pressure			
All alternatives vs. subset without pooling as driver	-54.59	1.00	accepted
All alternatives vs. subset without pooling as passenger	-436.48	1.00	accepted
All alternatives vs. subset without public transport	4.01	1.00	accepted
All alternatives vs. subset without own car	670.59	<.001	rejected

Table 6.10 Log-Likelihood, McFadden's R^2 and the Likelihood Ratio Test for the Multinomial Logit Models for all Four Present Scenarios including all Alternatives (own illustration).

	Log-Likelihood	R^2	**Likelihood ratio test**	
Scenario			χ^2	*p-value*
Commuting - Low time pressure	-2927.6	0.20	1474.3	<.001
Commuting - High time pressure	-2142.2	0.20	1050.3	<.001
Leisure time - Low time pressure	-2974.6	0.17	1208.1	<.001
Leisure time - High time pressure	-2121.6	0.22	1193.2	<.001

Estimation of Nested Logit Models. As illustrated in Figure 6.5, the next step is to estimate nested logit models that do not underlie the IIA-restriction. Table 6.11 presents an overview about the tested nesting structures. Here, four nesting structures with two nests were considered. Specifically, the differentiations between (1) conventional means of transport (i.e., own car and public transport) and pooling, (2) driving yourself and being driven, (3) travelling by public transport and travelling by car and (4) travelling in your own car in contrast to all other alternatives were considered. Finally, a fifth nesting structure with three nests was considered, namely travelling by public transport (i.e., nest 1) in contrast to pooling (i.e., nest 2) in contrast to traveling by your own car (i.e., nest 3).

Since the nested models were not selected as the final models for this thesis, Table 6.12 only summarizes the key statistics of the different tested nested models. Comparing the R^2 of the NLs listed in Table 6.12 with the R^2 of MNLs listed in Table 6.10, shows that the different nesting structures do not significantly improve the overall model fit. Instead, the R^2 of the NLs more or less equals the R^2 of MNLs or is even marginally smaller. Nevertheless, with most $R^2 \geq .20$, the NLs already show a very good model fit (see Table 6.7 for conventions). Regarding the inclusive value parameters of the NLs, Table 6.12 shows that the parameters are either very close to the cut-off score of 1.00 or even ≥ 1.00. Taken together, the results of the R^2, the results of the inclusive value parameters and the comparison of the NLs with the MNLs does not suggest that the NLs should be selected as the final class of models. Therefore, none of the nested models was chosen as the final model.

Table 6.11 Overview of Tested Nesting Structures in the Present Scenario (own illustration; PT = public transport; own illustration).

Nesting structures	Nest 1	Nest 2	Nest 3
Conventional means of transport vs. pooling	Own car Public transport	Pooling as driver Pooling as passenger	x
Drive yourself vs. being driven	Own car Pooling as driver	Public transport Pooling as passenger	x
Public transport vs. travelling by car	Public transport	Own car Pooling as driver Pooling as passenger	x
Travelling in your own car vs. else	Own car	Public transport Pooling as driver Pooling as passenger	x
Public transport vs. pooling vs. own car	Public transport	Pooling as driver Pooling as passenger	Own car

Estimation of Mixed Logit Models. Table 6.13 summarizes the model coefficients of the final MMNL models of all four present scenarios. All effects with $p > .10$ were omitted from the models. Hence, Table 6.13 contains all effects with $p \leq .05$ and all effects with $.05 < p \leq .10$, whereas the latter are highlighted in blue for better differentiation of the effects. More details about the final estimates can be found in Appendix K to Appendix N. Besides the estimates of the coefficients, the appendices also contain the standard errors of the estimates, the *z*-values and the *p*-values for each coefficient.

"As utility is a dimensionless index meant for comparing the attractiveness of alternatives on a common scale, one of the alternatives is set as the [reference level] against which the other alternatives are compared" [154, p. 8]. In order to make the results of the present and future scenario comparable, public transport was chosen as the reference level because this is the only mode that is integrated in both, the present and future scenario.

First of all, the results concerning the **intercepts** and **random intercepts** will be reported. Mode-specific intercepts "capture the effect of unobserved variables and measurement errors" [154, p. 8]. Since public transport is the reference level in the present analysis, public transport has an intercept value and a random intercept value of 0. Regarding commuting under low time pressure, own car has the biggest intercept and regarding commuting under high time pressure, pooling as a driver has the biggest intercept. Concerning leisure time trips under low and high time pressure, pooling as a passenger has the biggest intercept in both scenarios. The big intercepts of pooling as a driver and pooling as a passenger might be explained by the relatively small percentage of pooled rides in the dataset compared to the percentage of rides by car and public transport (see Figure 6.10). With regard to the random intercepts, own car has the biggest random intercept in all four present scenarios, perhaps due to the high relevance of alternative-specific random effects for this mode. This aspect will be described in more detail below in the section focusing on random effects.

Next, the results regarding the **individual-specific variables** will be described:

- **Age** has small effects in all four scenarios. The older the traveler, the more likely they are to choose a private car compared to public transport. In contrast, pooling as a driver and passenger is associated with a younger age in all scenarios except for leisure trips with high time pressure where the effect is the other way around. Here, older travelers are more likely to choose pooling as a passenger compared to public transport.

- Regarding **gender**, men compared to women are less likely to choose (1) pooling as a passenger compared to public transport during commuting under low time pressure, (2) their own car compared to public transport during commuting under high time pressure, and (3) pooling as a driver compared to public transport during leisure time trips under low time pressure. In contrast, men compared to women are more likely to choose (1) pooling as a passenger compared to public transport during leisure time trips under low time pressure, (2) their own car, and (3) pooling as a driver compared to public transport during leisure time trips under high time pressure.

- **Income** has positive effects on choosing pooling as a driver compared to public transport in all scenarios except for leisure time trips under high time pressure. Income also has positive effects on own car usage compared to public transport usage during commuting under high time pressure. However, regarding leisure time trips, income has negative effects on own car usage compared to public transport usage.

- **Having children** compared to not having children reduces the probability to choose pooling as a passenger compared to public transport in all scenarios except for commuting under high time pressure where having children has no effect on pooling as a passenger. In the two conditions with low time pressure, having children enhance the probability to choose a private car compared to public transport. During leisure time with high time pressure, having children reduces the probability to choose pooling as a driver compared to public transport whereas during commuting under high time pressure it enhances the probability to choose pooling as a driver compared to public transport. **Living alone** compared to living together with a partner, children or roommates, reduces the probability to choose pooling as a passenger compared to public transport in all scenarios except for commuting under high time pressure. Here, living alone enhances the probability for carpooling as a passenger. Moreover, travelers who live alone are less likely to choose their own car in the two scenarios with high time pressure and pooling as a driver during commuting under low time pressure.

- The results concerning the **place of residence** show that living in less populated areas (i.e., medium city, small city, town, and village) compared to living in large cities enhances the probability to choose a private car or carpooling compared to public transport. The models only contain one marginally significant negative effect of place of residence, namely that inhabitants of medium cities are less likely to choose pooling as a passenger compared to public transport during leisure time trips under low time pressure. Similarly, travelers who have a longer **way from their home to the next public transport station** are more likely to choose their own car or carpooling in most scenarios.

- A **higher commuting time** or, regarding leisure time trips, an on average **longer way to leisure time activities** enhances the probability to choose carpooling as a driver compared to public transport in all scenarios except for commuting under high time pressure.

- Regarding the effect of **pre-trip information collection**, the collection of pre-trip information reduces the probability to choose a private car and carpooling compared to public transport during commuting. It has also a negative effect on private car usage during leisure time and a positive effect on carpooling during leisure time trips under low time pressure.

Next, the results on the **alternative-specific variables** will be described. Here, the reference level is always the lowest level of the alternative-specific variable. The lowest level is then compared to the medium and the highest level of the same variable:

- The results concerning the alternative-specific variables show nearly constantly negative effects of **costs** during commuting. In the context of commuting under high time pressure higher costs do not negatively affect the probability to choose public transport. Moreover, during commuting under high time pressure, the negative effect of costs on carpooling as a passenger is only significant regarding the third level of costs and not regarding the second level of costs. During leisure time trips, the medium cost level compared to the lower cost level only shows negative effects on carpooling during low time pressure. During leisure time, higher costs do not reduce the probability to choose public transport compared to lower costs. All other modes are affected negatively by the third cost level compared to the lower cost level during leisure time trips. Additionally, **parking costs** affect the probability to choose private car or pooling as a driver negatively in all scenarios except for leisure time trips under high time pressure.

- Higher **travel times** show constantly negative effects in all scenarios and on all modes except of public transport in the context of leisure time trips under high time pressure.

- **Waiting times** only show a significant negative effect of the medium level compared to the lower level on pooling as a passenger during commuting with low time pressure while choosing public transport is only affected negatively by the third level of waiting time in this scenario. Waiting times did not significantly affect the probability to choose public transport or pooling as a passenger in the scenario commuting with high time pressure. During leisure time trips, both, public transport and pooling as a passenger are affected negatively by the third level of waiting time compared to the lower level of waiting time.

- Similar to waiting times, **walking times**, show more significant effects for the contrast of the third to the first level than for the contrast of the second to the first level of walking times. In sum, however, walking times show more negative effects than waiting times. Besides the effects of walking times on pooling as a passenger and public transport, especially in the two scenarios with low time pressure, higher walking times affect the probability to choose private cars and pooling as a driver negatively.

- **Additional features** affect the probability to choose pooling as a passenger positively in scenarios with low time pressure. In scenarios with high time pressure, however, additional features did not show significant effects.

Finally, the analysis of the **random effects** shows a lot of individual-specific random effects regarding the alternative-specific attributes. During both, commuting and leisure time trips, the importance of individual-specific random effects is higher in scenarios with high time pressure compared to scenarios with low time pressure (i.e., more and higher significant effects). This is especially the case for the attributes associated with private car usage. The probability to choose carpooling is constantly affected by individual-specific random effects in all scenarios and concerning all alternative-specific attributes.

In sum, the MMNL models express a significantly better overall model fit than the MNL models and NL models presented above. With R^2 between 0.31 and 0.36, the R^2 of the MMNL models are approximately by 0.10 greater than the R^2 of the MNL models (0.17-0.22) and the NL models (0.15-0.21). Moreover, the Log-Likelihoods of the MMNL models ((-2469.2) - (-1733.8)) are significantly greater than the Log-Likelihoods of the MNL models ((-2974.6) - (-2121.6)) and the NL models ((-3030.6) - (-2139.3)).

Table 6.12 Log-Likelihood, McFadden's R^2, Likelihood Ratio Tests and the Inclusive Value Parameter for the Tested Nested Logit Models for all Four Present Scenarios (PT = public transport; ***p <. 001; own illustration).

Scenario	**Log-Likelihood**	R^2	**Likelihood ratio test**		**Inclusive value parameter**		
			χ^2	***p-value***	**Nest 1**	**Nest 2**	**Nest 3**
Commuting - Low time pressure							
Conventional vs. pooling	-2924.7	0.20	1480.1	<.001	0.86***	0.85***	
Drive vs. being driven	-2927.3	0.20	1475.1	<.001	0.98***	0.94***	
PT vs. car	-2927.2	0.20	1475.3	<.001	1.04***	1.05***	
Own car vs. else	-2925.9	0.20	1477.9	<.001	0.94***	0.90***	
PT vs. pooling vs. own car	-2926.2	0.20	1477.3	<.001	0.98***	0.92***	0.92***
Commuting - High time pressure							
Conventional vs. pooling	-2139.7	0.20	1055.3	<.001	1.01***	1.15***	
Drive vs. being driven	-2141.5	0.20	1051.8	<.001	0.92***	0.94***	
PT vs. car	-2141.1	0.20	1052.6	<.001	1.08***	1.12***	
Own car vs. else	-2140.7	0.20	1053.3	<.001	1.06***	1.21***	
PT vs. pooling vs. own car	-2139.3	0.20	1056.0	<.001	1.17***	1.23***	1.15***
Leisure time - Low time pressure							
Conventional vs. pooling	-3030.6	0.15	1096.2	<.001	0.95***	0.99***	
Drive vs. being driven	-3029.3	0.15	1098.8	<.001	0.93***	0.86***	
PT vs. car	-3028.8	0.15	1099.9	<.001	1.11***	1.04***	
Own car vs. else	-3029.3	0.15	1098.8	<.001	0.90***	1.00***	
PT vs. pooling vs. own car	-3028.0	0.15	1101.3	<.001	1.09***	1.02***	0.95***
Leisure time - High time pressure							
Conventional vs. pooling	-2152.8	0.21	1130.8	<.001	1.07***	1.02***	
Drive vs. being driven	-2153.0	0.21	1130.3	<.001	0.96***	0.95***	
PT vs. car	-2150.8	0.21	1134.8	<.001	1.01***	0.87***	
Own car vs. else	-2151.0	0.21	1134.3	<.001	0.97***	1.11***	
PT vs. pooling vs. own car	-2151.1	0.21	1134.2	<.001	1.03***	0.97***	0.93***

Table 6.13 Summary of Final MMNL Results of all Four Present Scenarios (own illustration: OC = Own Car, PD = Pooling as a Driver, PP = Pooling as a Passenger, PT = Public Transport, RL = Reference Level; only coefficients with $p \leq .05$ are listed, coefficients with $0.5 < p \leq .10$ are highlighted in blue; prohibitions of attributes are highlighted in orange).

	Commuting – Low time pressure				**Commuting – High time pressure**				**Leisure time trips – Low time pressure**				**Leisure time trips – High time pressure**			
Mode	**OC**	**PD**	**PP**	**PT**	**OC**	**PD**	**PP**	**PT**	**OC**	**PD**	**PP**	**PT**	**OC**	**PD**	**PP**	**PT**
Intercept	-1.61	-0.68	-0.31	RL	0.35	-2.88	0.86	RL	0.10	-1.81	-3.37	RL	0.36	-1.05	-3.43	RL
Individual-specific																
Age	0.02	-0.09	-0.03	Reference level	0.07		-0.04	Reference level	0.04	-0.06	-0.03	Reference level	0.03		0.06	Reference level
Gender			-0.43		-0.61					-0.54	0.43		1.39	1.05		
Income		0.41			0.35	0.54			-0.33	0.31	0.64		-0.35			
Kids	1.13		-1.48			0.77			1.42		-2.73			-0.75	-1.65	
Alone		-1.10	-1.28		-1.21		0.64				-0.53		-0.95		-0.58	
Medium city	0.94	2.56	1.96		3.38	4.29	1.51				-0.66		2.17	1.45	0.65	
Small city	1.20	1.25	1.04		2.58	2.92	1.27		0.66	1.68	0.73		3.24	2.85	2.24	
Town		1.02			3.23	3.94	2.68		0.60	1.35			3.51	4.92	2.15	
Village	0.82	2.50	1.17		1.82	2.42	2.04		0.74	2.30	1.54		3.23	2.55	0.82	
PT access	0.19	0.10	0.09		-0.16	0.17				0.08	0.19					
Time in car		0.01					-0.01		-0.01	0.02	-0.01			0.01	0.02	
Frq. info.		-0.36	-0.47		-1.17	-1.24	-0.91		-2.09	0.67	1.05		-1.27	-0.73		
Alternative-specific																
Cost 2	-0.49	-0.84	-0.48	-0.36	-0.59	-0.64				-1.08	-0.76					
Cost 3	-0.93	-1.45	-1.28	-0.85	-0.52	-0.85	-0.59		-0.73	-1.18	-1.41	-0.62	-0.71	-0.80	-0.70	
Time 2	-0.73	-0.79	-0.43	-0.56	-0.52	-0.80	-0.79	-0.55	-0.40	-0.70	-0.44	-0.70	-0.46	-0.86	-0.72	
Time 3	-1.10	-2.18	-1.05	-0.94	-1.38	-1.69	-1.64	-1.05	-1.11	-1.63	-0.71	-1.20	-0.63	-1.28	-0.96	-0.49
Wait 2			-0.52													
Wait 3				-0.39							-0.55	-0.41			-0.61	-0.52
Walk 2		-0.33	-0.49	-0.45						-0.73		-0.78				
Walk 3	-0.34		-0.98	-0.57			-0.51		-0.97	-0.73	-0.70	-0.66			-0.60	-0.52

	Commuting – Low time pressure				Commuting – High time pressure				Leisure time trips – Low time pressure				Leisure time trips – High time pressure			
Mode	**OC**	**PD**	**PP**	**PT**	**OC**	**PD**	**PP**	**PT**	**OC**	**PD**	**PP**	**PT**	**OC**	**PD**	**PP**	**PT**
Parking costs 2	-0.73	-0.86			-0.68	-0.54			-0.64	-0.68						
Parking costs 3	-1.05	-1.30			-0.85	-0.64			-1.18	-1.21						
Features 2			0.30								0.56					
Features 3			0.64								0.65					
Random effects																
Intercept	3.98	2.59	2.14	RL	4.36	1.93	2.07	RL	4.29	3.23	2.94	RL	4.03	2.54	3.12	RL
Cost 2		-0.77	0.76	0.53	0.56	1.23			-0.38	0.77	-0.32		0.38	0.43	0.41	0.47
Cost 3	0.81		0.92	0.97	-1.32		0.45	-0.60		-0.32			-0.36	1.01	0.48	0.40
Time 2			-0.30	0.36	0.88		-0.35	-0.57	0.34	-0.33	0.30	0.81		0.73	0.55	
Time 3		-0.82			0.66	0.52	0.92		-0.62	-0.58	0.72		-0.31	0.63	1.25	
Wait 2											0.78				-0.67	
Wait 3			0.47	0.44			-0.58				1.14				-0.96	
Walk 2		0.43		0.73	1.64	-0.76	1.04					-0.35	0.50			
Walk 3		-0.52	0.84	0.50		-0.52					0.76		-0.43	-0.50		
Parking costs 2					-0.77	1.12							0.59	0.78		
Parking costs 3					0.38				-0.34							
Features 2							-0.55									
Features 3			0.89								0.91				-0.32	
Model summary (Log-Likel. = Log-Likelihood)																
Log-Likel.	-2469.2				-1828.4				-2313.0				-1733.8			
R^2	0.33				0.31				0.35				0.36			
Likelihood ratio test	χ^2		*p-value*		χ^2		*p-value*		χ^2		*p-value*		χ^2		*p-value*	
	2391.1		<.001		1678.0		<.001		2531.4		<.001		1968.8		<.001	

6.3.3 Attitude Towards Carpooling

This section presents the results of the qualitative clustering of the participants' perceived advantages and disadvantages of carpooling in the present scenario. The coding of the free text answers revealed eleven categories of advantages and disadvantages. Regarding the advantages, (1) cost savings, (2) entertainment, conversation and fun and (3) community and meet new people were listed most frequently as advantages of carpooling. Regarding the disadvantages of carpooling, (1) dependence on others, (2) social interaction, communication, and unpleasant strangers, and (3) lack of flexibility were mentioned most frequently. The number of participants who see no advantages at all in carpooling (n = 90) is more than twice as high as the number of participants who see no disadvantages at all in carpooling (n = 37). Table 6.14 summarizes the qualitative results on perceived advantages and disadvantages of carpooling.

Table 6.14 Perceived Advantages and Disadvantages of Carpooling (own illustration).

Advantage	***n***	**Disadvantage**	***n***
Cost savings	223	Dependence on others	124
Entertainment / conversations / fun	216	Social interaction / communication / unpleasant strangers	109
Community / meet new people	115	Lack of flexibility	82
Environmental aspects	72	Unpunctuality / unreliability of others	66
Do not drive yourself / take turns while driving	26	Detours	57
Traffic reduction	17	Comfort restrictions during the trip	56
Speed	16	Waiting time	52
Relaxation / comfort	13	Increased overall time expenses and increased travel time	38
Simplicity / flexibility	9	Coordination efforts	23
Possibility to work / productivity	4	Safety / driving behavior	20
Security	3	Dirt and damage to car	8
Nothing	90	Nothing	37
Everything	4	Everything	12
Other	13	Other	23

6.4 Method and Design of the Future Scenario

In order to learn about the parameters that influence the travelers' modal choices in a future scenario with robo-taxis, an online survey was conducted. This section describes the method and design of the online survey. Similar to the present scenario (see Figure 6.3), the survey can be divided in five main parts, namely (1) an introduction, (2) an assessment of the participants' mobility habits and pre-trip habits, (3) a choice-based conjoint (CBC) analysis, (4) an exploration of the participants' attitude towards ridepooling, and (5) a sociodemographic questionnaire (see Figure 6.11).

The following paragraphs first concentrate on the survey design in general (see Chapter 6.4.1). Figure 6.11 summarizes the overall structure of the survey design. Since the overall structure of the survey and all items apart from the choice tasks are very similar to the present scenario, this chapter does not repeat the detailed description of methods and items presented in Chapter 6.2. Instead, Table 6.15 provides an overview of the content of the future scenario and its differences to the present scenario. A detailed description of the survey part concerning mobility habits and pre-trip habits can be found in Chapter 6.2.2. In order to avoid any repetition, this description is skipped here. Hence, the description of the overall survey structure is directly followed by the description of the CBC analysis (see Chapter 6.4.2). Since Chapter 6.2.3 already contains a detailed introduction to CBC designs, Chapter 6.4.2 only describes the applied AS-CBC design without repeating the methodological background. Finally, Chapter 6.4.3 describe the considered sample of the future scenario and Chapter 6.4.4. provides an overview about the applied data analysis.

6.4.1 Overall Survey Structure

This chapter introduces the overall survey structure of the future scenario. Generally, the survey was conducted very similar to the present scenario. The core focus of the survey was to assess the factors that influence the travelers' modal decisions and willingness for ridepooling in a future scenario. Similar to the present scenario, the route purpose is differentiated within-subject (travelling to work, university or school vs. travelling during leisure time) and the amount of time pressure (high vs. low) is differentiated between-subject. In order to avoid repeating the detailed description of items provided in Chapter 6.2, Figure 6.11 gives an overview about the overall survey structure. Moreover, Table 6.15 illustrates the accordances and differences between the survey of the present and future scenario.

The main difference compared to the present scenario is the focus on robo-taxis and ridepooling. Since the participants are not used to the operation of robo-taxis, the operation was introduced briefly. The introduction to robo-taxis (see Figure 6.11) contained an explanation that robo-taxis are autonomous vehicles that can be used on-demand. They can be reserved with the help of an app and they can either be used alone or shared. Since robo-taxis operate completely autonomously, the participants were told that they could then use the travel time for relaxing, sleeping, working or anything they would like to do. In order to explain, why the own car or carpooling was no longer a possible mobility option in the choice sets, the participants were told that due to legal requirements it would no longer be allowed to drive with a private car into the city center. Instead, the city center might only be reached using public transport or (shared) robo-taxis.

Another difference to the present scenario is that the future scenario contains additional attitude scales. These items were integrated based on the literature review presented in Chapter 2.2.2, which highlighted that attitudes become much more important in future discrete choice models [e.g., 81]. For example, based on the findings of Haboucha, Ishaq and Shiftan [81], two scales assessing the participant's interest in new technologies and trust in robo-taxis were included in the survey. Additionally, the participant's trust in public transport was included in the survey in order to have a comparative level to the participant's trust in robo-taxis. Furthermore, following the insights gained in Chapter 5 of the present thesis, the two most important predictors of the developed technology acceptance model were assessed, namely the participant's hedonic motivation and their performance expectancy. Table 6.16 lists all items and scales that were assessed in the future scenario. All items were assessed on a 5-point Likert scale ranging from 1 = *not agree at all* to 5 = *agree totally*. Since the study includes a German sample, all items were translated to German according to an adaption of Brislin's translation model [104].

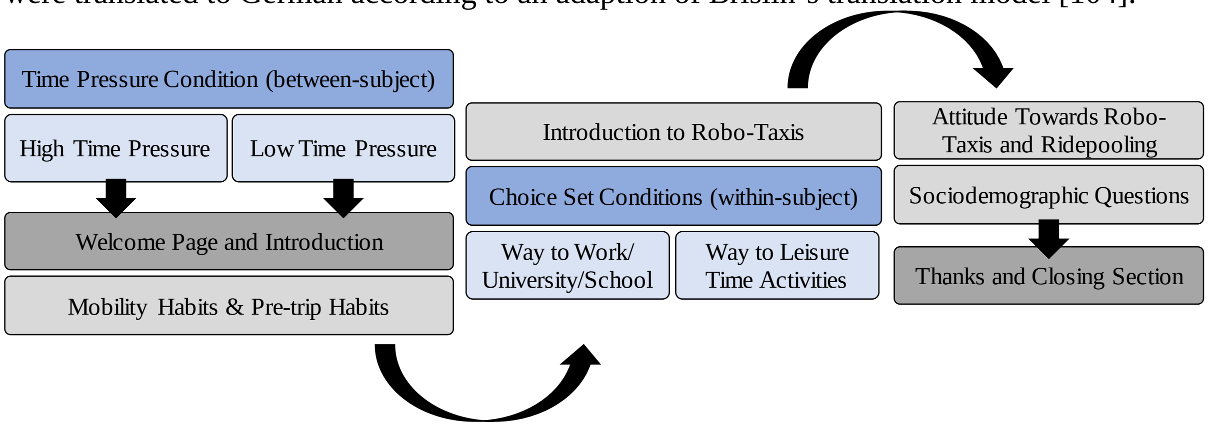


Figure 6.11 Overall Survey Structure of the Future Scenario (own illustration).

Table 6.15 List of Item Content and Answer Options of the Future Scenario (own illustration).

Item content
Mobility habits
As in present scenario (see Table 6.3).
Pre-trip habits
As in present scenario (see Table 6.3).
Calibration of choice sets
No calibration of choice sets because of future scenario.
Instead of calibration of choice sets an introduction to the operation of robo-taxis was presented to the participants.
Choice sets
As in present scenario (see Table 6.3) but with different alternatives, attributes, and attribute levels (see Table 6.17).
Attitude towards ridepooling
As in present scenario (see Table 6.3) but with focus on Ridepooling.
Additional Attitude Scales (see Table 6.16)

Table 6.16 Overview of Scales, Items and Sources (items that were also integrated in the evaluation described in Chapter 5 are highlighted in blue; own illustration).

Scale	Item	Source
Performance expectancy	Robo-taxis will be useful in my daily life.	Venkatesh, Thong, & Xu (2012) [203, p. 178]
	Using robo-taxis will help me accomplish things more quickly.	
	Using robo-taxis will increase my productivity.	
Hedonic motivation	Using robo-taxis will be fun.	
	Using robo-taxis will be enjoyable.	
	Using robo-taxis will be very entertaining.	
Interest in new technologies	I try new products before my friends and neighbors.	Haboucha, Ishaq, & Shiftan (2017) [81, p. 42]
	I know more than others on latest new products.	
	I often purchase new technology products, even though they are expensive.	
	I am excited by the possibilities offered by new technologies.	
	I have little to no interest in new technology.	
Trust in robo-taxis	I would feel safe in robo-taxis	Adapted from Haboucha, Ishaq, & Shiftan (2017) [81, p. 42]
	I would feel nervous in robo-taxis.	
	I would trust the safety of robo-taxis.	
	I would trust the safety of robo-taxis so much that I would allow my children to take robo-taxis to go to school or to sport on their own.	
Trust in public transport	I feel safe in public transport.	
	I feel nervous in public transport.	
	I trust the safety of public transport.	

6.4.2 Choice-Based Conjoint Analysis

This chapter concentrates on the core element of the future scenario, i.e., the CBC analysis. Similar to the present scenario, the future scenario contains an AS-CBC design. Apart from different alternatives, attributes, and attribute levels, the structure of the AS-CBC design applied in the future scenario is similar to the AS-CBC design applied in the present scenario.
Chapter 6.2.3 has already elaborated how the AS-CBC design applied in this thesis looks like and why this is the most suitable method among the different CBC designs for the purpose of this thesis. Therefore, the following paragraphs will skip the theoretical background on CBC analysis. Instead, the concrete determination of choice sets including the considered attributes and their levels will be illustrated. Additionally, the efficiency test that was made before starting the data collection will be reported and discussed.

Determination of Choice Sets. This paragraph concentrates on the specific determination of the choice sets presented in the future scenario. Each choice set consisted of three different modal alternatives of which the participants were asked to choose one, namely (1) public transport, (2) robo-taxis and (3) shared robo-taxi or rather ridepooling. Similar to the present scenario, the choice sets did not include a “none” option, all alternatives were presented exactly once within each choice set, and the stimuli were presented in a fixed order (see Chapter 6.2.3). Moreover, as in the present scenario (see Chapter 6.2.3), each participant answered *n* = 16 choice sets in total, of which *n* = 8 choice sets focused travelling to work, university or school and *n* = 8 choice sets focused travelling during leisure time. The route purpose condition was introduced at the beginning of the two different sets of choice sets with a short explanation. Figure 6.12 visualizes an exemplary choice set presented in the future scenario.

Selection of Attributes and Attribute Levels. This paragraph describes the selection of attributes and attribute levels considered in the future scenario. Similar to the present scenario (see Table 6.4), each attribute was differentiated on three ordinal levels. The attributes price, waiting time, walking time, travel time and additional features were both, implemented in the present and future scenario. The reason for the integration of these attributes was already elaborated in Chapter 6.2.3. The attribute levels of waiting time, walking time, and additional features in the future scenario were the same as in the present scenario. However, the attributes levels of price and travel time differed between the present and the future scenario. The formulas used in the present scenario to calculate the levels of price and travel time individually (see Table 6.4), were not applicable in the future scenario. Therefore, the future scenario contained fixed (in contrast to individually calculated) levels with the same grading of levels as in the present scenario (i.e., lower level: -10%, base level: +10%, and upper level: +50%). The base price was taken from a recent pricing analysis regarding robo-taxis [200, p. 44]. The levels of travel time were based on an expert discussion with *n* = 5 experts from the field of future traffic simulations.

Compared to the present scenario, the future scenario does no longer include the attribute parking costs because neither travelling by public transport nor travelling by robo-taxi requires paying parking tickets. Hence, the attribute was dropped in the future scenario.

Furthermore, the future scenario contained two new attributes for (shared) robo-taxis, namely security information and individual offers. These two attributes were selected based on the literature review presented in Chapter 2.2.2. As elaborated in the literature review, recent research [e.g., 81,223] supported the necessity to expand traditional choice models among predictors regarding the equipment and security of autonomous vehicles. Concerning security, the future scenario contained an attribute that differentiated three levels of available security information in (shared) robo-taxis, namely (1) no security information, (2) a digital brochure with security information and a video guide, and (3) a digital security assistant. Concerning the equipment of the robo-taxi, the future scenario contained an attribute that differentiated three different levels of individual offers, namely (1) no additional offers, (2) an individual account with a saved seating position, the possibility to access an individual message and entertainment account, and (3) the individual account plus the offer of snacks and drinks. Table 6.17 illustrates all attributes and attribute levels considered in the future scenario. Figure 6.12 illustrates the implementation of the different alternatives, attributes and attribute levels into an exemplary choice set.

Table 6.17 Attributes and Attributes Levels for the Future Scenario (blue highlighting = these attributes were not integrated in the present scenario; PT = Public Transport, IA = Individual Account, C = Catering; own illustration).

Mode	Attribute	Reference			Attribute levels		
Robo-taxi	Price (€)	Grading of levels as in present scenario. Base price taken from recent pricing analysis [200, p. 44].					
		-10%	Base +10%	+50%	3.58€	4.38€	5.97€
	Waiting time (min.)	Attribute levels as in present scenario			3	5	7
	Walking time (min.)	-	-	-	-	-	-
	Travel time (min.)	Grading of levels as in present scenario.					
		-20%	Base	+20%	12	15	18
	Additional features	Grading of levels as in present scenario.			Small	Mid-range	Upper-range
	Security information	New attribute			None	Digital bro-chure + video	Digital assis-tant
	Individual offers	New attribute			None	IA	IA + C
Shared robo-taxi	Price (€)	Grading of levels as in present scenario. Base price taken from recent pricing analysis [200, p. 44].					
		-10%	Base* 0.50 +10%	+50%	1.79€	2.19€	2.99€
	Waiting time (min.)	Attribute levels as in present scenario			3	5	7
	Walking time (min.)	Attribute levels as in present scenario			0	3	6
	Travel time (min.)	Grading of levels as in present scenario. Base = travel time by robo-taxi + 5-minute detour time					
		-20%	Base	20%	17	20	23
	Additional features	Grading of levels as in present scenario.			Small	Mid-range	Upper-range
	Security information	New attribute			None	Digital bro-chure + video	Digital assis-tant
	Individual offers	New attribute			None	IA	IA + C
PT	Price (€)	-10%	+10%	+50%	1.79€	2.19€	2.99€
	Waiting time (min.)	Attribute levels as in present scenario			3	5	7
	Walking time (min.)	Attribute levels as in present scenario			0	3	6
	Travel time (min.)	Grading of levels as in present scenario. Base = travel time by robo-taxi + 5-minute detour time					
		-20%	Base	20%	17	20	23
	Additional features	-	-	-	-	-	-

Mode	Attribute	Reference	Attribute levels		
	Security information	New attribute	-	-	-
	Individual offers	New attribute	-	-	-

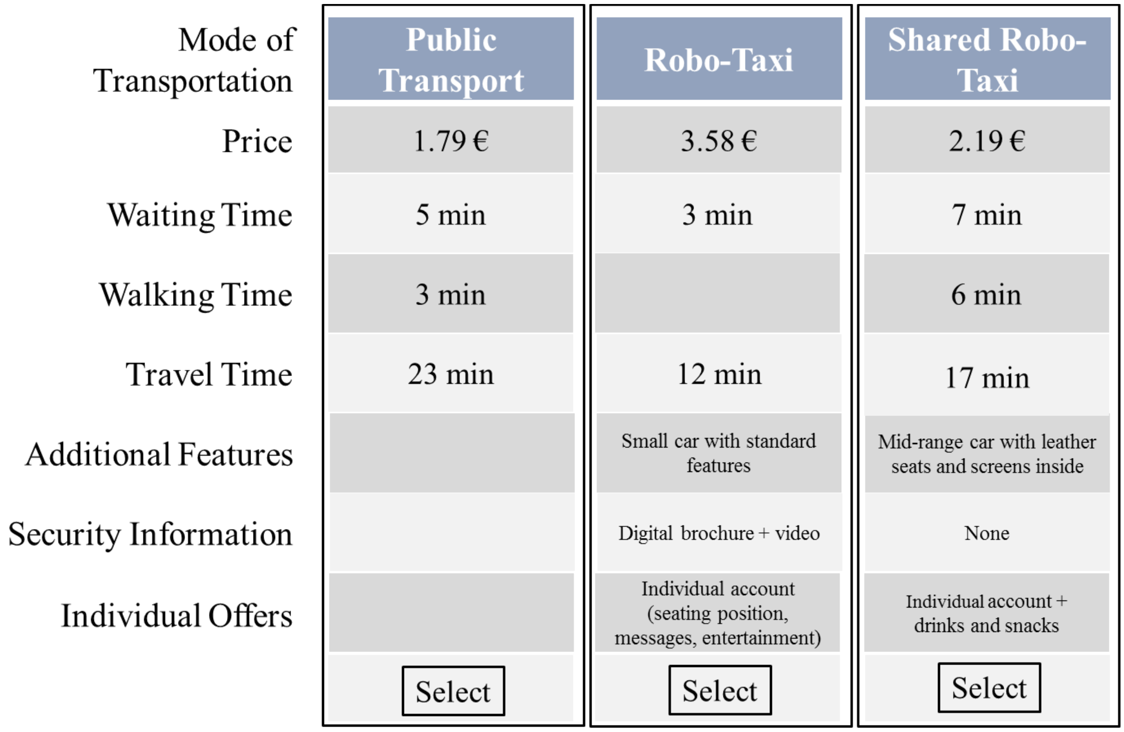


Figure 6.12 Exemplary Choice Set Presented in the Future Scenario (own illustration).

Efficiency Testing. After describing the selection of attributes and attribute levels, this paragraph focuses on the efficiency of the survey design. Similar to the present scenario (see Chapter 6.2.3), a complete enumeration approach was applied because this approach is recommended in the context of an AS-CBC design [169]. Table 6.18 illustrates the efficiency test of the AS-CBC design calculated with complete enumeration as task generation method based on n = 300 versions with n = 8 choice sets in each version (i.e., 2400 modal decisions in total). The efficiency testing was estimated with the help of Sawtooth. The results of the efficiency test comply with the conventions for standard errors for common attributes ≤ 0.05 and for alternative-specific attributes ≤ 0.10 [169]. In conclusion, the efficiency testing confirmed the goodness of the design of the future scenario and showed that a sample size of *n* = 300 participants represents an efficient sample size.

Table 6.18 Efficiency Test of the AS-CBC Design of the Future Scenario with Complete Enumeration as Task Generation Method (Based on 300 versions with 8 Choice Sets in each Version and 2400 Total Choice Tasks) (blue highlighting = alternative-specific attributes; own illustration).

Attribute	Attribute level	Standard error	Attribute	Attribute level	Standard error
Price robo-taxi	-10%	0.061	**Travel time other modes**	-20%	0.039
	+10%	0.061		Base	0.039
	+50%	0.061		+20%	0.039
Price other modes	-10%	0.039	**Additional features**	Small	0.039
	+10%	0.039		Mid-range	0.039
	+50%	0.039		Upper-range	0.039
Waiting time	3 Min	0.029	**Walking time**	0 Min	0.039
	5 Min	0.029		3 Min	0.039
	7 Min	0.029		6 Min	0.039
Security information	None	0.039	**Individual offers**	None	0.039
	Digital Brochure + Video	0.038		Individual Account	0.039
	Digital Assistant	0.039		Individual Account + Snacks + Drinks	0.039
Travel time robo-taxi	-20%	0.061			
	Base	0.062			
	+20%	0.061			

6.4.3 Participants

After the recruiting phase from January 2019 until February 2019, *n* = 617 participants answered the survey completely. The participants were recruited in the BMW World in Munich (Germany) and via e-mail and answered the survey in German. As in the present scenario, informed consent was obtained and only full data sets were included in the analysis. In order to obtain a high-quality sample, the same cut-off scores as in the present scenario were used. These cut-off scores made sure that only participants who answered the survey conscientiously and did not just “click through” the survey were included in the further analysis. In sum, *n* = 27 (4.38%) were excluded from the analysis because they answered all choice tasks in less than 120 seconds and chose the same alternative in all choice tasks. Additionally, *n* = 9 participants (1.46%) were excluded because of lacking variance in their answers (i.e., SD = 0 on multiple survey pages), which indicates that they clicked through the survey. Furthermore, two participants (0.32%) were excluded from further analysis because of an outlier in their number of owned cars (i.e., number of owned cars > 10). Hence, further analysis was made with *n* = 579 participants ($n_{\text{high time pressure}}$ = 267, $n_{\text{low time pressure}}$ = 312). Since every participant answered *n* = 16 choice tasks, this equals a total number of *n* = 9,264 decisions ($n_{\text{high time pressure}}$ = 4,272, $n_{\text{low time pressure}}$ = 4,992). Among these participants, the age ranged between 18 and 80 years (*M* = 32.29, *SD* = 11.98). Among the participants, *n* = 292 were male (50.43%), *n* = 280 were female (48.36%) and seven participants (1.21%) did not give details about their gender. With regard to their occupation status, most participants were working professionals and students, namely 53.71% were working professionals (*n* = 311) and 31.09% of the participants were students (*n* = 180). More details on the sample can be found in Table 6.19.

Table 6.19 Demographic Characteristics of the Sample of the Future Scenario (own illustration).

	n	**%**			***n***	**%**
Final sample of participants	579	100		**Place of residence**		
Sample high time pressure	267	46.11		Large city (> 500.000)	355	61.31
Sample low time pressure	312	53.89		Medium city (> 100.000 - 499.999)	53	9.15
Final sample of decisions	9264	100		Small city (20.000 - 99.999)	53	9.15
Decisions high time pressure	4272	46.11		Town (5.000 - 19.999)	59	10.19
Decisions low time pressure	4992	53.89		Village (< 5.000)	59	10.19
Gender				**Household situation**		
Male	292	50.43		Single	149	25.73
Female	280	48.36		Shared apartment	144	24.87
No Details	7	1.21		With partner	164	28.32
Occupation status				With partner and children	74	12.78
Working professionals	311	53.71		Single parent	16	2.76
Students	180	31.09		Other	32	5.53
Other	26	4.49		**Education**		
In education (apprentice)	21	3.63		Secondary school	11	1.90
PhD Students	18	3.11		Junior high school	35	6.04
Retired	15	2.59		High school	157	27.12
Unemployed	8	1.38		Apprenticeship	71	12.26
Net-Income (Euro/Month)				Master craftsman	13	2.25
≤ 1000	88	15.20		Bachelor	114	19.69
1001-2000	194	33.51		Master	144	24.87
2001-3000	147	25.39		PhD	16	2.76
3001- 4000	50	8.64		Other	18	3.11
≥ 4001	46	7.94		**Car class of private car**		
No Details	54	9.33		Small car	140	32.11
Car ownership				Mid-range car	249	57.11
Yes	368	63.56		Upper-range car	47	10.78
No	211	36.44				

	Min	Max		Mean	SD
Age	18	80		32.29	11.98
Access to PT (in minutes from home)	0.5	11		5.50	3.07
Cars in household	0	8		1.29	1.19

6.4.4 Data Analysis

This chapter focuses on the tools used to analyze the collected data of the future scenario. Since the data collection of the future scenario was handled completely analogous to the data collection and analysis of the present scenario, this chapter only briefly summarizes the procedure which was already explained in detail in Chapter 6.2.5. The data of the future scenario was collected with the help of the online survey tool Sawtooth [170] which is embedded in Lighthouse Studio 9.6.1.

After the data collection, Microsoft Excel (2013) was used for preparatory analysis. RStudio Version 1.1.463 [165] relaying on R 3.5.2 [165] was used for higher level analysis. Within RStudio, the mlogit package [52] was used for estimating MNL, NL and MMNL models.

The data was mainly analyzed using descriptive statistics, discrete choice modelling, and qualitative clustering. The theory of the applied modelling procedure was already explained in detail in Chapter 6.1. Additionally, Figure 6.5 in Chapter 6.2.5 summarizes briefly the applied systematic procedure for discrete choice modelling. Furthermore, qualitative data was analyzed according to the clustering procedure described in Chapter 3.3.1.

6.5 Results of the Future Scenario

This chapter summarizes the results of the future scenario. The results will be presented in the same order as the data for the different parts of the questionnaire was collected (see Figure 6.11). Similar to the structure of Chapter 6.3, the following paragraphs will first describe the results concerning the participants' current mobility habits and pre-trip habits (see Chapter 6.5.1). Next, the results of the main part of the survey will be reported, i.e., the results from the AS-CBC study (see Chapter 6.5.2). The CBC-data will be analyzed according to the procedure illustrated in Figure 6.5 which includes multinomial logit models, nested logit models and mixed multinomial logit models. Finally, the results regarding the participants' attitude towards ridepooling will be outlined (see Chapter 6.5.3).

6.5.1 Mobility Habits and Pre-trip Habits

The following paragraphs summarize the participants' current mobility habits and pre-trip habits descriptively. In order to better understand the main results of the future scenario (i.e., the AS-CBC results), Figure 6.13 to Figure 6.16 provide an overview about the participants' current mobility habits, modal decisions, and pre-trip habits. Similar to Chapter 6.3.1, the results will only be described very briefly because the main focus of the results section is the discrete choice modelling presented in Chapter 6.5.2.

Figure 6.13 illustrates that most participants use their own car or public transport for commuting whereas carsharing (never: 78.93 %), carpooling as a driver (never: 75.65 %), and carpooling as a passenger (never: 67.53 %) are rarely used for commuting. Moreover, nearly half of the participants (46.98%) never use their bike for commuting. Compared to commuting, Figure 6.14 illustrates that carpooling as a driver (never: 69.43%) and carpooling as a passenger (never: 55.44%) is more frequently used for leisure time trips than for commuting. Similar to commuting, carsharing is also rarely used for leisure time trips (never: 78.24%). Own car and public transport remain as the two main modes of the present sample.

The participants' pre-trip habits are summarized in Figure 6.15 and Figure 6.16. Figure 6.15 illustrates that only few participants always inform themselves before their trip (i.e., commuting: 18.48%, leisure time trips: 24.35%). Before commuting, 29.71% of the participants never inform themselves about their upcoming trip (compared to 25.08% in the present scenario). Concerning leisure time trips, only 17.10% of the participants never inform themselves pre-trip (compared to 42.13% in the present scenario). Regarding the type of information that is collected pre-trip, Figure 6.15 visualizes that, similar to the present scenario, traffic, travel time and departure time are the top three information needs.

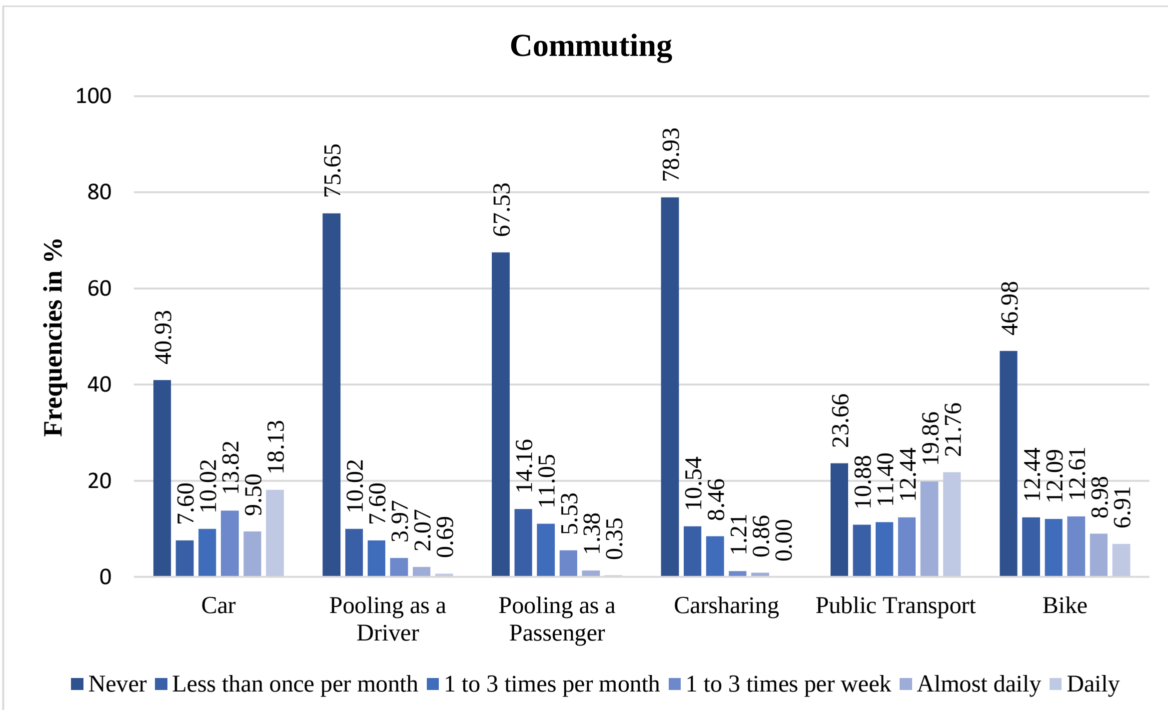


Figure 6.13 Current Mobility Habits of the Sample of the Future Scenario with regard to Commuting (own illustration).

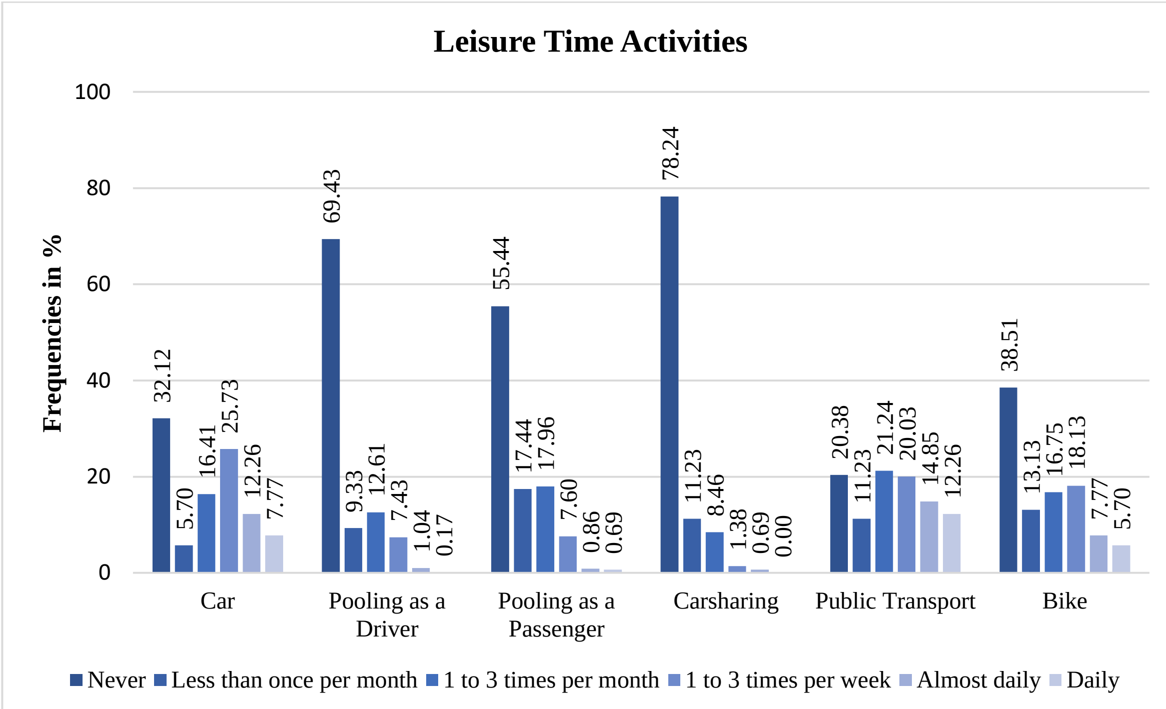


Figure 6.14 Current Mobility Habits of the Sample of the Future Scenario with regard to Leisure Time Trips (own illustration).

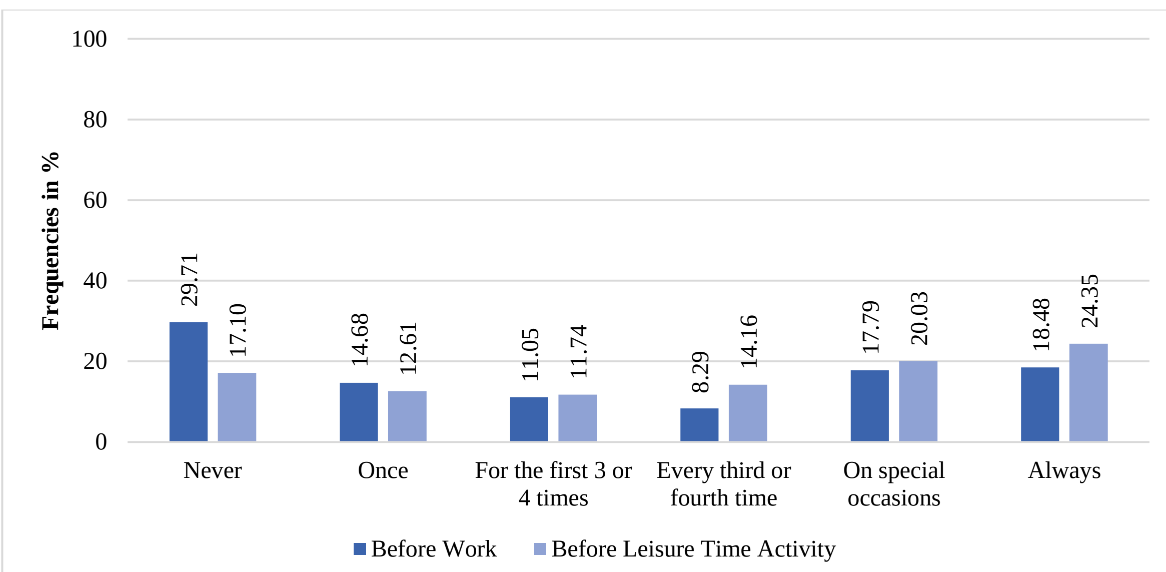


Figure 6.15 Frequency of Pre-trip Information Collection Depending on the Purpose of the Route (future scenario; own illustration).

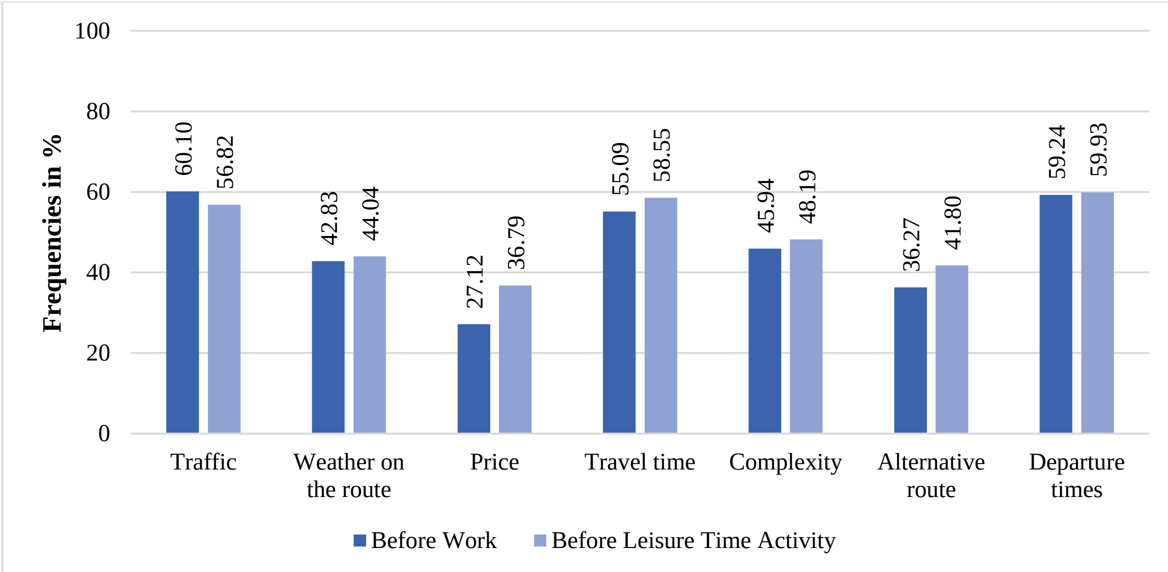


Figure 6.16 Type of Mobility-Centered Information that is Accessed Pre-trip by the Participants' of the Future Scenario (own illustration).

6.5.2 Discrete Choice Modelling

This section presents the core results of the future scenario, namely the discrete choice models. After presenting a descriptive overview of the modal decisions, the final selection of predictors will be reported. This also includes the reporting of inter-correlations between possible predictors and the subsequent decision of predictor inclusion or exclusion. Since the IIA-assumption does not hold for the present scenario, the MNL results are only reported briefly. Next, the nested model (NL) results will be described. Since, the nested models were not selected as the final models with the best model fit, the NL results are also only reported briefly. Finally, the mixed model (MMNL) results are selected as the final class of models and presented in detail.

Descriptive Overview of Modal Decisions. Figure 6.17 illustrates the participants' modal decisions within the four different future scenarios descriptively (i.e., commuting and leisure time trips each with low and high time pressure). Similar to Figure 6.10 illustrating the modal decisions of the present scenario, Figure 6.17 also supports the assumption that all presented modes were selected in all four future scenarios. Thus, there is no mode that was not selected at all or so rare that it cannot be included in the following modelling procedure. Furthermore, the diagram highlights that the frequencies with which the modes were selected differ depending on the trip purpose and the time pressure. Non-shared robo-taxis are selected more frequently in the conditions with high time pressure compared to the conditions with low time pressure. In the conditions with low time pressure, shared robo-taxis and public transport are selected more frequently than non-shared robo-taxis.

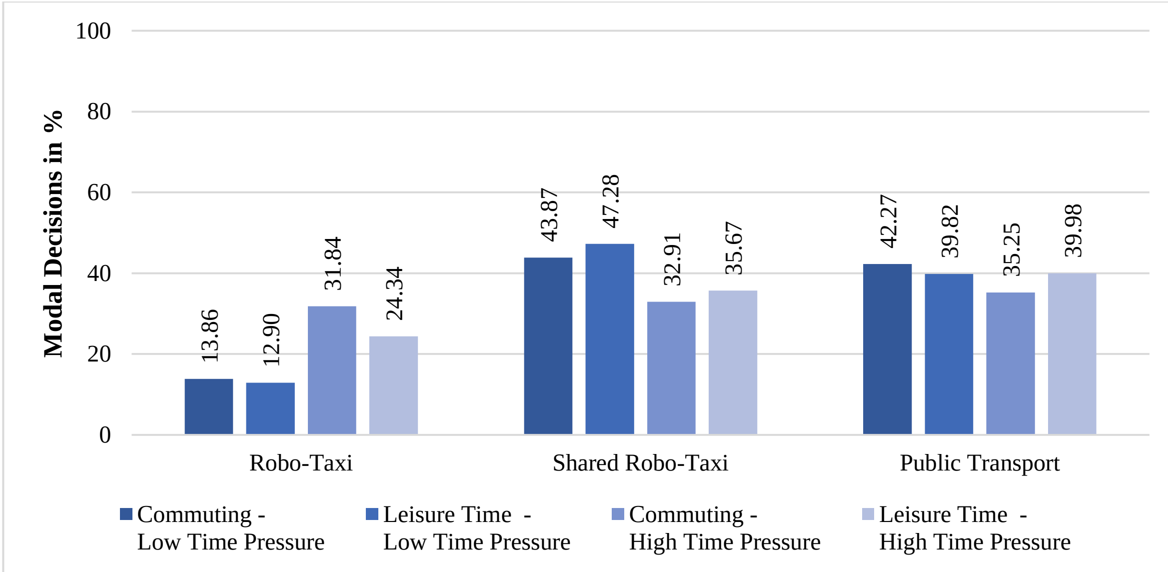


Figure 6.17 Overview of Modal Decisions in all Four Future Scenarios (*n* = 9264; own illustration).

Selection of Predictors. Table 6.20 summarizes the final selection of predictors included in all four discrete choice models of the future scenario. As in the present scenario, predictors with large inter-correlations (i.e., r ≥ .50) were excluded from the models (see Table 6.20). Appendix G to Appendix J provide a detailed overview about the inter-correlation of all predictors considered in the future scenario and their significance. Since the discrete choice models of the future scenario contain the same demographic variables as the discrete choice models of the present scenario, the detailed discussion of the scales (i.e., metric, ordinal, and binary) can be found above in Chapter 6.3.2. Compared to the discrete choice models of the present scenario, the discrete choice models of the future scenario contain four additional attitude scales and two more alternative-specific variables. These additional predictors are highlighted in blue in Table 6.20.

Table 6.20 Selection of Predictors Included in the Future Scenario (own illustration).

Included predictors	**Scale**	**Included in present scenario**
Individual-specific		
Demographic		
Age	metric	yes
Gender	binary (male vs. female)	yes
Income	metric	yes
Household situation		yes
• Kids	binary (yes vs. no)	yes
• Single apartment	binary (yes vs. no)	yes
Place of residence	ordinal with 5 levels (see Table 6.19)	yes
Access to public transport	metric (in minutes from home)	yes

Included predictors	Scale	Included in present scenario
Attitudes		
Frequency of pre-trip information collection	binary (always or regularly vs. not regularly)	yes
Trust in public transport	metric	no
Trust in robo-taxis	metric	no
Hedonic motivation regarding robo-taxis	metric	no
Interest in new technologies	metric	no
Alternative-specific (for levels see Table 6.17)		
Cost	ordinal with 3 levels	yes
Travel time	ordinal with 3 levels	yes
Waiting time	ordinal with 3 levels	yes
Walking time	ordinal with 3 levels	yes
Type of robo-taxi	ordinal with 3 levels	no
Security information in robo-taxi	ordinal with 3 levels	no
Individual offers in robo-taxi	ordinal with 3 levels	no
Excluded predictors	**Reason**	
Education	large inter-correlation with occupation status and income	
Occupation status	large inter-correlation with education and income	
More levels of household situation (e.g. single parent)	model economy	
Performance expectancy regarding robo-taxis	large inter-correlation with hedonic motivation regarding robo-taxis	
Parking costs Actual commuting time in car	These predictors were integrated in the present scenario but excluded from the future scenario because the future scenario only regards public transport, robo-taxis and ridepooling and no cars. Additionally, the future scenario did not include any individual reference to the participant's actual commute time in the choice sets.	
Features of car	similar to type of robo-taxi	

MNL Estimation and Test of IIA-assumption. The multinomial logit model (MNL) can only be estimated for dependent variables with more than two alternatives. Otherwise the model has to be reduced to a simple logistic regression model for binary dependent variables. The Hausman McFadden test procedure requires that the MNL is calculated for the sample with all alternatives i and then tested against different samples with i-1 alternatives. Since in the future scenario, i = 3 alternatives were considered, the subset of i-1 = 2 alternatives would be reduced to a simple logistic regression model. Consequently, the Hausman McFadden Test cannot be applied in the context of the future scenario.

Nevertheless, the IIA-assumption was rejected due to conceptual reasons. As the present scenario, the future scenario concentrates on pooling. The results of the present scenario as well as previous research [e.g., 132] have shown that especially in the case of pooling nesting structures should be explored. Thus, the IIA cannot be assumed to hold. Therefore, Table 6.21 summarizes the key results of the MNLs briefly as the baseline models. In the following, nested and mixed logit models will be reported.

Table 6.21 Log-Likelihood, McFadden's R^2 and the Likelihood Ratio Test for the Multinomial Logit Models for all Four Future Scenarios including all Alternatives (own illustration).

Scenario	**Log-Likelihood**	R^2	**Likelihood ratio test**	
			χ^2	***p-value***
Commuting - Low time pressure	-1871.1	0.25	1246.6	<.001
Commuting - High time pressure	-1877.6	0.20	934.14	<.001
Leisure time - Low time pressure	-1820.7	0.26	1275.9	<.001
Leisure time - High time pressure	-1832.6	0.20	940.94	<.001

Estimation of Nested Logit Models. Since the IIA-assumption was rejected due to conceptual reasons, the next step is to estimate nested logit models that do not underlie the IIA-restriction. Table 6.22 presents an overview about the tested nesting structures. Here, three different nesting structures with two nests each were considered. Hence, all possible nesting structures were considered. Since the nested models were not selected as the final models for the future scenario, Table 6.23 only summarizes the key statistics of the different tested nested models. Similar to the present scenario, comparing the R^2 of the NL models listed in Table 6.23 with the R^2 of the MNL models listed in Table 6.21, shows that the integration of nesting structures does not significantly improve the overall model fit. Instead, the R^2 of the NL models more or less equals the R^2 of the MNL models or is even marginally smaller. Nevertheless, similar to the present scenario, with most $R^2 \geq .20$, the NL models already show a very good model fit (see Table 6.7 for conventions). Regarding the inclusive value parameters of the NLs, Table 6.23 shows that the parameters are either very close to the cut-off score of 1.00 or even ≥ 1.00. In sum, the results of the R^2, the results of the inclusive value parameters and the comparison of the NL models with the MNL models does not suggest that the NL models should be selected as the final class of models in the future scenario.

Table 6.22 Overview of Tested Nesting Structures in the Future Scenario (own illustration).

Nesting structures	**Nest 1**	**Nest 2**
Conventional public transport vs. autonomous vehicles	Public transport	Robo-taxi shared robo-taxi
Travelling alone vs. travelling surrounded by others	Robo-taxi	Public transport shared robo-taxi
Ridepooling vs. else	Shared robo-taxi	Public transport robo-taxi

Estimation of Mixed Logit Models. Table 6.24 summarizes the model coefficients of the final MMNL models of all four future scenarios. As in the present scenario (see Chapter 6.3.2), all effects with p > .10 were omitted from the models. Hence, Table 6.24 contains all effects with

$p \leq .05$ and all effects with $.05 < p \leq .10$, whereas the latter are highlighted in blue. More details about the final estimates can be found in Appendix O to Appendix R. Besides the estimates of the coefficients, the appendices also contain the standard errors of the estimates, the *z*-values and the *p*-values for each coefficient. Similar to the present scenario, public transport was chosen as the reference level in the future scenario.

First of all, the results concerning the **intercepts** and **random intercepts** will be reported. Mode-specific intercepts “capture the effect of unobserved variables and measurement errors” [154, p. 8]. Since public transport is the reference level in the present analysis, public transport has an intercept value and a random intercept value of 0. Robo-taxi has the biggest intercepts and the biggest random intercepts in all four future scenarios. This might be explained by the relatively small percentage of rides by robo-taxis in the dataset compared to the percentage of rides by shared robo-taxis and public transport (see Figure 6.17).

Next, the results regarding the **individual-specific variables** will be described (reference level as in present scenario = public transport):

- **Age** has small negative effects in all four scenarios. The effects indicate that older travelers are less likely to choose robo-taxis and ridepooling compared to public transport for commuting under low and high time pressure. In the context of leisure time activities, older travelers are less likely to choose robo-taxis compared to public transport under low time pressure and shared robo-taxis compared to public transport under high time pressure.

- Regarding **gender**, men compared to women are less likely to choose (1) shared robo-taxis compared to public transport during commuting under low time pressure and (2) robo-taxis compared to public transport during leisure time trips under low time pressure. In contrast, men compared to women are more likely to choose robo-taxis compared to public transport during leisure time trips under high time pressure.

- **Income** has positive effects on choosing robo-taxis compared to public transport in all scenarios except for commuting under low time pressure. Regarding commuting under low time pressure, income has a marginally significant negative effect on choosing robo-taxis compared to public transport.

- **Having children** compared to not having children only has a significant effect during leisure time trips under low time pressure. Here, having children enhances the probability to choose robo-taxis compared to public transport. **Travelers who live alone** are, however, less likely to choose robo-taxis and shared robo-taxis during commuting under low time pressure. During commuting under high time pressure this negative effect only remains marginally significant for the probability to choose shared robo-taxis compared to public transport. During leisure time trips, travelers who live alone are more likely to choose robo-taxis compared to public transport under low and high time pressure.

- The results concerning the **place of residence** show that living in less populated areas (i.e., medium city, small city, town, and village) compared to living in large cities enhances the probability to choose robo-taxis and shared robo-taxis compared to public transport in most scenarios. During commuting and leisure time trips under high time pressure, inhabitants of small cities (i.e., commuting) and small cities and towns (i.e., leisure time trips) are, however, less likely to choose robo-taxis compared to public transport. Similarly, travelers who have a longer **way from their home to the next public transport station** are more likely to choose robo-taxis (i.e., commuting under low and high time pressure and leisure time trips under low time pressure) and shared robo-taxis (i.e., commuting under high time pressure).

- Regarding the effect of **pre-trip information collection**, the collection of pre-trip information reduces the probability to choose a robo-taxi compared to public transport during commuting and leisure time trips under low time pressure.

In the following, the results concerning the **individual-specific attitudes** will be reported (reference level as in present scenario = public transport):

- The results concerning the travelers' **perceived trust in public transport** indicates that travelers with a high trust in public transport are less likely to choose robo-taxis and shared robo-taxis compared to public transport during commuting under low and high time pressure. Moreover, travelers with a high trust in public transport are less likely to choose shared robo-taxis compared to public transport during leisure time trips under low time pressure and robo-taxis compared to public transport during leisure time trips under high time pressure.

- Travelers with (1) a high **perceived trust in autonomous vehicles and robo-taxis**, (2) a high **hedonic motivation towards using robo-taxis** and (3) a high **interest in new technologies** are more likely to choose robo-taxis and shared robo-taxis compared to public transport in all four scenarios. Only in the context of leisure time trips under low time pressure the travelers' technology interest did not significantly affect the probability to choose shared robo-taxis compared to public transport.

Next, the results regarding the **alternative-specific variables** will be described (reference level as in present scenario = lowest ordinal level):

- The results concerning the alternative-specific variables show constantly negative effects of both **cost** levels in all four future scenarios on all three modes.

- Regarding **travel times**, only the contrasts between the lowest and the highest travel time level show constantly negative effects in all scenarios and on all modes. With regard to the contrast between the medium travel time level and the lowest travel time level, constantly negative effects on all three modes were found for the scenarios under high time pressure. In the scenarios under low time pressure, however, the contrast between the medium travel time level and the lowest travel time level is only significant for robo-taxi and public transport during commuting and solely for public transport during leisure time trips.

- Similar to travel times, concerning **waiting times,** only the contrast between the lowest and the highest waiting time level show constantly negative effects in all scenarios and on all modes. The contrast between the medium and lowest waiting time level is, however, only significant for (1) shared robo-taxis during commuting under low and high time pressure, (2) for robo-taxis during commuting under high time pressure and leisure time trips under low and high time pressure, and (3) for public transport during leisure time trips under high time pressure.

- Similar to travel times and waiting times, regarding **walking times**, only the contrast between the lowest and the highest walking time level shows constantly negative effects in all scenarios and on all modes that contain walking times (i.e., shared robo-taxis and public transport). The contrast between the medium and the lowest walking time level is significant for both modes in the scenarios under high time pressure but only significant for public transport in the scenarios under low time pressure.

- Additional features of robo-taxis such as the **taxi type**, the provision of **security information** and **individual offers**, do not show any significant effects in the scenarios under high time pressure. During commuting under low time pressure and leisure time trips under low time pressure, a higher **taxi type** enhances the probability to choose a shared robo-taxi compared to a lower taxi type. Regarding **security information**, the contrast between the lowest and the medium level of security information does not show any significant effects. The contrast between the third and the second level of security information only has a positive effect on choosing shared robo-taxis during leisure time trips under low time pressure. **Individual offers** show only one significant effect, namely a negative effect of the second level of individual offers compared to no individual offers (i.e., the lowest level) during leisure time trips under low time pressure.

Finally, the analysis of the **random effects** shows a lot of individual-specific random effects regarding the alternative-specific attributes. Thereby, the importance of individual-specific random effects is more or less equal in all four scenarios (i.e., more or less equal amount of random effects in all scenarios). Especially, the probability of choosing robo-taxis and shared robo-taxis is constantly affected by individual-specific random effects.

In sum, the MMNL models express a significantly better overall model fit than the MNL models and NL models presented above. With R^2 between 0.28 and 0.33, the R^2 of the MMNL models are approximately by 0.08 to 0.10 greater than the R^2 of the MNL models (0.20-0.26) and the NL models (0.18-0.25). Moreover, the Log-Likelihoods of the MMNL models ((-1699.8) - (-1591.2)) are significantly greater than the Log-Likelihoods of the MNL models ((-1877.6) - (-1820.7)) and the NLs ((-1883.5) - (-1865.3)).

Table 6.23 Log-Likelihood, McFadden's R^2, Likelihood Ratio Tests and the Inclusive Value Parameter for the Tested Nested Logit Models for all Four Future Scenarios (PT = public transport; ***p <. 001; own illustration).

Scenario	**Log-Likelihood**	R^2	**Likelihood ratio test**		**Inclusive value parameter**	
			χ^2	***p-value***	**Nest 1**	**Nest 2**
Commuting - Low time pressure						
Conventional vs. autonomous	-1870.8	0.25	1247.3	<.001	0.98***	1.02***
Alone vs. PT	-1870.8	0.25	1247.2	<.001	1.08***	1.04***
Ridepooling vs. else	-1870.9	0.25	1247.0	<.001	1.03***	1.04***
Commuting - High time pressure						
Conventional vs. autonomous	-1875.6	0.20	938.19	<.001	0.89***	0.93***
Alone vs. PT	-1877.3	0.20	934.73	<.001	0.98***	0.90***
Ridepooling vs. else	-1875.0	0.20	939.38	<.001	1.16***	1.24***
Leisure time - Low time pressure						
Conventional vs. autonomous	-1865.3	0.24	1186.70	<.001	0.84***	0.87***
Alone vs. PT	-1868.1	0.24	1181.00	<.001	1.09***	1.00***
Ridepooling vs. else	-1866.6	0.24	1184.00	<.001	1.09***	1.13***
Leisure time - High time pressure						
Conventional vs. autonomous	-1883.3	0.18	839.44	<.001	1.02***	1.05***
Alone vs. PT	-1883.5	0.18	839.14	<.001	1.00***	1.04***
Ridepooling vs. else	-1883.1	0.18	839.76	<.001	1.00***	0.98***

Table 6.24. Summary of Final MMNL Results of all Four Future Scenarios (own illustration: RT = Robo-Taxi, SRT = Shared Robo-Taxi, PT = Public Transport, RL = Reference Level; table contains estimates of model coefficients; only coefficients with $p \leq .05$ are listed, coefficients with $0.5 < p \leq .10$ are highlighted in blue; prohibitions of attributes are highlighted in orange).

	Commuting – Low time pressure			**Commuting – High time pressure**			**Leisure time trips – Low time pressure**			**Leisure time trips – High time pressure**		
Mode	**RT**	**SRT**	**PT**	**RT**	**SRT**	**PT**	**RT**	**SRT**	**PT**	**RT**	**SRT**	**PT**
Intercept	-7.92	-3.23	RL	-3.79	0.18	RL	-10.85	-2.84	RL	-8.52	-2.76	RL
Individual-specific												
Age	-0.04	-0.02	Reference level	-0.04	-0.03	Reference level	-0.07		Reference level		-0.02	Reference level
Gender		-0.72					-0.80			1.50		
Income	-0.25			0.60			0.52			0.39		
Kids							2.18					
Alone	-1.09	-0.40			-0.44		1.58			1.10		
Medium city	1.66				1.18		2.93			1.66		
Small city				-1.31	0.64					-2.44	0.64	
Town	0.84	0.85			0.72		1.57			-1.26		
Village	1.36	1.38						1.84				
PT access	0.18			0.21	0.10		0.30					
Frq. inf. commute	-0.75						-1.35					
Attitudes												
PT trust	-1.49	-0.74	Reference level	-1.37	-1.10	Reference level		-0.72	Reference level	-0.76		Reference level
Robo-taxi trust	0.78	0.66		0.66	0.50		1.29	0.79		1.13	0.34	
Hedonic motiv.	0.53	0.71		0.72	0.41		0.51	0.59		0.83	0.36	
Tech. intr.	1.78	0.34		0.56	0.43		0.89			0.43	0.50	
Alternative-specific												
Cost 2	-1.80	-0.54	-1.73	-1.01	-0.80	-0.70	-1.59	-1.39	-0.77	-1.50	-1.39	-0.57
Cost 3	-2.41	-2.43	-2.57	-1.53	-1.56	-1.56	-3.96	-2.83	-2.90	-2.16	-2.48	-1.91
Time 2	-0.59		-0.56	-0.71	-0.85	-0.67			-0.48	-0.56	-0.90	-0.51
Time 3	-1.21	-0.67	-0.80	-1.52	-1.66	-1.13	-0.78	-0.75	-0.94	-1.85	-1.57	-1.18

	Commuting – Low time pressure			Commuting – High time pressure			Leisure time trips – Low time pressure			Leisure time trips – High time pressure		
Mode	**RT**	**SRT**	**PT**	**RT**	**SRT**	**PT**	**RT**	**SRT**	**PT**	**RT**	**SRT**	**PT**
Wait 2		-0.49		-0.71	-0.80		-1.79			-0.88		-0.51
Wait 3	-1.05	-0.68	-0.35	-1.07	-1.21	-0.41	-1.51	-0.49	-0.45	-1.08	-0.49	-0.75
Walk 2			-0.41		-0.48	-0.85			-0.53		-0.75	-0.93
Walk 3		-0.85	-0.79		-1.47	-1.41		-0.52	-1.33		-1.41	-1.30
Taxi type 2		0.31						0.31				
Taxi type 3		0.69										
Security info 2												
Security info 3								0.42				
Individual offer 2							-0.50					
Individual offer 3												
Random effects												
Intercept	3.24	1.40	RL	2.69	1.33	RL	4.05	1.34	RL	4.01	1.04	RL
Cost 2	1.59	-0.41			-0.66			0.39	-0.42	0.88		
Cost 3	-2.09	1.49	-0.42	0.42	0.66	-0.53	2.03	1.57	1.13	0.77	1.17	1.37
Time 2	-0.42			0.59	0.60	-0.88	1.19				-0.56	
Time 3	-0.87	-0.99	-0.55		0.78	0.52	-0.92		-1.00	-0.90	-0.99	-0.42
Wait 2		-0.34		-0.62			2.13			-0.83	-0.44	
Wait 3	1.49			1.11	1.12		1.59	-0.39	-0.58	0.86	1.46	-0.48
Walk 2			-0.66			0.39						
Walk 3		0.58			1.64	-1.02			0.88		-1.66	-0.80
Taxi type 2	-0.49	0.66			-0.77		0.50				-0.36	
Taxi type 3	1.33	-0.36			0.54		2.32			-0.96		
Security info 2				-0.76				-0.43				
Security info 3		-0.44			-0.38			0.89		-1.19		
Individual offer 2	-0.54	-0.63		0.52	0.96		-0.75	-0.72			0.59	
Individual offer 3	-1.04				-0.73		1.20				0.40	

	Commuting – Low time pressure			Commuting – High time pressure			Leisure time trips – Low time pressure			Leisure time trips – High time pressure		
Mode	**RT**	**SRT**	**PT**	**RT**	**SRT**	**PT**	**RT**	**SRT**	**PT**	**RT**	**SRT**	**PT**
Model summary												
Log- Likelihood	-1699.8			-1691.9			-1645.2			-1591.2		
R^2	0.32			0.28			0.33			0.31		
Likelihood ratio test	χ^2	*p-value*		χ^2	*p-value*		χ^2	*p-value*		χ^2	*p-value*	
	1589.3	<.001		1305.5	<.001		1626.9	<.001		1423.7	<.001	

6.5.3 Attitude Towards Robo-Taxis and Ridepooling

This section presents the results concerning the participants' attitude towards robo-taxis and ridepooling in the future scenario. This includes two main parts, namely (1) the results of the qualitative clustering of the participants' perceived advantages and disadvantages of ridepooling and (2) the descriptive statistics of the attitude scales assessing for example the participants perceived hedonic motivation, performance expectancy and trust.

The coding of the free text answers revealed seventeen categories of advantages and twelve categories of disadvantages. Regarding the advantages, (1) cost savings, (2) community and meet new people, and (3) environmental aspects were listed most frequently as advantages of ridepooling. Regarding the disadvantages of ridepooling, (1) social interaction, communication, and unpleasant strangers, (2) safety and driving behavior, and (3) detours were mentioned most frequently. The number of participants who see no advantages at all in ridepooling (n = 40) more or less equals the number of participants who see no disadvantages at all in ridepooling (n = 43). Table 6.25 summarizes the qualitative results on perceived advantages and disadvantages of ridepooling.

Table 6.25 Perceived Advantages and Disadvantages of Ridepooling (own illustration; new categories that were not identified in the present scenario are highlighted in green).

Advantage	*n*	Disadvantage	*n*
Cost savings	139	Social interaction / communication / unpleasant strangers	127
Community / meet new people	85	Safety / driving behavior	86
Environmental aspects	60	Detours	45
Entertainment / conversations / fun	54	Increased overall time expenses and increased travel time	23
Simplicity / flexibility and efficiency	27	Comfort restrictions during the trip	21
Relaxation / comfort	26	Privacy	15
Speed	22	Waiting time	13
Possibility to work / productivity	18	Unpunctuality / unreliability of others	12
Autonomous driving / new technologies / innovation	18	Dependence on others	7
Traffic reduction	13	Coordination efforts	4
Equipment and cleanliness of vehicle	10	Lack of flexibility	4
Do not drive yourself / take turns while driving	9	Dirt and damage to car	2
Individuality	7		
Security	2		
No waiting time	2		
No transfers	2		
Not as busy as public transport	2		

Advantage	*n*	Disadvantage	*n*
Nothing	40	Nothing	43
Everything	1	Everything	6
Other	7	Other	7

Table 6.26 summarizes the descriptive statistics regarding the attitude scales. For all constructs, Cronbach's alpha is greater than the convention of $\alpha > .70$. This means that the internal consistency of the attitude scales is ensured [83, p. 111]. Hence, the scales show enough reliability to be included as predictors in the discrete choice models. Moreover, the answers of the participants ranged among the whole scale from *totally agree* to *not agree at all*. Since the means of all scales are > 3.00, the participants agree on average that they would experience hedonic motivation (M = 3.52, SD = 1.21), performance expectancy (M = 3.25, SD = 1.15), and trust in robo-taxis (M = 3.07, SD = 1.16). Here, the trust in public transport was assessed as a comparative level, which is 0.86 higher than the trust in robo-taxis. Moreover, the participants agree on average that they are interested in new technologies (M = 3.40, SD = 1.26).

Table 6.26 Mean, Standard Deviation, Minimum, Maximum, and Cronbach's alpha for all Attitude Scales (own illustration).

Construct	Mean	SD	Min	Max	Cronbach's alpha
Trust in public transport	3.93	1.00	1	5	0.82
Trust in robo-taxis	3.07	1.16	1	5	0.86
Performance expectancy regarding robo-taxis	3.25	1.15	1	5	0.84
Hedonic motivation regarding robo-taxis	3.52	1.21	1	5	0.91
Interest in new technologies	3.40	1.26	1	5	0.81

6.6 Combined Discussion of Present and Future Scenario

This section discusses the results of the present and future scenario described in Chapter 6.3 and Chapter 6.5. The following paragraphs will discuss the core findings of the two studies with regard to answering research question three: Which factors should be included in pre-trip information systems in order to support modal choices of travelers? Thereby, the core findings of the present and future scenario (see Chapter 6.6.1) will be summarized and visualized in two artefacts, namely a summary of individual-specific characteristics that enhance the probability for carpooling and ridepooling (see Figure 6.18) and a sensitivity-barometer of alternative-specific attributes for carpooling and ridepooling (see Figure 6.19). Moreover, limitations of the studies and ideas for future research in the field of discrete choice modelling in the context of pre-trip ISs will be elaborated (see Chapter 6.6.2). Finally, this chapter ends with a conclusion on the theoretical and practical implications of the present and future scenario (see Chapter 6.6.3).

6.6.1 Core Findings

The aim of the two studies presented in this chapter was to investigate the determinants of the travelers' modal decisions in a present and future scenario. Thereby, this chapter especially focuses on carpooling and ridepooling as means to reduce urban traffic and use private cars and future robo-taxis more efficiently. In order to analyze modal decisions, this thesis uses state-of-the-art methods for data generation and modelling, namely two AS-CBCs designs for collecting stated preference data (see Chapter 6.2.3 and 6.4.2) and discrete choice modelling including nested and mixed multinomial logit models (see Chapter 6.1.2). With the help of two customer surveys in the BMW World in Munich (Germany), the determinants of the travelers' modal decisions in a present and future scenario were assessed (see Chapter 6.2.1 and 6.4.1).

Individual-Specific Characteristics. First of all, the findings on the individual-specific characteristics will be discussed. Figure 6.18 summarizes these findings into an overview of individual-specific characteristics that enhance the probability for pooling. Similar to previous research [62,63,109], the present studies showed that socio-demographic variables such as age, gender and income affect modal choices. Specifically, pooling is mostly associated with a younger age, a higher income, a place of residence in a less populated area and – closely connected to the place of residence – a poorer access to public transport. Only in the context of leisure time trips under high time pressure, carpooling as a passenger was associated with an older age. This might be due to the fact that older travelers might desire to relax while being driven instead of having to deal with traffic in a stressful situation.

Regarding the household situation, carpooling as a passenger was mostly associated with travelers who do not live alone but do not have children. The effect regarding children might be explained due to the fact that children typically enhance the private coordination efforts of a traveler. For example, commuters need to bring their children to kindergarten before work. This might be the reason why having children leads to preferring carpooling as a driver and not as passenger during commuting. Being the driver, makes it possible to pick up a colleague and drop off the children at kindergarten or school on the way to work. The fact that not living alone mostly enhances the probability of carpooling might be explained in combination with the findings of the qualitative clustering. Here, entertainment, conversations, fun, community and meeting new people were identified as frequently listed advantages of carpooling. Probably, travelers living together with their partner, their family or roommates tend to be more extraverted and like to be surrounded by others. Contrary, choosing to live alone might be confounded with a more introverted personality. Possibly people that live alone might prefer to be alone and enjoy their privacy and silence – also while travelling.

Regarding the effect of pre-trip information collection on modal choices, carpooling was only associated with a higher frequency of pre-trip information collection during leisure time trips under low time pressure. Again, this finding might be explained in combination with the findings of the qualitative clustering. One result of the qualitative clustering was that pooling is negatively associated with time-consuming coordination efforts. Possibly, in the context of commuting, the participants expected long-term coordinated carpooling with less coordination efforts because the points of arrival and departure are always the same and therefore the possible fellow passengers might also be the same (e.g., known colleagues). Hence, also people that are not willing to invest considerable coordination efforts, might see advantages in pooling in this situation because they perceive it as pooling with respectively few coordination efforts. In contrast, in the context of varying leisure time trips, the coordination effort of carpooling might be much higher. Hence, only travelers who are willing to invest considerable coordination efforts are also willing to pool in this situation. Possibly, travelers who are willing to invest considerable coordination efforts pre-trip are also travelers who regularly inform themselves about their mobility options pre-trip. This might close the circle between pre-trip information collection and accepting coordination efforts for pooling.

Similarly, the effect of the duration of the trip might be explained in combination with coordination efforts. With regard to the duration of the trip, carpooling as a driver was mostly associated with longer routes whereas carpooling as a passenger was also associated with shorter routes. Concerning the probability of matching two travelers for pooling, one is much more likely to find a lift on a shorter route than on a longer route. On a shorter route the point of arrival and departure of the driver and the passenger might vary significantly but still the short part of the route overlaps. In the context of a larger route, there is, however, less possibility for variation because the amount of overlap between the route of the driver and the passenger has to be larger. Due to this probability of driver-passenger-matching, the participants might have a tendency to prefer being the driver on longer routes because they associate longer routes with higher difficulties to find a match and subsequently higher coordination efforts during the search for a match. Interestingly, this finding stresses the potential of carpooling on shorter routes such as daily commuting. Since carpooling providers such as BlaBlaCar.de (see Chapter 2.2) currently mostly focus on long-distance trips, this potential can be used for providing future carpooling services.

Comparing the influence of socio-demographic characteristics on carpooling and ridepooling, Figure 6.18 highlights that socio-demographic characteristics have a stronger influence on carpooling than on ridepooling. In the context of ridepooling during commuting, only age, household situation, place of residence, and access to public transport had an effect on the probability to choose ridepooling compared to public transport. In the context of ridepooling during leisure time, only age and place of residence showed significant effects. Similar to carpooling, travelers who are interested in ridepooling tend not to live alone, have a younger age and live in less populated areas. Additionally, they might also have a poorer access to public transport.

	Carpooling driver	Carpooling passenger	Ride-pooling		Carpooling driver	Carpooling passenger	Ride-pooling
Age		younger	younger			older	younger
Gender					female		
Income	higher			**High**			
Household situation	kids	living alone	not living alone		no kids	no kids not living alone	
Place of residence	less populated	less populated	less populated		less populated	less populated	small city
Access to PT	poorer access		poorer access				
Actual time in car commute and leisure		shorter route			longer route	longer route	
Pre-trip info. collection	less informed	less informed			less informed		
Attitudes			+ + + +				/ + + +
	Commuting			**Time Pressure**	**Leisure Time**		
Age	younger	younger	younger		younger	younger	
Gender		female	male		male	female	
Income	higher				higher	higher	
Household situation	not living alone	no kids not living alone	not living alone			no kids not living alone	
Place of residence	less populated	less populated	town or village		small city to village	small city to village	village
Access to PT	poorer access	poorer access			poorer access	poorer access	
Actual time in car commute and leisure	longer route			**Low**	longer route	shorter route	
Pre-trip info. collection	less informed	less informed			more informed	more informed	
Attitudes			+ + + +				+ + + /

Figure 6.18 Summary of Individual-Specific Characteristics that Enhance the Probability for Carpooling and Ridepooling (own illustration).

In contrast to the rather rare and small influences of socio-demographic characteristics, the results indicate that attitudes on autonomous driving and robo-taxis highly influence the probability to share rides in robo-taxis. The traveler's perceived trust in public transport and autonomous vehicles, their interest in new technologies and their perceived hedonic motivation towards travelling by robo-taxis highly influenced their willingness to use robo-taxis at all and also their willingness to share their ride. These findings empirically prove the demanded modification and expansion of existing choice and demand models by the personality and psychology of the traveler [53,223]. This finding goes along with recent research that has theoretically elaborated [53] this need for change in mode choice models as well as recent research that has already found qualitative insights that strengthen this need for change [223] (for details see Chapter 2.2.2).

Furthermore, these findings can be integrated into the findings of Haboucha, Ishaq and Shiftan [81] who have studied future ODM choice models empirically. As described in more detail in Chapter 2.2.2, the authors found that, among the latent variables, the traveler's positive attitude towards autonomous vehicles had the strongest effect on choosing both, shared and private autonomous vehicles. Contrary to the present thesis, the authors have studied this effect in a scenario in which privately owned vehicles still exist. The present thesis has, however, replicated this effect in a scenario in which it was no longer allowed to drive with a private car into the city center due to legal requirements. Hence, the participants had to choose to travel to the city center by robo-taxi, shared robo-taxi or public transport.

In conclusion, the present thesis found stronger effects of socio-demographic variables on carpooling than on ridepooling. Regarding ridepooling, especially the individual-specific attitudes (i.e., interest in new technologies, hedonic motivation, and trust) showed significant effects on the willingness to share rides. Figure 6.18 summarizes the effects of all individual-specific variables on a conceptual level.

Alternative-Specific Characteristics. Next, the findings on the alternative-specific characteristics will be discussed. Figure 6.19 summarizes these findings into a sensitivity-barometer for the alternative-specific attributes for carpooling and ridepooling. Here, completely filled circles stand for the highest sensitivity whereas completely empty circles represent no significant sensitivity. The two most important alternative-specific attributes in all scenarios were cost and time. Consequently, most travelers are highly price-focused and time-focused. For carpooling, the effect of time-sensitivity even remains during low time pressure whereas the effect of cost-sensitivity is reduced by high time pressure. Hence, travelers are willing to pay more for carpooling during higher time pressure. Nevertheless, they are not willing to invest considerable more time for carpooling even in situations with low time pressure.

A similar effect was found for parking costs: Whereas travelers are also highly price-focused in terms of parking costs, they were not sensitive to parking costs during leisure time trips under high time pressure. However, during commuting under high time pressure, the price-sensitivity regarding parking costs remained high. The high cost-sensitivity is also reflected in the free text answers (see Table 6.14 and Table 6.25). Here, cost savings were mentioned as the top advantage of both, carpooling and ridepooling.

With regard to walking times, in most scenarios the travelers were more sensitive to walking to a lift (i.e., carpooling as passenger) than walking to the parking lot of their own car (i.e., carpooling as a driver). As elaborated in detail in the beginning of this thesis, the private car is still perceived as the most convenient mode of transport by lots of travelers. Hence, travelers might be more willing to walk to their own car than to a lift because they still perceive a higher overall convenience when travelling by their own car. Regarding ridepooling, the travelers are much more sensitive on walking times in contexts of high time pressure compared to contexts of low time pressure. Obviously, this finding is in accordance with the high time-focus of travelers.

Interestingly, the results indicate that travelers are less sensitive to waiting times than to walking times in the context of carpooling during commuting. However, during leisure time trips, travelers are as sensitive to walking times as they are to waiting times. Regarding ridepooling, the findings for walking times are similar to the findings for waiting times. Here, travelers are more sensitive to walking times during high time pressure than they are during low time pressure.

	Commuting			Leisure Time		
	Carpooling driver	**Carpooling passenger**	**Ride-pooling**	**Carpooling driver**	**Carpooling passenger**	**Ride-pooling**
Time Pressure: High						
Cost	●	◑	●	◑	◑	●
Time	●	●	●	●	●	●
Wait		○	●		◑	◑
Walk	○	◑	●	○	◑	●
Parking	●			○		
Features/ Taxi type		○	○		○	○
Security In.			○			○
Ind. Offer			○			○
Time Pressure: Low						
Cost	●	●	●	●	●	●
Time	●	●	◑	●	●	◑
Wait		◔	●		◑	◑
Walk	◔	●	◑	●	◑	◑
Parking	●			●		
Features/ Taxi type		◕	●		●	◑
Security In.			○			◑
Ind. Offer			○			○

Figure 6.19 Sensitivity-Barometer of Alternative-Specific Attributes for Carpooling and Ridepooling (own illustration: ● high sensitivity to ○ low sensitivity; prohibitions of attributes are highlighted in orange).

Furthermore, the present study identified only few effects of optional equipment. More precisely, in the context of both, carpooling and ridepooling, additional features or rather taxi type only affected the probability to choose pooling compared to public transport in the two scenarios with low time pressure. Additional features or rather taxi type did, however, not show any significant effects in the scenarios with high time pressure. Regarding the optional equipment in the context of ridepooling, individual offers did not show to enhance the probability of pooling whereas security information only had a positive effect on ridepooling during leisure time trips under low time pressure. Obviously, this finding shows that under high time pressure, travelers are focused on reaching their destination and do not concentrate on any luxury equipment such as massage seats or in-vehicle entertainment on mobile tablets. However, during low time pressure, travelers possibly have the time to enjoy their ride and use their travel time for entertainment or relaxation. Thus, optional equipment gains importance in this scenario. Furthermore, this finding should again be discussed in combination with the results of the qualitative clustering. Especially in the context of ridepooling, the participants listed aspects such as comfort, equipment, and individuality as perceived advantages of robo-taxis and ridepooling. However, especially for ridepooling, the present study did not support these advantages as decision-relevant criteria in the choice sets. This aspect will be discussed further in the limitations and future research section.

In sum, the present findings highlighted that travelers are very price-focused and time-focused regarding carpooling and ridepooling. These preferences were significantly influenced by the two contextual factors trip purpose (i.e., commuting and leisure time) and time pressure (i.e., low vs. high). Especially, optional equipment such as additional features of a car or a robo-taxi only showed significant effects in the scenarios with low time pressure. After discussing the limitations of the present studies and presenting ideas on how to overcome these shortcomings in future research, the theoretical and practical implications are summarized in the following.

6.6.2 Limitations and Future Research

Although the core findings of the two user studies provide considerable insights into the determinants of the travelers' modal decisions in a present and future scenario, the results underlie some restrictions. First of all, the discrete choice models are based on the participants' stated preferences for modal choices and their conscious self-evaluation of their mobility habits, pre-trip habits and their attitudes. As already discussed in Chapter 5.4.2, stated preference data and self-evaluations may always be biased by barriers to human expression and social desirability. This bias exists even in the context of a high-quality research design. Since participants' might be unaware of the actual cues they integrate consciously or unconsciously into their decision-making processes, they might misreport their attitudes and decisions unintentionally [107,138,139]. In order to avoid these limitations, future research should validate the presented findings using revealed preference data. Since, in the context of ridepooling, revealed preference data will not be available for a few years, laboratory experiments might serve to validate the relationships in a small sample.

Another interesting aspect for future research is the further investigation of the effects of optional equipment in the context of carpooling, robo-taxis, and ridepooling. As discussed above, the present study identified only few effects of optional equipment in terms of car type, the provision of security information and the offer of individual equipment and snacks and drinks. Therefore, future research should investigate the effects of optional equipment in the context of carpooling with a field study. Here, different levels of optional equipment could be varied systematically in an experimental setting and the effects on the number of requests and customer satisfaction after rides should be assessed. In the context of ridepooling, the effects of optional equipment could be studied experimentally in controlled laboratory settings. These studies could show whether the non-significant effects in the present studies can be explained by an overshadowing effect of the traveler's cost- and time-sensitivity or if the non-significant effects in the present studies are due to the fact that the participants could not imagine the different kinds of optional equipment well enough. The more realistic experience of optional equipment in a field study might lead to characterize the actual effect of optional equipment more precisely.

Finally, the results of the qualitative clustering concerning the perceived advantages and disadvantages of carpooling and ridepooling can be integrated in future studies. It would be interesting to analyze the effect of the identified categories quantitatively and more causally. For example, the different categories such as the character of the fellow passenger or amount of coordination efforts can be used as attributes for further AS-CBC studies. Hence, their effect on the traveler's modal choices could be investigated empirically and quantitatively. This idea for future research is also closely connected to the open questions concerning the impact of optional equipment in the context of pooling because optional equipment and cleanliness of the vehicle were also identified as influencing factors in the qualitative analysis.

In sum, the insights of the discrete choice models reported above provide considerable insights into the factors that predict the travelers' modal decisions in a present and future scenario. Future research can extend these findings with the help of revealed preference data and longitudinal studies. Moreover, future research should investigate the effects of optional equipment in the context of carpooling, robo-taxis, and ridepooling in field studies, experimental studies and laboratory experiments. Furthermore, future research should use the gained insights to develop further simulations and algorithms in the context of on-demand mobility and pooling. This idea will be elaborated in more detail in the following paragraphs about the implications of the present research.

6.6.3 Implications and Conclusion

In conclusion, the presented results have practical and theoretical implications. From a theoretical perspective, the findings help to understand the determinants of the travelers' willingness for carpooling and ridepooling more accurately. The present studies extend existing research by the detailed analysis and comparison of discrete choice models for carpooling and ridepooling in four different scenarios and the direct comparison of individual- and alternative-specific attributes of carpooling and ridepooling. Thereby, the importance of contextual factors such as route purpose and time pressure was highlighted. The context-specific application and the extension of discrete choice models for carpooling and ridepooling help transportation research to better understand the determinants of modal choices and their relevance in the context of pre-trip ISs. The specified models show a good fit in predicting the travelers' willingness for pooling in different contexts. Especially individual-specific attitudes, such as the traveler's interest in new technologies, hedonic motivation, and trust were identified as important decision-relevant criteria that should also be studied in future transportation research.

More precisely, the present findings indicate that attitudes and feelings of trust and enjoyment are much more important for discrete choice models in the context of future ODM services than socio-demographic characteristics of the traveler.

Additionally, the present findings stress the importance of modelling individual-specific random effects with regard to the alternative-specific attributes such as walking times and optional equipment. Methodologically, this finding highlights the importance of extending discrete choice models by individual-specific random effects instead of overgeneralizing the effects of alternative-specific attributes. This is especially important in the context of pre-trip ISs which intend to provide an individual recommendation for a single customer who has to accept and use the system and is subsequently not interested in a recommendation that simply fits an average traveler. Regarding future stated preference studies, this once again stresses the importance to make choice tasks as realistic as possible and try to adapt them to single participants. Hence, an interesting implication for future research is to focus on more adaptive CBC designs (for adaptive conjoint analysis see [15, p. 113 ff.]).

From a practical perspective, the presented model parameters can be used for simulations and the development of algorithms in the context of on demand mobility. For example, parts of the utility functions can be integrated in simulations and algorithms for car-passenger matching in the context of ridehailing, carpooling and ridepooling services. More precisely, the coefficients of the discrete choice models can be used to estimate cut-off scores for the maximum waiting time and the maximum walking time that is accepted by the customer. These scores can be used for decision rules in the context of car-passenger matching. Moreover, these scores can be used to avoid that bookings are canceled due to unfulfilled customer preferences. If the car-passenger matching considers the maximum accepted waiting time and maximum accepted walking time from the travelers' perspective, this might reduce the number of canceled bookings because the recommended match is closer to the customer's desired match.

Furthermore, the parameters of the discrete choice models can be used for the pricing of ridehailing, carpooling and ridepooling services. More precisely, the model coefficients can be converted to willingness-to-pay parameters. "In a model […] where we estimate a single parameter for price, we can compute the average willingness-to-pay for a particular level of an attribute by dividing the coefficient for that level by the price coefficient" [39, p. 376]. For example, the model parameters can be used to estimate at which price customers become indifferent between two levels of robo-taxi type, security offers in robo-taxi or individual offers in robo-taxis. "This same willingness to pay value can be computed for every attribute in the study and reported to decision makers to help them understand how much customers value various features" [39, p. 376]. In conclusion, willingness to pay values can deepen our understanding of the desires of the customer and can be used in practice to decide about the integration of different features such as the integration of digital assistants in robo-taxis. Willingness to pay values can help to evaluate whether the costs for optional equipment will be paid off or not.

Moreover, the insights presented above can be used to model the decision-making process of travelers artificially in the recommendation algorithm integrated in pre-trip ISs. The remaining challenge concerning recommender systems in the context of pre-trip information is to reduce the travelers' cognitive load by taking modal decisions from them. In order to take decisions from travelers, pre-trip ISs need to rely on a recommendation algorithm. This algorithm should ideally be very close to the traveler's individual decision-making process, i.e., relaying on the same decision-relevant criteria and the same weighting scheme of decision-relevant criteria. Here, the sensitivity-barometer of alternative-specific attributes (see Figure 6.19) can be transferred into decision rules of a recommender system. Additionally, the sensitivity-barometer can be used to design user interfaces of pre-trip ISs. For example, in order to reduce the traveler's cognitive load, only the three parameters with the highest sensitivity may actually be displayed in the user interface.

Another interesting field of application for the identified individual-specific effects are marketing and advertising purposes. For example, ODM providers could enhance their marketing and advertising in specific residential areas, such as areas with a high percentage of young inhabitants or areas with poorer access to public transport (see Figure 6.18). Additionally, the advertising should be designed in a manner that especially addresses specific customer segments, such as young families that live in less populated areas. Specific customer segments can be addressed using specific pictures or slogans.

The identified individual-specific effects can also be used for optimizing ODM infrastructure, the overall fleet management, and the allocation of vehicles. For example, ODM service providers and possibly also departments of the city council should consider individual-specific effects when planning pick up and drop off areas for carpooling and ridepooling. Moreover, the presented insights can be integrated in algorithms that support the overall fleet management and the allocation of vehicles. Again, specific residential areas, such as areas with poorer access to public transport or areas with a high percentage of young inhabitants should be focused.

Another finding that is closely connected to ODM infrastructure is that in most scenarios the travelers were more sensitive to walking to a lift (i.e., carpooling as passenger) than to walking to the parking lot of their own car (i.e., carpooling as a driver). Consequently, especially in the context of ridepooling, walking times have to be minimized for customers. Thus, this stresses the need to plan and build many pick up and drop off locations because travelers will only accept ridepooling services with very few walking times. This is closely connected to legal issues because in Germany road traffic laws regulate where ODM service providers are allowed or not allowed to pick up and drop off their customers. Hence, the construction of pick up and drop off areas should be planned in cooperation with city councils.

Furthermore, the importance of individual-specific characteristics, attitudes, and random effects can be integrated in pre-trip ISs. These findings could be used to develop a user-centered calibration of pre-trip ISs. The idea is that before customers put their new pre-trip recommender system into operation, they calibrate the system to their individual alternative-specific sensitivities and their individual-specific characteristics and attitudes. Since attitudes and feelings of trust and enjoyment were found to be much more important for discrete choice models in the context of future ODM services than socio-demographic characteristics of the traveler, an early idea would be to integrate a short calibration that consists of questions regarding the traveler's attitudes. Additionally, some exemplary modal choice tasks could be presented in order to let the system adapt to the traveler's individual sensitivities regarding alternative-specific attributes such as cost and walking time. This would allow the recommendation algorithm to consider individual-specific random effects. In conclusion, Figure 6.20 summarizes the core fields of applications for the insights presented in this chapter.

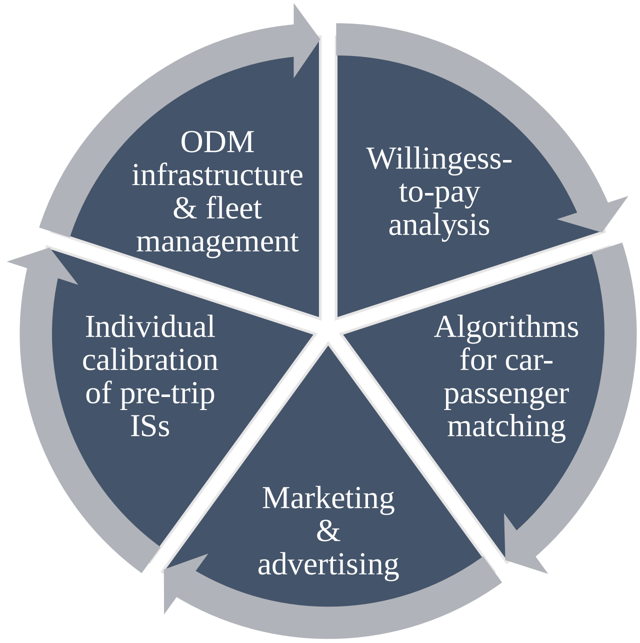


Figure 6.20 Summary of Practical Implications and Future Research of the Discrete Choice Models (own illustration).

7 Conclusion and Future Research

This chapter reflects on the contribution to research and practice made in the present thesis and classifies its overall impact. Since an overall summary of the context, motivation, objectives, method and results of this thesis can be found in the executive summary, this chapter focuses on an overall conclusion in order to avoid any repetitions. Moreover, this section gives an outlook on future research on integrating user-centered choice models in pre-trip ISs. Since ideas for future research were already discussed in detail at the end of each empirical chapter (see Chapter 3.5.2, Chapter 5.4.2, and Chapter 6.6.2), this section concentrates on a more comprehensive outlook and does not repeat the detailed research ideas described above. Figure 7.1 summarizes the research questions focused in this thesis, the artefacts that were developed in order to answer these research questions, and the remaining ideas for future research.

This dissertation developed a pre-trip prototype as well as a technology acceptance model and discrete choice models that can be applied in the context of pre-trip ISs. The models were developed as the basis for the further development of pre-trip ISs that influence traveler's in an economically efficient and ecologically friendly way. Specifically, this thesis regards pre-trip ISs as having a high potential to counteract the extent of urban traffic by influencing the traveler's modal decisions and achieving changes on the traveler's individual behavioral level. Thereby, especially the traveler's willingness for pooling in terms of sharing rides in private cars and sharing rides in robo-taxis was analyzed in detail.

Chapter 3 started with the analysis of a user-centered analysis of pre-trip traveler needs (i.e., RQ 1). The pre-study showed that travelers currently suffer from a lack of availability of pre-trip information. Thus, without putting a considerable amount of effort in the search for information, the travelers' pre-trip information need is not satisfied by current pre-trip ISs. This finding was underlined by a high stress level associated with pre-trip information collection. Furthermore, specific mobility-centered pragmatic needs (e.g., time and type of information) and non-mobility-centered additional digital needs (e.g., entertaining features) were analyzed in the pre-trip situation and aggregated into requirements for pre-trip ISs. The pre-study identified the combination of purely functional mobility-centered information with additional hedonic product qualities as a promising strategy to motivate travelers to use pre-trip ISs and rethink their habitual mobility decisions. Subsequently, in Chapter 4, these insights were implemented into a pre-trip prototype which was presented on a smart mirror prototype (i.e., the BMW Connected Mirror). As illustrated in Figure 7.1, future research should test the effect of hedonic product qualities in pre-trip ISs experimentally. Here, it would be interesting to test purely pragmatic pre-trip ISs against dual-purposed pre-trip ISs (i.e., pre-trip ISs with a combination of pragmatic and hedonic product qualities). Such experimental settings or A-B-test can be used to quantify the impact of hedonic product qualities in pre-trip ISs on individual mobility decisions.

In a next step, Chapter 5, analyzed the factors that motivate travelers to accept and use pre-trip ISs (i.e., RQ 2). Here, the pre-trip prototype described above was evaluated in a user study. The core artefact of the evaluation is a technology acceptance model for pre-trip ISs. Within the technology acceptance model, the impact of the travelers' performance expectancy and their hedonic motivation to use the pre-trip prototype were highlighted as the two most important predictors for the acceptance and use of pre-trip ISs. Moreover, besides behavioral intention, the impact of satisfaction and loyalty as additional outcome variables of technology acceptance was stressed. The presented technology acceptance model was applied to the context of pre-trip ISs and can be used in future user-centered development processes of pre-trip ISs. Future research should further extend the framework by mobility-specific predictors such as time and costs (see Figure 7.1).

Afterwards, Chapter 6 analyzed the factors that predict the travelers' willingness for carpooling (i.e., RQ 3a) and ridepooling (i.e., RQ 3b) in order to find out which factors should be included in pre-trip ISs in order to support modal choices of travelers (i.e., RQ 3). The research question was analyzed with the help of two discrete choice models that were summarized into (1) an overview of individual-specific effects in the context of pooling and (2) a sensitivity-barometer of alternative-specific effects in the context of pooling. As discussed in detail in Chapter 6.6.2, future research can use the identified individual-specific and alternative-specific effects and their weighting of sensitivity for optimizing algorithms in the context of car-passenger-matching and analyze their user acceptance in field tests with ridepooling pilots. This idea for future research is closely connected to the idea of integrating the presented findings in the planning of ODM infrastructure (e.g., pick up and drop off locations for pooling) which should also be tested in field tests. Additionally, the identified individual-specific and alternative-specific effects should be integrated in future pricing analyses. In this context, especially the analysis of the monetary value of optional equipment such as massage seats and the provision of snacks and drinks would be interesting. Furthermore, the insights should be used to develop individual calibration techniques for pre-trip ISs and test them in user studies (see Figure 7.1).

Although the core findings of the present thesis provide considerable insights into the user-centered development of pre-trip ISs, the results underlie some restrictions and provide ideas for future research (see Figure 7.1). In sum, the results presented in this thesis are only valid for the focus group of travelers considered here, i.e., mostly German native speakers that live in Munich or in areas close to Munich. Thus, the external validity or rather the generalizability of the presented results to other areas or countries should be analyzed by replications of the presented research designs. This goes along with the limitations of stated preference data that were already discussed in detail at the end of Chapter 5 and Chapter 6. From a methodological perspective, the findings of the present thesis stress that stated preference data is a valuable resource for analyzing individual behavior and individual preferences in a first step. However, findings based on stated preference data should always be validated with the help of revealed preference data and field tests. For example, the findings regarding optional equipment (e.g., massage seats, digital assistants in robo-taxis or the provision of snacks and drinks during a ride) presented in Chapter 6 should be validated in field studies. In order to express their actual preferences for specific optional equipment, travelers need to experience the different kinds of optional equipment. This can be realized in a field study with vehicle prototypes. A simple description of possible optional equipment in choice sets may be too abstract for participants. Thus, effects of optional equipment might be under estimated. In conclusion, a further research agenda definitely includes replication studies with a multi-regional and multi-national focus, longitudinal studies, and replication studies with revealed preference data and field tests.

Finally, future research should combine the insights presented in the Chapter 3 to 6 and should concentrate on implementing the presented insights in simulations, algorithms, and finally in functioning pre-trip prototypes. Subsequently, these pre-trips prototypes can be used for laboratory experiments and field studies in order to investigate the actual impact in terms of decision influencing. Similar to previous research on decision influencing in the context of transportation research [77], these studies should concentrate on theories from behavioral economics and potential psychological biases in decision-making processes. Investigating these aspects iteratively in the context of pre-trip ISs and combing them with the insights regarding technology acceptance of pre-trip ISs presented in this thesis, will help to develop recommender systems for modal decisions that will be accepted and used by travelers.

In conclusion, the results of the present thesis provide the basis for supporting modal decision-making processes of travelers with the help of pre-trip ISs. Motivating travelers to use pre-trip ISs and developing pre-trip ISs according to the traveler's needs offers a high economic and ecological potential. Additionally, one can assume a high level of customer satisfaction and loyalty and thus experiential customer benefits. Therefore, on-demand mobility providers should further invest in the user-centered development and optimization of pre-trip ISs and their individual calibration to the traveler's needs. Thereby, hedonic product qualities and the traveler's hedonic motivation to use pre-trip ISs should become the center of the development process. However, further research and especially field tests are needed to realize this promising customer benefit. Figure 7.1 summarizes the artefacts and ideas for future research developed in this thesis.

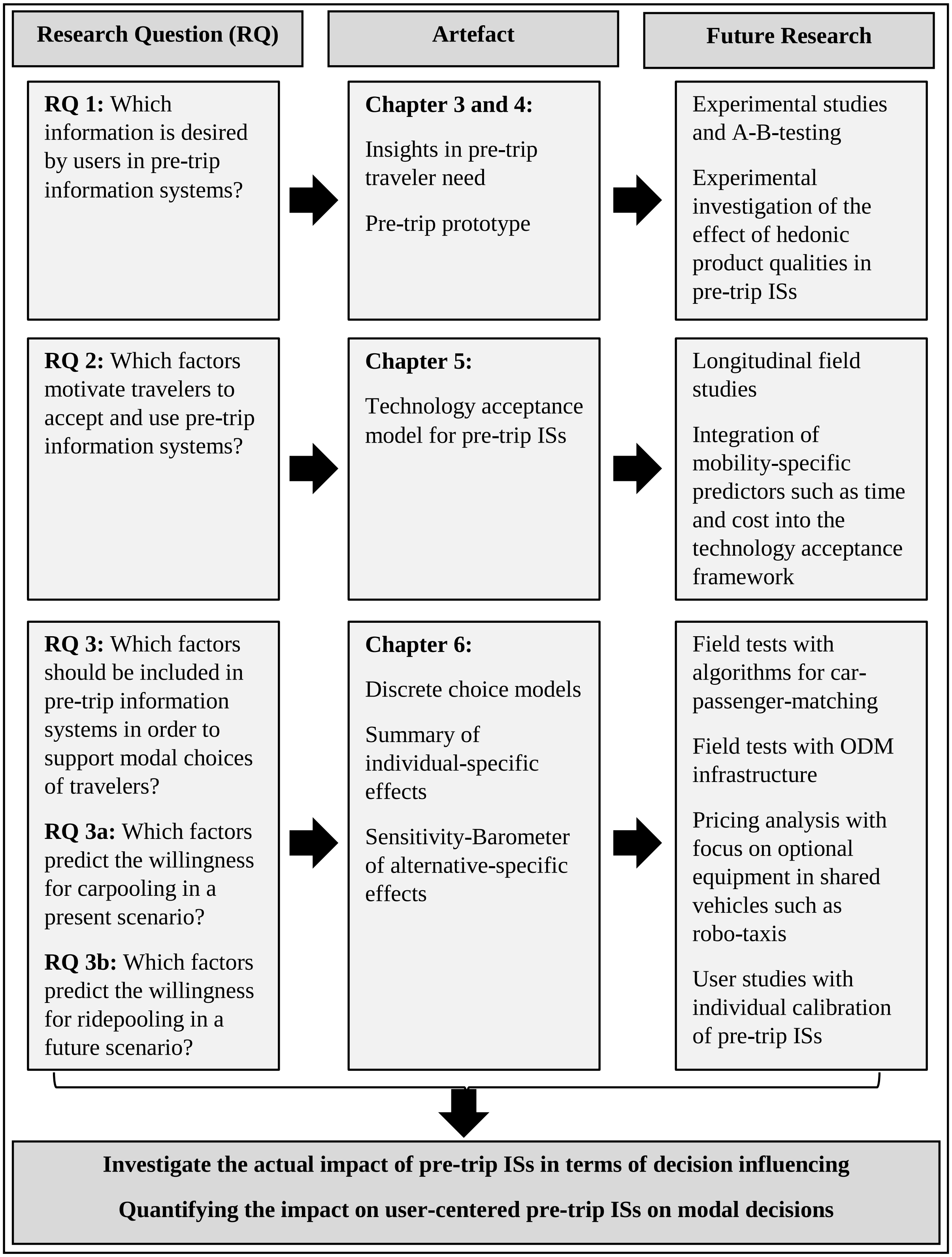


Figure 7.1 Summary of Research Questions (RQs), Artefacts Developed in the Present Thesis, and Ideas for Future Research (own illustration).

Abbreviations

AS-CBC	Alternative Specific Choice-based Conjoint
AV	Autonomous Vehicle
AVE	Average Variance Extracted
CBC	Choice-based Conjoint
DRS	Dynamic Ridesharing
H	Hypothesis
HB	Hierarchical Bayes
HB-CBC	Hierarchical Bayes Choice-based Conjoint
i.i.d.	independent identically distributed
IIA	Independence of Irrelevant Alternatives
IS	Information System
ISO	International Organization for Standardization
ITIS	Intelligent Traveler Information Systems
ITS	Intelligent Transportation Systems
LCM	Latent Class Model
MMNL	Mixed Multinomial Logit Model
MNL	Multinomial Logit Model
MOP	German Mobility Panel
NL	Nested Logit Model
ODM	On-demand Mobility
PAV	Privately owned Autonomous Vehicle
PLS	Partial Least Squares
SAV	Shared Autonomous Vehicle
SD	Standard Deviation
SEM	Structured Equation Modelling
SML	Simulated-Maximum Likelihood
TAM	Technology Acceptance Model
TCA	Traditional Conjoint Analysis
UTAUT	Unified Theory of Acceptance and Use of Technology
UTAUT2	Unified Theory of Acceptance and Use of Technology II

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1. Wittek, D., Goffart, K., & Bogenberger, K. (in press). Towards Designing Pre-trip Traveler Information Systems: A Quantitative Evaluation. In: Proceedings of the 6th International Conference on Models and Technologies for Intelligent Transportation Systems, Krakow, Poland.

2. Wittek, D., Wiesche, M., Goffart, K., & Krcmar, H. (2019). Theory-Based Affordances of Utilitarian, Hedonic and Dual-Purposed Technologies: A Literature Review. In: Proceedings of the 14th International Conference on Wirtschaftsinformatik. Siegen, Germany, pp. 1205-1219.

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Appendix

List of Appendices

Appendix A. Full List of Digital Mobility Services, their Categorization and Modularization (Source: [176]).

Service	General information		Service components						
	Type	Transported item	Routing	Location Sharing	Map view	POIs	Parking information	Traffic information	Matching
Deliveroo	Smart logistics	Goods	0	1	1	1	0	0	1
Foodora	Smart logistics	Goods	0	0	1	0	0	0	1
Take eat easy	Smart logistics	Goods	0	0	1	0	0	0	1
Waze	Trip planner	People	1	1	1	1	0	1	0
Moovit	Trip planner	People	1	0	1	1	0	0	0
Google Maps	Navigation	People	1	0	1	1	0	1	0
Moovel	Trip planner	People	1	0	1	1	0	0	0
Quixxit	Trip planner	People	1	0	1	0	0	1	0
Drivy	Car-/Ride-sharing	People	0	0	1	0	0	0	1
DriveNow	Car-/Ride-sharing	People	0	0	1	1	0	0	0
Car2go	Car-/Ride-sharing	People	0	0	1	1	0	0	0
BlaBlaCar	Car-/Ride-sharing	People	1	0	1	0	0	0	1
Lyft	Car-/Ride-sharing	People	1	0	1	1	0	1	1
My Taxi	Car-/Ride-sharing	People	1	1	1	1	0	1	0
Uber	Car-/Ride-sharing	People	1	1	1	1	0	0	0
Gett	Car-/Ride-sharing	People	1	1	1	0	0	0	0
Blacklane	Car-/Ride-sharing	People	-	1	1	0	0	0	0
Flywheel	Car-/Ride-sharing	People	-	1	1	1	0	0	0
Instantcab	Car-/Ride-sharing	People	1	1	1	0	0	0	0
Sidecar	Smart logistics	Goods	1	1	1	1	0	0	1
Uberrush	Smart logistics	Goods	0	-	1	0	0	0	0
Instacart	Smart logistics	Goods	0	1	-	-	0	0	0
Uber cargo	Smart logistics	Goods	1	1	1	0	0	0	0
Cargomatic	Smart logistics	Goods	1	1	1	0	0	0	1
MyCityWay	Trip planner	People	1	0	1	1	1	1	0
Chargepoint	Location-based information	People	1	0	1	1	1	0	0
ChargeNOW	Location-based information	People	1	0	1	1	0	1	0
ParkN0w	Parking service	People	1	0	1	1	1	0	0
Ampido	Parking service	People	1	0	1	1	1	0	1
ParkPocket	Parking service	People	1	0	1	11	1	0	1
Parknav	Parking service	0	1	0	1	1	1	0	0

Service	General information		Service components						
	Type	Transported item	Routing	Location Sharing	Map view	POIs	Parking information	Traffic information	Matching
Flinc	Car-/Ride-sharing	People	0	0	1	0	0	0	1
Öffi	Trip planner		1	0	1	1	0	0	0
Blitzer.de	Location-based information	People	0	0	1	0	0	1	0
HERE Maps	Navigation	People	1	1	1	1	0	1	0
BVG Fahrinfo	Trip planner	People	1	0	1	1	0	0	0
TomTom Blitzer	Location-based information	People	1	0	1	0	0	1	0
Karten und Navigation GPS	Navigation	People	1	1	1	1	0	1	0
HVV	Trip planner	None	1	0	1	1	0	0	0
Blitzer POIbase	Location-based information	People	1	0	1	1	0	1	0
FahrPlaner	Trip planner	People	1	0	1	1	0	0	0
RMV	Trip planner	People	1	0	1	1	0	0	0
Bus & Bahn	Trip planner	People	1	0	1	1	0	0	0
easyGo	Trip planner	People	1	0	1	1	0	0	0
München Navigator	Trip planner	People	1	0	1	0	0	0	0
Stau-informationen	Location-based information	People	0	0	1	0	0	1	0
Navmii	Navigation	People	1	0	1	1	0	1	0
Citymapper	Trip planner	People	1	0	1	1	0	0	0
ADAC Maps	Navigation	People	1	0	1	1	1	1	0
tripwolf	Trip planner	People	1	0	1	1	0	0	0
Maps.ME	Navigation	People	1	0	1	1	0	0	0
City Maps 2 Go	Navigation	People	1	1	1	1	0	0	0
Urban Engines	Trip planner	People	1	1	1	1	1	1	0
Car Jump	Car-/Ride-sharing	People	1	0	1	1	0	0	0
Nunav	Parking service	People	1	0	1	1	0	1	0
nextbike	Car-/Ride-sharing	People	0	0	1	1	0	0	0
waymate	Trip planner	People	1	0	0	0	0	0	0
Blitzer Radar	Location-based information	People	1	0	1	1	0	1	0
Wunder	Car-/Ride-sharing	People	1	0	1	1	1	0	1

Service	General information		Service components						
	Type	Transported item	Routing	Location Sharing	Map view	POIs	Parking information	Traffic information	Matching
Sum			**45**	**16**	**57**	**51**	**9**	**18**	**12**

Appendix B. Full List of Digital Mobility Services and their Underlying Data Sources (Source: [176]).

Service	Data sources						
	Google	Other private providers	Public transportation provider	Public administration	Device sensors	Crowdsourced	Others
Deliveroo	0	1	0	0	1	1	Apple maps
Foodora	1	1	0	0	1	1	
Take eat easy	1	1	0	0	1	1	
Waze	1	1	0	0	1	1	
Moovit		1	1	1	1	1	
Google Maps	1	1	1	1	1	1	Uber
Moovel	1	1	1	1	1	1	
Quixxit	1	1	1	1	1	1	
Drivy	1	1	0	0	0	1	
DriveNow	1	1	0	0	1	1	
Car2go	1	1	0	0	1	1	
BlaBlaCar	1	1	0	0	1	1	
Lyft	1	0	0	0	1	1	Waze
My Taxi	1	0	0	0	1	0	
Uber	1	0	0	0	1	0	
Gett	1	0	0	0	1	0	
Blacklane	-	-	0	0	1	-	
Flywheel	-	0	0	0	1	0	
Instantcab	1	0	0	0	1	0	
Sidecar	1	0	0	0	1	1	
Uberrush	1	0	0	0	1	0	
Instacart	-	-	0	0	1	0	
Uber cargo	1	1	0	0	1	0	
Cargomatic	1	0	0	0	0	1	
MyCityWay		1	1	0	1	1	
Chargepoint	1	1	0	1	1	0	
ChargeNOW	1	1	0	1	1	1	
ParkN0w	0	1	0	1	1	0	
Ampido	1	1	0	0	1	1	
ParkPocket	1	1	0	1	1	1	
Parknav	0	1	0	1	1	1	
Flinc	1	1	0	0	1	1	Navigon, Deutsche Bahn
Öffi	1	0	1	1	1	0	

Service	Data sources						
	Google	Other private providers	Public transportation provider	Public administration	Device sensors	Crowdsourced	Others
Blitzer.de	1	0	0	0	1	1	Blablacar
HERE Maps	0	0	1	1	1	0	
BVG Fahrinfo	0	0	1	1	1	0	
TomTom Blitzer	0	0	0	0	1	1	Tom tom
Karten und Navigation GPS	1	0	1	1	1	1	
HVV	1	0	1	1	1	0	
Blitzer POIbase	1	0	0	0	1	1	
FahrPlaner	1	1	1	0	1	0	Airport
RMV	0	1	1	1	1	0	Openstreetmaps
Bus & Bahn	1	1	1	0	1	0	
easyGo	0	1	1	0	1	0	Openstreetmaps
München Navigator	1	0	1	1	1	0	
Stauinformationen	1	0	0	1	1	1	
Navmii	1	0	0	0	1	1	
Citymapper	1	0	1	0	1	0	Uber
ADAC Maps	0	0	0	1	1	0	
tripwolf	1	1	0	0	1	0	tripadvisor
Maps.ME	0	0	0	0	1	0	
City Maps 2 Go	0	1	0	0	1	0	Openstreetmaps
Urban Engines	0	0	1	1	1	0	
Car Jump	0	1	0	0	1	0	Car-share companies
Nunav	1	0	0	1	1	1	
nextbike	1	0	0	0	1	0	
waymate	0	1	0	0	0	0	Regional and international carriers
Blitzer Radar	1	0	0	0	1	0	
Wunder	1	0	0	0	1	1	
Sum	**40**	**29**	**17**	**20**	**56**	**29**	**0**

Appendix C. Inter-Correlations of Predictors in the Present Scenario: Commuting - Low Time Pressure (own illustration; Depending on the class of the variable Pearson or Spearman correlation coefficients are reported: *p < .05, **p < .01, ***p <. 001).

	1	2	3	4	5	6	7	8	9	10
	Age	Gender	Income	Kids	Alone	Place of Residence	Car Ownership	Cars in Household	Commute Time PT	Commute Time Car
1	1									
2	-0.212***	1								
3	0.475***	0.116***	1							
4	0.398***	-0.058***	0.225***	1						
5	-0.159***	0.05***	-0.081***	-0.201***	1					
6	0.145***	-0.06***	-0.015	0.167***	-0.144***	1				
7	-0.052***	-0.145***	-0.176***	-0.152***	0.141***	-0.21***	1			
8	-0.054***	0.072***	-0.057***	0.062***	-0.102***	0.29***	-0.363***	1		
9	-0.192***	0.059***	-0.056***	0.059***	-0.044***	0.275***	-0.182***	0.231***	1	
10	-0.213***	0.056***	-0.035***	0.026**	-0.006	0.228***	-0.137***	0.233***	0.913***	1
11	0.057***	-0.107***	-0.002	0.142***	-0.039***	0.169***	-0.118***	0.091***	0.151***	0.026**
12	-0.029**	-0.049***	-0.038***	0.04***	-0.033***	-0.038***	-0.039***	0.156***	0.012	0.02*
13	-0.021*	-0.086***	-0.041***	0.081***	0.011	0.126***	-0.114***	0.092***	0.128***	0.142***
14	-0.122***	-0.048***	-0.066***	-0.09***	0.026**	-0.122***	0.063***	-0.013	-0.005	0.023*
15	-0.06***	0.055***	-0.044***	0.006	0.03**	-0.174***	0.006	-0.041***	-0.147***	-0.139***
16	0	0	-0.002	0.002	-0.001	0.001	0	0	-0.001	-0.002
17	-0.001	0.004	0.004	0.002	-0.002	0.001	-0.002	-0.002	-0.001	0.001
18	-0.001	-0.001	0	-0.001	0.001	-0.001	0	0	-0.001	0
19	-0.003	0.002	0	-0.002	0.001	-0.003	-0.003	0.001	-0.002	-0.004
20	0	0.001	0.001	0	0.001	-0.001	-0.002	0	-0.001	-0.001
21	-0.001	0	0	-0.001	0	-0.001	-0.001	0.001	0	0.001

	11	12	13	14	15	16	17	18	19	20	21
	Leisure Time PT	Leisure Time Car	Access to PT	Frq.Info. Commute	Frq.Info. Leisure	Cost	Time	Wait	Walk	Parking Costs	Features
1											
2											
3											
4											
5											
6											
7											
8											
9											
10											
11	1										
12	0.432***	1									
13	0.144***	0.053***	1								
14	-0.011	0.012	-0.051***	1							
15	0.003	0.085***	-0.041***	0.438***	1						
16	0.004	0.004	-0.002	0.007	0.004	1					
17	-0.003	-0.002	0	0	-0.006	-0.009	1				
18	0	0.001	0	-0.001	0	0.004	-0.006	1			
19	0.001	0.004	0.001	0.003	0.002	0.006	-0.002	-0.003	1		
20	-0.001	-0.001	0	0	-0.001	-0.004	0.009	-0.871***	0.001	1	
21	0	0	0	0	0	0.003	-0.005	0.529***	0	-0.532***	1

Appendix D. Inter-Correlations of Predictors in the Present Scenario: Commuting - High Time Pressure (own illustration; Depending on the class of the variable Pearson or Spearman correlation coefficients are reported: *p < .05, **p < .01, ***p <. 001).

	1	2	3	4	5	6	7	8	9	10
	Age	Gender	Income	Kids	Alone	Place of Residence	Car Ownership	Cars in Household	Commute Time PT	Commute Time Car
1	1									
2	-0.011	1								
3	0.418***	0.187***	1							
4	0.354***	-0.116***	0.126***	1						
5	-0.127***	0.106***	0.051***	-0.265***	1					
6	-0.016	0.037***	0.004	0.002	-0.076***	1				
7	-0.3***	-0.105***	-0.179***	-0.05***	0.019	-0.153***	1			
8	-0.023*	0.072***	-0.048***	0.035**	-0.1***	0.388***	-0.389***	1		
9	-0.027*	0.075***	-0.005	-0.054***	0.012	0.27***	-0.238***	0.151***	1	
10	0.034**	0.12***	0.08***	-0.051***	-0.026*	0.027*	-0.125***	0.069***	0.444***	1
11	0.061***	0.12***	0.072***	0.124***	-0.033**	0.239***	-0.169***	0.09***	0.553***	0.018
12	-0.004	0.032**	0.11***	0.13***	-0.019	-0.041***	0.021*	0.053***	-0.004	0.065***
13	0.096***	0.016	-0.026*	0.074***	-0.163***	0.268***	-0.109***	0.214***	0.228***	0.196***
14	-0.035**	-0.075***	-0.034**	-0.052***	0.098***	-0.142***	0.103***	-0.103***	0.018	0.084***
15	-0.115***	-0.115***	-0.122***	-0.1***	0.079***	-0.166***	0.096***	-0.152***	0.021	0.032**
16	0	0	-0.004	0	-0.003	0	0.001	-0.001	0.001	0.002
17	-0.008	-0.007	-0.009	0.002	-0.002	0	0.006	0.001	0.004	0.005
18	-0.001	0	0	0	0	0.002	0	-0.001	0	0
19	-0.001	-0.001	-0.001	0.001	-0.003	0.001	0.001	0	0.001	0.002
20	0.001	-0.002	0.001	0.001	0	0.001	0.001	0.001	0.001	0.001
21	0	0	-0.001	0.001	0	-0.001	-0.001	0	0.001	0.001

	11	12	13	14	15	16	17	18	19	20	21
	Leisure Time PT	Leisure Time Car	Access to PT	Frq.Info. Commute	Frq.Info. Leisure	Cost	Time	Wait	Walk	Parking Costs	Features
1											
2											
3											
4											
5											
6											
7											
8											
9											
10											
11	1										
12	0.415***	1									
13	0.173***	0.023*	1								
14	-0.083***	-0.006	-0.049***	1							
15	-0.102***	-0.016	-0.054***	0.534***	1						
16	0.002	0.003	0.001	0.001	0	1					
17	0	0.005	-0.001	-0.001	-0.001	0.001	1				
18	-0.002	-0.001	0.001	-0.001	0	0.004	0.005	1			
19	-0.004	-0.002	0	-0.001	-0.004	0.004	-0.001	-0.002	1		
20	0.001	0.001	0.002	-0.001	-0.002	-0.004	0.002	-0.871***	0.003	1	
21	0	0	0	0.001	0	0	0.001	0.534***	-0.003	-0.532***	1

Appendix E. Inter-Correlations of Predictors in the Present Scenario: Leisure Time Trips - Low Time Pressure (own illustration; Depending on the class of the variable Pearson or Spearman correlation coefficients are reported: *p < .05, **p < .01, ***p <. 001).

	1	2	3	4	5	6	7	8	9	10
	Age	Gender	Income	Kids	Alone	Place of Residence	Car Ownership	Cars in Household	Commute Time PT	Commute Time Car
1	1									
2	-0.212***	1								
3	0.475***	0.116***	1							
4	0.398***	-0.058***	0.225***	1						
5	-0.159***	0.05***	-0.081***	-0.201***	1					
6	0.145***	-0.06***	-0.015	0.167***	-0.144***	1				
7	-0.052***	-0.145***	-0.176***	-0.152***	0.141***	-0.21***	1			
8	-0.054***	0.072***	-0.057***	0.062***	-0.102***	0.29***	-0.363***	1		
9	-0.192***	0.059***	-0.056***	0.059***	-0.044***	0.275***	-0.182***	0.231***	1	
10	-0.213***	0.056***	-0.035***	0.026**	-0.006	0.228***	-0.137***	0.233***	0.913***	1
11	0.057***	-0.107***	-0.002	0.142***	-0.039***	0.169***	-0.118***	0.091***	0.151***	0.026**
12	-0.029**	-0.049***	-0.038***	0.04***	-0.033***	-0.038***	-0.039***	0.156***	0.012	0.02*
13	-0.021*	-0.086***	-0.041***	0.081***	0.011	0.126***	-0.114***	0.092***	0.128***	0.142***
14	-0.122***	-0.048***	-0.066***	-0.09***	0.026**	-0.122***	0.063***	-0.013	-0.005	0.023*
15	-0.06***	0.055***	-0.044***	0.006	0.03**	-0.174***	0.006	-0.041***	-0.147***	-0.139***
16	0	0	-0.002	0.002	-0.001	0.001	0	0	-0.001	-0.002
17	-0.001	0.004	0.004	0.002	-0.002	0.001	-0.002	-0.002	-0.001	0.001
18	-0.001	-0.001	0	-0.001	0.001	-0.001	0	0	-0.001	0
19	-0.003	0.002	0	-0.002	0.001	-0.003	-0.003	0.001	-0.002	-0.004
20	0	0.001	0.001	0	0.001	-0.001	-0.002	0	-0.001	-0.001
21	-0.001	0	0	-0.001	0	-0.001	-0.001	0.001	0	0.001

	11	12	13	14	15	16	17	18	19	20	21
	Leisure Time PT	Leisure Time Car	Access to PT	Frq.Info. Commute	Frq.Info. Leisure	Cost	Time	Wait	Walk	Parking Costs	Features
1											
2											
3											
4											
5											
6											
7											
8											
9											
10											
11	1										
12	0.432***	1									
13	0.144***	0.053***	1								
14	-0.011	0.012	-0.051***	1							
15	0.003	0.085***	-0.041***	0.438***	1						
16	0.004	0.004	-0.002	0.007	0.004	1					
17	-0.003	-0.002	0	0	-0.006	-0.009	1				
18	0	0.001	0	-0.001	0	0.004	-0.006	1			
19	0.001	0.004	0.001	0.003	0.002	0.006	-0.002	-0.003	1		
20	-0.001	-0.001	0	0	-0.001	-0.004	0.009	-0.871***	0.001	1	
21	0	0	0	0	0	0.003	-0.005	0.529***	0	-0.532***	1

Appendix F. Inter-Correlations of Predictors in the Present Scenario: Leisure Time Trips - High Time Pressure (own illustration; Depending on the class of the variable Pearson or Spearman correlation coefficients are reported: *p < .05, **p < .01, ***p <. 001).

	1	2	3	4	5	6	7	8	9	10
	Age	Gender	Income	Kids	Alone	Place of Residence	Car Ownership	Cars in Household	Commute Time PT	Commute Time Car
1	1									
2	-0.011	1								
3	0.418***	0.187***	1							
4	0.354***	-0.116***	0.126***	1						
5	-0.127***	0.106***	0.051***	-0.265***	1					
6	-0.016	0.037***	0.004	0.002	-0.076***	1				
7	-0.3***	-0.105***	-0.179***	-0.05***	0.019	-0.153***	1			
8	-0.023*	0.072***	-0.048***	0.035**	-0.1***	0.388***	-0.389***	1		
9	-0.027*	0.075***	-0.005	-0.054***	0.012	0.27***	-0.238***	0.151***	1	
10	0.034**	0.12***	0.08***	-0.051***	-0.026*	0.027*	-0.125***	0.069***	0.444***	1
11	0.061***	0.12***	0.072***	0.124***	-0.033**	0.239***	-0.169***	0.09***	0.553***	0.018
12	-0.004	0.032**	0.11***	0.13***	-0.019	-0.041***	0.021*	0.053***	-0.004	0.065***
13	0.096***	0.016	-0.026*	0.074***	-0.163***	0.268***	-0.109***	0.214***	0.228***	0.196***
14	-0.035**	-0.075***	-0.034**	-0.052***	0.098***	-0.142***	0.103***	-0.103***	0.018	0.084***
15	-0.115***	-0.115***	-0.122***	-0.1***	0.079***	-0.166***	0.096***	-0.152***	0.021	0.032**
16	0	0	-0.004	0	-0.003	0	0.001	-0.001	0.001	0.002
17	-0.008	-0.007	-0.009	0.002	-0.002	0	0.006	0.001	0.004	0.005
18	-0.001	0	0	0	0	0.002	0	-0.001	0	0
19	-0.001	-0.001	-0.001	0.001	-0.003	0.001	0.001	0	0.001	0.002
20	0.001	-0.002	0.001	0.001	0	0.001	0.001	0.001	0.001	0.001
21	0	0	-0.001	0.001	0	-0.001	-0.001	0	0.001	0.001

	11	12	13	14	15	16	17	18	19	20	21
	Leisure Time PT	Leisure Time Car	Access to PT	Frq.Info. Commute	Frq.Info. Leisure	Cost	Time	Wait	Walk	Parking Costs	Features
1											
2											
3											
4											
5											
6											
7											
8											
9											
10											
11	1										
12	0.415***	1									
13	0.173***	0.023*	1								
14	-0.083***	-0.006	-0.049***	1							
15	-0.102***	-0.016	-0.054***	0.534***	1						
16	0.002	0.003	0.001	0.001	0	1					
17	0	0.005	-0.001	-0.001	-0.001	0.001	1				
18	-0.002	-0.001	0.001	-0.001	0	0.004	0.005	1			
19	-0.004	-0.002	0	-0.001	-0.004	0.004	-0.001	-0.002	1		
20	0.001	0.001	0.002	-0.001	-0.002	-0.004	0.002	-0.871***	0.003	1	
21	0	0	0	0.001	0	0	0.001	0.534***	-0.003	-0.532***	1

Appendix G. Inter-Correlations of Predictors in the Future Scenario: Commuting - Low Time Pressure (own illustration; Depending on the class of the variable Pearson or Spearman correlation coefficients are reported: *p < .05, **p < .01, ***p <. 001).

	1	2	3	4	5	6	7	8	9	10
	Age	Gender	Income	Kids	Alone	Place of Residence	Access to PT	Hedonic Motivation	Perform. Expectanc.	Robo-Taxi Trust
1	1									
2	-0.338***	1								
3	0.336***	0.179***	1							
4	0.412***	-0.171***	0.127***	1						
5	-0.035**	-0.01	-0.103***	-0.257***	1					
6	-0.048***	0.087***	0.068***	0.021	-0.074***	1				
7	-0.02	0.012	0.081***	0.027*	-0.098***	0.135***	1			
8	-0.039***	-0.068***	0.016	0.111***	-0.063***	-0.029*	0.025*	1		
9	-0.021	-0.061***	0.038***	0.111***	-0.096***	0.057***	0.077***	0.593***	1	
10	-0.035**	0.145***	0.079***	-0.056***	-0.008	0	0.075***	0.449***	0.417***	1
11	-0.081***	0.19***	0.019	0.066***	-0.022	0.005	0.013	0.285***	0.331***	0.257***
12	-0.044***	0.072***	-0.015	-0.049***	-0.05***	-0.058***	-0.081***	0.056***	0.074***	0.226***
13	-0.109***	-0.091***	-0.149***	0.007	0.095***	-0.037**	-0.056***	0.185***	0.218***	0.063***
14	0.137***	-0.252***	-0.054***	0.125***	0.024*	-0.126***	-0.015	0.111***	0.136***	-0.016
15	0.004	0.002	0.007	0.008	-0.002	-0.001	0.003	0.003	-0.002	-0.001
16	-0.002	0.004	-0.008	-0.002	0.006	0.004	-0.005	0.004	0.002	0.008
17	0	0	0	0	0	0	0	0	0	0
18	0.002	-0.001	0	0	-0.001	0	-0.002	0.002	0.001	-0.001
19	0	0	0	0	0.001	0.001	0.001	-0.001	0	0.001
20	0	0	0.002	0.001	-0.003	0.003	0.004	0	-0.002	-0.003
21	0	-0.001	-0.002	0	-0.002	0	-0.002	0	0.001	0

	11	12	13	14	15	16	17	18	19	20	21
	Tech.Intr.	PT Trust	Frq.Info. Commute	Frq.Info. Leisure	Cost	Time	Wait	Walk	Robo-Taxi Type	Security Info	Individual Offer
1											
2											
3											
4											
5											
6											
7											
8											
9											
10											
11	1										
12	0.074***	1									
13	0.037**	0.054***	1								
14	-0.109***	0.028*	0.386***	1							
15	0.001	0	-0.008	0.005	1						
16	0.003	0.005	-0.001	-0.004	0.007	1					
17	0	0	0	0	0.005	0.008	1				
18	0.001	-0.001	0	0.001	-0.001	0.001	-0.008	1			
19	0.001	0.002	-0.002	-0.002	0.006	0.013	-0.004	-0.36***	1		
20	0.001	-0.001	-0.001	-0.001	-0.007	0.012	0	-0.359***	0.717***	1	
21	-0.001	0.001	0	-0.001	0.001	0.01	-0.002	-0.362***	0.719***	0.718***	1

Appendix H. Inter-Correlations of Predictors in the Future Scenario: Commuting - High Time Pressure (own illustration; Depending on the class of the variable Pearson or Spearman correlation coefficients are reported: *p < .05, **p < .01, ***p <. 001).

	1	2	3	4	5	6	7	8	9	10
	Age	Gender	Income	Kids	Alone	Place of Residence	Access to PT	Hedonic Motivation	Perform. Expectanc.	Robo-Taxi Trust
1	1									
2	0.112***	1								
3	0.434***	0.118***	1							
4	0.416***	-0.042***	0.405***	1						
5	0.01	0.066***	-0.079***	-0.245***	1					
6	0.039**	0.025*	0.13***	0.1***	-0.111***	1				
7	0.126***	-0.088***	0.084***	0.142***	-0.084***	0.117***	1			
8	-0.181***	-0.025*	-0.061***	-0.095***	0.079***	-0.048***	-0.03*	1		
9	-0.151***	0.035**	0.01	0.006	-0.021	-0.054***	0.025*	0.616***	1	
10	-0.184***	0.138***	0.035**	-0.062***	-0.028*	-0.001	-0.066***	0.443***	0.408***	1
11	-0.042***	0.351***	0.116***	0.062***	0.12***	-0.027*	0.004	0.211***	0.3***	0.324***
12	-0.05***	0.009	0.005	-0.031*	-0.137***	0.105***	0.046***	0.103***	0.058***	0.104***
13	-0.069***	-0.121***	-0.131***	-0.109***	0.049***	-0.16***	0.13***	0.047***	0.086***	0.036**
14	-0.101***	-0.146***	-0.094***	-0.111***	0.021	-0.218***	-0.014	0.086***	0.083***	0.072***
15	0.001	0.005	0	0.007	0.007	-0.003	-0.003	0.001	-0.001	-0.002
16	0	-0.001	-0.001	0.002	-0.008	0.001	0.009	0.005	0.004	-0.002
17	0	0	0	0	0	0	0	0	0	0
18	0.002	-0.002	0	0	-0.005	0	0.004	0.002	0.001	-0.001
19	0.001	-0.004	-0.001	0	-0.001	-0.003	0.001	0.001	0	0.001
20	-0.003	0.002	0	0.001	0.003	-0.001	-0.004	0.002	0.002	0
21	0	-0.002	0	-0.001	0.001	-0.002	-0.001	0.001	0.001	0.002

	11	12	13	14	15	16	17	18	19	20	21
	Tech.Intr.	PT Trust	Frq.Info. Commute	Frq.Info. Leisure	Cost	Time	Wait	Walk	Robo-Taxi Type	Security Info	Individual Offer
1											
2											
3											
4											
5											
6											
7											
8											
9											
10											
11	1										
12	0.051***	1									
13	0.044***	0.079***	1								
14	0.012	0.148***	0.513***	1							
15	0.004	0.005	0.001	-0.001	1						
16	-0.001	0.002	-0.003	-0.005	-0.005	1					
17	0	0	0	0	-0.008	0.005	1				
18	-0.002	-0.001	0.004	0.002	0.004	-0.005	0.003	1			
19	0	-0.001	0.001	0.001	-0.001	0.005	0.004	-0.36***	1		
20	0.001	0	-0.001	-0.001	0.001	-0.005	0.014	-0.359***	0.714***	1	
21	-0.001	0.001	-0.003	0	0	-0.004	0.009	-0.355***	0.72***	0.721***	1

Appendix I. Inter-Correlations of Predictors in the Future Scenario: Leisure Time Trips - Low Time Pressure (own illustration; Depending on the class of the variable Pearson or Spearman correlation coefficients are reported: *p < .05, **p < .01, ***p <. 001).

	1	2	3	4	5	6	7	8	9	10
	Age	Gender	Income	Kids	Alone	Place of Residence	Access to PT	Hedonic Motivation	Perform. Expectanc.	Robo-Taxi Trust
1	1									
2	-0.338***	1								
3	0.336***	0.179***	1							
4	0.412***	-0.171***	0.127***	1						
5	-0.035**	-0.01	-0.103***	-0.257***	1					
6	-0.048***	0.087***	0.068***	0.021	-0.074***	1				
7	-0.02	0.012	0.081***	0.027*	-0.098***	0.135***	1			
8	-0.039***	-0.068***	0.016	0.111***	-0.063***	-0.029*	0.025*	1		
9	-0.021	-0.061***	0.038***	0.111***	-0.096***	0.057***	0.077***	0.593***	1	
10	-0.035**	0.145***	0.079***	-0.056***	-0.008	0	0.075***	0.449***	0.417***	1
11	-0.081***	0.19***	0.019	0.066***	-0.022	0.005	0.013	0.285***	0.331***	0.257***
12	-0.044***	0.072***	-0.015	-0.049***	-0.05***	-0.058***	-0.081***	0.056***	0.074***	0.226***
13	-0.109***	-0.091***	-0.149***	0.007	0.095***	-0.037**	-0.056***	0.185***	0.218***	0.063***
14	0.137***	-0.252***	-0.054***	0.125***	0.024*	-0.126***	-0.015	0.111***	0.136***	-0.016
15	0.003	0.001	0.007	0.002	-0.004	-0.003	0.004	0.003	0.006	0.005
16	0	-0.002	0.002	0.002	0.003	0.003	0.004	0.001	0.002	0.004
17	0	0	0	0	0	0	0	0	0	0
18	0.001	-0.001	-0.004	0.002	0.001	0.003	0.004	-0.001	0.001	0.002
19	0.002	-0.003	0	0.001	-0.001	0.001	0	0	0.001	0.001
20	-0.001	0.001	-0.002	-0.002	0.001	0	-0.001	-0.001	-0.002	-0.001
21	-0.002	0	0.001	-0.002	0.002	0	0.003	0	-0.001	0

	11	12	13	14	15	16	17	18	19	20	21
	Tech.Intr.	PT Trust	Frq.Info. Commute	Frq.Info. Leisure	Cost	Time	Wait	Walk	Robo-Taxi Type	Security Info	Individual Offer
1											
2											
3											
4											
5											
6											
7											
8											
9											
10											
11	1										
12	0.074***	1									
13	0.037**	0.054***	1								
14	-0.109***	0.028*	0.386***	1							
15	0.01	0.002	0.003	-0.005	1						
16	-0.006	-0.005	-0.005	0.008	0.003	1					
17	0	0	0	0	-0.013	0	1				
18	0.001	-0.002	-0.001	-0.003	0	-0.005	-0.005	1			
19	0.001	0.001	0.001	0.002	-0.006	-0.002	0.007	-0.355***	1		
20	0	0	0.003	0.001	0.009	-0.001	0.011	-0.362***	0.712***	1	
21	-0.005	0	0.002	0.004	0.004	-0.005	0.012	-0.352***	0.715***	0.718***	1

Appendix J. Inter-Correlations of Predictors in the Future Scenario: Leisure Time Trips - High Time Pressure (own illustration; Depending on the class of the variable Pearson or Spearman correlation coefficients are reported: *p < .05, **p < .01, ***p <. 001).

	1	2	3	4	5	6	7	8	9	10
	Age	Gender	Income	Kids	Alone	Place of Residence	Access to PT	Hedonic Motivation	Perform. Expectanc.	Robo-Taxi Trust
1	1									
2	0.112***	1								
3	0.434***	0.118***	1							
4	0.416***	-0.042***	0.405***	1						
5	0.01	0.066***	-0.079***	-0.245***	1					
6	0.039**	0.025*	0.13***	0.1***	-0.111***	1				
7	0.126***	-0.088***	0.084***	0.142***	-0.084***	0.117***	1			
8	-0.181***	-0.025*	-0.061***	-0.095***	0.079***	-0.048***	-0.03*	1		
9	-0.151***	0.035**	0.01	0.006	-0.021	-0.054***	0.025*	0.616***	1	
10	-0.184***	0.138***	0.035**	-0.062***	-0.028*	-0.001	-0.066***	0.443***	0.408***	1
11	-0.042***	0.351***	0.116***	0.062***	0.12***	-0.027*	0.004	0.211***	0.3***	0.324***
12	-0.05***	0.009	0.005	-0.031*	-0.137***	0.105***	0.046***	0.103***	0.058***	0.104***
13	-0.069***	-0.121***	-0.131***	-0.109***	0.049***	-0.16***	0.13***	0.047***	0.086***	0.036**
14	-0.101***	-0.146***	-0.094***	-0.111***	0.021	-0.218***	-0.014	0.086***	0.083***	0.072***
15	0.001	0.004	0.002	-0.003	0.003	0.005	0.002	0	-0.003	0.003
16	-0.005	0.002	-0.007	-0.003	-0.002	-0.006	0.001	0.009	0.005	0.004
17	0	0	0	0	0	0	0	0	0	0
18	0.001	0.001	-0.002	0	-0.002	0.001	0	0.002	-0.001	0.003
19	0.001	0	0.003	-0.001	-0.002	-0.004	0.002	0.004	0.002	0.002
20	0	-0.004	0	-0.001	0	0.002	-0.002	-0.002	-0.007	-0.004
21	0	-0.002	-0.004	-0.002	0.001	0.001	-0.002	-0.003	-0.003	-0.001

	11	12	13	14	15	16	17	18	19	20	21
	Tech.Intr.	PT Trust	Frq.Info. Commute	Frq.Info. Leisure	Cost	Time	Wait	Walk	Robo-Taxi Type	Security Info	Individual Offer
1											
2											
3											
4											
5											
6											
7											
8											
9											
10											
11	1										
12	0.051***	1									
13	0.044***	0.079***	1								
14	0.012	0.148***	0.513***	1							
15	0	0.006	-0.003	0.004	1						
16	0	0.006	0.007	0.007	0.004	1					
17	0	0	0	0	0.002	-0.004	1				
18	-0.002	0.003	-0.001	-0.002	0.001	0.002	0.005	1			
19	0.002	0	0.002	-0.002	0.004	-0.005	0.007	-0.367***	1		
20	-0.003	0.002	0	0.001	0.001	-0.009	-0.001	-0.37***	0.716***	1	
21	-0.002	0	-0.002	0	0.004	-0.009	0.001	-0.365***	0.714***	0.716***	1

Appendix K. Final Discrete Choice Models of the Present Scenario: Commuting - Low Time Pressure (own illustration; *Est.* = Estimate, *SE* = Standard Error, *z* = *z*-value, *p* = *p*-value; prohibitions of attributes are highlighted in orange).

Mode	Own car				Pooling as a driver				Pooling as a passenger				Public transport			
	Est.	*SE*	*z*	*p*	*Est.*	*SE*	*z*	*p*	*Est.*	*SE*	*z*	*p*	*Est.*	*SE*	*z*	*p*
Intercept	-1.61	0.59	-2.73	0.01	-0.68	0.68	-1.00	0.32	-0.31	0.57	-0.54	0.59	Reference Level			
Individual-specific																
Age	0.02	0.01	1.66	0.10	-0.09	0.02	-5.73	0.00	-0.03	0.01	-2.32	0.02	Reference Level			
Gender									-0.43	0.21	-2.00	0.05				
Income					0.41	0.14	2.99	0.00								
Kids	1.13	0.38	2.96	0.00					-1.48	0.38	-3.95	0.00				
Alone					-1.10	0.24	-4.54	0.00	-1.28	0.21	-5.98	0.00				
Medium city	0.94	0.38	2.48	0.01	2.56	0.40	6.38	0.00	1.96	0.36	5.45	0.00				
Small city	1.20	0.37	3.27	0.00	1.25	0.37	3.39	0.00	1.04	0.31	3.30	0.00				
Town					1.02	0.30	3.39	0.00								
Village	0.82	0.29	2.85	0.00	2.50	0.30	8.28	0.00	1.17	0.26	4.42	0.00				
PT access	0.19	0.03	5.63	0.00	0.10	0.03	3.39	0.00	0.09	0.03	3.03	0.00				
Commute time car					0.01	0.00	6.93	0.00								
Frq. info. commute					-0.36	0.21	-1.72	0.09	-0.47	0.19	-2.51	0.01				
Alternative-specific																
Cost 2	-0.49	0.19	-2.55	0.01	-0.84	0.20	-4.15	0.00	-0.48	0.18	-2.62	0.01	-0.36	0.19	-1.93	0.05
Cost 3	-0.93	0.20	-4.72	0.00	-1.45	0.21	-6.89	0.00	-1.28	0.19	-6.74	0.00	-0.85	0.20	-4.30	0.00
Time 2	-0.73	0.19	-3.76	0.00	-0.79	0.19	-4.16	0.00	-0.43	0.17	-2.50	0.01	-0.56	0.18	-3.04	0.00
Time 3	-1.10	0.20	-5.59	0.00	-2.18	0.24	-9.25	0.00	-1.05	0.18	-5.72	0.00	-0.94	0.19	-5.01	0.00
Wait 2									-0.52	0.18	-2.92	0.00				
Wait 3													-0.39	0.19	-2.11	0.03
Walk 2					-0.33	0.20	-1.65	0.10	-0.49	0.18	-2.74	0.01	-0.45	0.19	-2.35	0.02
Walk 3	-0.34	0.20	-1.68	0.09					-0.98	0.19	-5.05	0.00	-0.57	0.20	-2.90	0.00

Mode	Own car				Pooling as a driver				Pooling as a passenger				Public transport			
	Est.	*SE*	*z*	*p*	*Est.*	*SE*	*z*	*p*	*Est.*	*SE*	*z*	*p*	*Est.*	*SE*	*z*	*p*
Parking costs 2	-0.73	0.20	-3.67	0.00	-0.86	0.20	-4.30	0.00								
Parking costs 3	-1.05	0.20	-5.28	0.00	-1.30	0.21	-6.08	0.00								
Features 2									0.30	0.17	1.75	0.08				
Features 3									0.64	0.18	3.46	0.00				
Random effects																
Intercept	3.98	0.20	19.44	0.00	2.59	0.16	16.69	0.00	2.14	0.13	16.92	0.00	Reference level			
Cost 2					-0.77	0.19	-4.00	0.00	0.76	0.18	4.17	0.00	0.53	0.19	2.85	0.00
Cost 3	0.81	0.23	3.56	0.00					0.92	0.18	5.25	0.00	0.97	0.18	5.37	0.00
Time 2									-0.30	0.16	-1.82	0.07	0.36	0.16	2.28	0.02
Time 3					-0.82	0.21	-3.88	0.00								
Wait 2																
Wait 3									0.47	0.16	2.85	0.00	0.44	0.20	2.17	0.03
Walk 2					0.43	0.20	2.15	0.03					0.73	0.17	4.16	0.00
Walk 3					-0.52	0.20	-2.56	0.01	0.84	0.18	4.71	0.00	0.50	0.19	2.61	0.01
Parking costs 2																
Parking costs 3																
Features 2																
Features 3									0.89	0.17	5.15	0.00				

Appendix L. Final Discrete Choice Models of the Present Scenario: Commuting - High Time Pressure (own illustration; *Est.* = Estimate, *SE* = Standard Error, *z* = *z*-value, *p* = *p*-value; prohibitions of attributes are highlighted in orange).

Mode	Own car				Pooling as a driver				Pooling as a passenger				Public transport			
	Est.	*SE*	*z*	*p*	*Est.*	*SE*	*z*	*p*	*Est.*	*SE*	*z*	*p*	*Est.*	*SE*	*z*	*p*
Intercept	0.35	0.65	0.54	0.59	-2.88	0.70	-4.10	0.00	0.86	0.69	1.25	0.21	Reference Level			
Individual-specific																
Age	0.07	0.01	5.67	0.00					-0.04	0.01	-3.26	0.00	Reference Level			
Gender	-0.61	0.23	-2.68	0.01												
Income	0.35	0.10	3.45	0.00	0.54	0.12	4.65	0.00								
Kids					0.77	0.37	2.09	0.04								
Alone	-1.21	0.26	-4.60	0.00					0.64	0.29	2.20	0.03				
Medium city	3.38	0.41	8.18	0.00	4.29	0.47	9.07	0.00	1.51	0.46	3.26	0.00				
Small city	2.58	0.35	7.41	0.00	2.92	0.39	7.46	0.00	1.27	0.36	3.55	0.00				
Town	3.23	0.44	7.30	0.00	3.94	0.49	7.96	0.00	2.68	0.48	5.61	0.00				
Village	1.82	0.32	5.77	0.00	2.42	0.37	6.49	0.00	2.04	0.35	5.77	0.00				
PT access	-0.16	0.04	-4.14	0.00	0.17	0.04	3.74	0.00								
Commute time car									-0.01	0.01	-2.28	0.02				
Frq. info. commute	-1.17	0.24	-4.90	0.00	-1.24	0.29	-4.35	0.00	-0.91	0.27	-3.40	0.00				
Alternative-specific																
Cost 2	-0.59	0.20	-2.99	0.00	-0.64	0.26	-2.48	0.01								
Cost 3	-0.52	0.20	-2.54	0.01	-0.85	0.24	-3.47	0.00	-0.59	0.24	-2.46	0.01				
Time 2	-0.52	0.20	-2.63	0.01	-0.80	0.22	-3.56	0.00	-0.79	0.24	-3.29	0.00	-0.55	0.23	-2.43	0.02
Time 3	-1.38	0.21	-6.59	0.00	-1.69	0.26	-6.44	0.00	-1.64	0.27	-6.08	0.00	-1.05	0.24	-4.28	0.00
Wait 2																
Wait 3																
Walk 2																
Walk 3									-0.51	0.25	-2.04	0.04				

Mode	Own car				Pooling as a driver				Pooling as a passenger				Public transport			
	Est.	*SE*	*z*	*p*	*Est.*	*SE*	*z*	*p*	*Est.*	*SE*	*z*	*p*	*Est.*	*SE*	*z*	*p*
Parking costs 2	-0.68	0.20	-3.34	0.00	-0.54	0.24	-2.22	0.03								
Parking costs 3	-0.85	0.21	-4.13	0.00	-0.64	0.25	-2.58	0.01								
Features 2																
Features 3																
Random effects																
Intercept	4.36	0.26	17.00	0.00	1.93	0.17	11.32	0.00	2.07	0.15	13.83	0.00	Reference level			
Cost 2	0.56	0.18	3.10	0.00	1.23	0.26	4.77	0.00								
Cost 3	-1.32	0.21	-6.32	0.00					0.45	0.20	2.31	0.02	-0.60	0.25	-2.36	0.02
Time 2	0.88	0.20	4.31	0.00					-0.35	0.21	-1.71	0.09	-0.57	0.20	-2.91	0.00
Time 3	0.66	0.20	3.29	0.00	0.52	0.24	2.14	0.03	0.92	0.28	3.33	0.00				
Wait 2																
Wait 3									-0.58	0.19	-2.99	0.00				
Walk 2	1.64	0.22	7.51	0.00	-0.76	0.20	-3.85	0.00	1.04	0.22	4.68	0.00				
Walk 3					-0.52	0.21	-2.46	0.01								
Parking costs 2	-0.77	0.18	-4.33	0.00	1.12	0.22	4.96	0.00								
Parking costs 3	0.38	0.15	2.51	0.01												
Features 2									-0.55	0.23	-2.36	0.02				
Features 3																

Appendix M. Final Discrete Choice Models of the Present Scenario: Leisure Time Trips - Low Time Pressure (own illustration; *Est.* = Estimate, *SE* = Standard Error, *z* = *z*-value, *p* = *p*-value; prohibitions of attributes are highlighted in orange).

Mode	Own car				Pooling as a driver				Pooling as a passenger				Public transport			
	Est.	*SE*	*z*	*p*	*Est.*	*SE*	*z*	*p*	*Est.*	*SE*	*z*	*p*	*Est.*	*SE*	*z*	*p*
Intercept	0.10	0.61	0.17	0.87	-1.81	0.72	-2.52	0.01	-3.37	0.66	-5.15	0.00	Reference Level			
Individual-specific																
Age	0.04	0.01	3.56	0.00	-0.06	0.02	-3.38	0.00	-0.03	0.01	-2.17	0.03	Reference Level			
Gender					-0.54	0.25	-2.11	0.04	0.43	0.20	2.12	0.03				
Income	-0.33	0.13	-2.50	0.01	0.31	0.16	2.00	0.05	0.64	0.13	4.80	0.00				
Kids	1.42	0.37	3.87	0.00					-2.73	0.42	-6.49	0.00				
Alone									-0.53	0.22	-2.40	0.02				
Medium city									-0.66	0.35	-1.87	0.06				
Small city	0.66	0.33	2.00	0.05	1.68	0.34	4.91	0.00	0.73	0.32	2.32	0.02				
Town	0.60	0.32	1.88	0.06	1.35	0.35	3.81	0.00								
Village	0.74	0.30	2.45	0.01	2.30	0.35	6.54	0.00	1.54	0.30	5.15	0.00				
PT access					0.08	0.03	2.46	0.01	0.19	0.03	6.00	0.00				
Leisure time car	-0.01	0.00	-1.74	0.08	0.02	0.00	4.78	0.00	-0.01	0.00	-4.76	0.00				
Frq. info. leisure trips	-2.09	0.22	-9.38	0.00	0.67	0.24	2.73	0.01	1.05	0.22	4.88	0.00				
Alternative-specific																
Cost 2					-1.08	0.23	-4.72	0.00	-0.76	0.19	-4.00	0.00				
Cost 3	-0.73	0.20	-3.72	0.00	-1.18	0.22	-5.32	0.00	-1.41	0.20	-7.05	0.00	-0.62	0.20	-3.10	0.00
Time 2	-0.40	0.18	-2.18	0.03	-0.70	0.22	-3.22	0.00	-0.44	0.18	-2.38	0.02	-0.70	0.19	-3.64	0.00
Time 3	-1.11	0.20	-5.64	0.00	-1.63	0.24	-6.86	0.00	-0.71	0.19	-3.74	0.00	-1.20	0.20	-6.05	0.00
Wait 2																
Wait 3									-0.55	0.20	-2.76	0.01	-0.41	0.19	-2.12	0.03
Walk 2					-0.73	0.23	-3.20	0.00					-0.78	0.21	-3.78	0.00
Walk 3	-0.97	0.20	-4.80	0.00	-0.73	0.22	-3.32	0.00	-0.70	0.20	-3.59	0.00	-0.66	0.20	-3.25	0.00

Mode	Own car				Pooling as a driver				Pooling as a passenger				Public transport			
	Est.	*SE*	*z*	*p*	*Est.*	*SE*	*z*	*p*	*Est.*	*SE*	*z*	*p*	*Est.*	*SE*	*z*	*p*
Parking costs 2	-0.64	0.19	-3.39	0.00	-0.68	0.22	-3.11	0.00								
Parking costs 3	-1.18	0.20	-5.95	0.00	-1.21	0.24	-5.11	0.00								
Features 2									0.56	0.18	3.05	0.00				
Features 3									0.65	0.19	3.36	0.00				
Random effects																
Intercept	4.29	0.21	20.47	0.00	3.23	0.17	18.55	0.00	2.94	0.16	18.66	0.00	Reference level			
Cost 2	-0.38	0.16	-2.42	0.02	0.77	0.23	3.39	0.00	-0.32	0.18	-1.81	0.07				
Cost 3					-0.32	0.18	-1.77	0.08								
Time 2	0.34	0.14	2.44	0.01	-0.33	0.19	-1.76	0.08	0.30	0.17	1.73	0.08	0.81	0.22	3.78	0.00
Time 3	-0.62	0.20	-3.17	0.00	-0.58	0.24	-2.37	0.02	0.72	0.19	3.79	0.00				
Wait 2									0.78	0.17	4.68	0.00				
Wait 3									1.14	0.18	6.29	0.00				
Walk 2													-0.35	0.19	-1.86	0.06
Walk 3									0.76	0.19	3.90	0.00				
Parking costs 2																
Parking costs 3	-0.34	0.16	-2.08	0.04												
Features 2																
Features 3									0.91	0.20	4.59	0.00				

Appendix N. Final Discrete Choice Models of the Present Scenario: Leisure Time Trips - High Time Pressure (own illustration; *Est.* = Estimate, *SE* = Standard Error, *z* = *z*-value, *p* = *p*-value; prohibitions of attributes are highlighted in orange).

Mode	Own car				Pooling as a driver				Pooling as a passenger				Public transport			
	Est.	*SE*	*z*	*p*	*Est.*	*SE*	*z*	*p*	*Est.*	*SE*	*z*	*p*	*Est.*	*SE*	*z*	*p*
Intercept	0.36	0.71	0.51	0.61	-1.05	0.75	-1.39	0.16	-3.43	0.80	-4.27	0.00	Reference Level			
Individual-specific																
Age	0.03	0.01	2.56	0.01					0.06	0.01	4.36	0.00	Reference Level			
Gender	1.39	0.27	5.25	0.00	1.05	0.30	3.56	0.00								
Income	-0.35	0.12	-2.95	0.00												
Kids					-0.75	0.44	-1.71	0.09	-1.65	0.43	-3.85	0.00				
Alone	-0.95	0.31	-3.10	0.00					-0.58	0.36	-1.64	0.10				
Medium city	2.17	0.37	5.92	0.00	1.45	0.41	3.49	0.00	0.65	0.38	1.70	0.09				
Small city	3.24	0.40	8.02	0.00	2.85	0.44	6.56	0.00	2.24	0.42	5.39	0.00				
Town	3.51	0.55	6.38	0.00	4.92	0.59	8.33	0.00	2.15	0.55	3.92	0.00				
Village	3.23	0.37	8.61	0.00	2.55	0.42	6.05	0.00	0.82	0.40	2.07	0.04				
PT access																
leisure time car					0.01	0.00	2.20	0.03	0.02	0.01	4.35	0.00				
Frq. info. leisure trips	-1.27	0.26	-4.86	0.00	-0.73	0.28	-2.61	0.01								
Alternative-specific																
Cost 2																
Cost 3	-0.71	0.21	-3.39	0.00	-0.80	0.26	-3.08	0.00	-0.70	0.24	-2.86	0.00				
Time 2	-0.46	0.21	-2.21	0.03	-0.86	0.23	-3.71	0.00	-0.72	0.24	-2.96	0.00				
Time 3	-0.63	0.20	-3.14	0.00	-1.28	0.25	-5.16	0.00	-0.96	0.27	-3.60	0.00	-0.49	0.26	-1.85	0.06
Wait 2																
Wait 3									-0.61	0.25	-2.47	0.01	-0.52	0.27	-1.95	0.05
Walk 2																
Walk 3									-0.60	0.25	-2.41	0.02	-0.52	0.28	-1.88	0.06

Mode	Own car				Pooling as a driver				Pooling as a passenger				Public transport			
	Est.	*SE*	*z*	*p*	*Est.*	*SE*	*z*	*p*	*Est.*	*SE*	*z*	*p*	*Est.*	*SE*	*z*	*p*
Parking costs 2	-0.99	0.21	-4.77	0.00	-0.74	0.25	-2.94	0.00								
Parking costs 3	-1.45	0.22	-6.50	0.00	-0.63	0.24	-2.60	0.01								
Features 2																
Features 3																
Random effects																
Intercept	4.03	0.22	18.23	0.00	2.54	0.17	15.14	0.00	3.12	0.22	14.28	0.00	Reference level			
Cost 2	0.38	0.18	2.07	0.04	0.43	0.22	1.92	0.05	0.41	0.21	1.94	0.05	0.47	0.26	1.80	0.07
Cost 3	-0.36	0.21	-1.75	0.08	1.01	0.25	4.08	0.00	0.48	0.22	2.19	0.03	0.40	0.23	1.78	0.07
Time 2					0.73	0.25	2.96	0.00	0.55	0.24	2.33	0.02				
Time 3	-0.31	0.18	-1.67	0.09	0.63	0.21	2.93	0.00	1.25	0.31	4.00	0.00				
Wait 2									-0.67	0.19	-3.43	0.00				
Wait 3									-0.96	0.24	-3.99	0.00				
Walk 2	0.50	0.18	2.75	0.01												
Walk 3	-0.43	0.21	-2.05	0.04	-0.50	0.20	-2.53	0.01								
Parking costs 2	0.59	0.20	2.96	0.00	0.78	0.25	3.13	0.00								
Parking costs 3																
Features 2																
Features 3									-0.32	0.19	-1.66	0.10				

Appendix O. Final Discrete Choice Models of the Future Scenario: Commuting - Low Time Pressure (own illustration; *Est.* = Estimate, *SE* = Standard Error, *z* = *z*-value, *p* = *p*-value; prohibitions of attributes are highlighted in orange).

Mode	Robo-Taxi				Shared Robo-Taxi				Public transport			
	Est.	*SE*	*z*	*p*	*Est.*	*SE*	*z*	*p*	*Est.*	*SE*	*z*	*p*
Intercept	-7.92	1.28	-6.21	0.00	-3.23	0.85	-3.78	0.00	Reference Level			
Individual-specific												
Age	-0.04	0.01	-3.14	0.00	-0.02	0.01	-2.16	0.03	Reference Level			
Gender					-0.72	0.18	-3.91	0.00				
Income	-0.25	0.15	-1.74	0.08								
Kids												
Alone	-1.09	0.29	-3.79	0.00	-0.40	0.19	-2.18	0.03				
Medium city	1.66	0.38	4.37	0.00								
Small city												
Town	0.84	0.44	1.89	0.06	0.85	0.28	3.04	0.00				
Village	1.36	0.39	3.52	0.00	1.38	0.28	4.85	0.00				
PT access	0.18	0.04	4.48	0.00								
Frq. info. commute	-0.75	0.26	-2.85	0.00								
Attitudes												
PT trust	-1.49	0.27	-5.42	0.00	-0.74	0.18	-4.09	0.00	Reference Level			
Robo-Taxi trust	0.78	0.22	3.53	0.00	0.66	0.15	4.50	0.00				
Hedonic motivation	0.53	0.15	3.44	0.00	0.71	0.09	7.63	0.00				
Tech. Intr.	1.78	0.22	8.14	0.00	0.34	0.14	2.34	0.02				
Alternative-specific												
Cost 2	-1.80	0.31	-5.82	0.00	-0.54	0.19	-2.83	0.00	-1.73	0.21	-8.13	0.00
Cost 3	-2.41	0.36	-6.72	0.00	-2.43	0.24	-10.24	0.00	-2.57	0.22	-11.49	0.00
Time 2	-0.59	0.27	-2.20	0.03					-0.56	0.20	-2.82	0.00
Time 3	-1.21	0.27	-4.43	0.00	-0.67	0.20	-3.39	0.00	-0.80	0.20	-3.97	0.00
Wait 2					-0.49	0.20	-2.50	0.01				

Mode	Robo-Taxi				Shared Robo-Taxi				Public transport			
	Est.	*SE*	*z*	*p*	*Est.*	*SE*	*z*	*p*	*Est.*	*SE*	*z*	*p*
Wait 3	-1.05	0.31	-3.35	0.00	-0.68	0.20	-3.47	0.00	-0.35	0.20	-1.73	0.08
Walk 2									-0.41	0.20	-2.00	0.05
Walk 3					-0.85	0.20	-4.30	0.00	-0.79	0.20	-3.96	0.00
Taxi type 2					0.31	0.18	1.72	0.08				
Taxi type 3					0.69	0.19	3.70	0.00				
Security Info 2												
Security Info 3												
Individual Offer 2												
Individual Offer 3												
Random effects												
Intercept	3.24	0.27	11.85	0.00	1.40	0.13	11.14	0.00	Reference level			
Cost 2	1.59	0.32	4.97	0.00	-0.41	0.20	-2.09	0.04				
Cost 3	-2.09	0.33	-6.28	0.00	1.49	0.24	6.25	0.00	-0.42	0.20	-2.12	0.03
Time 2	-0.42	0.22	-1.90	0.06								
Time 3	-0.87	0.30	-2.89	0.00	-0.99	0.20	-4.90	0.00	-0.55	0.23	-2.43	0.01
Wait 2					-0.34	0.20	-1.73	0.08				
Wait 3	1.49	0.27	5.55	0.00								
Walk 2									-0.66	0.25	-2.64	0.01
Walk 3					0.58	0.22	2.62	0.01				
Taxi type 2	-0.49	0.29	-1.66	0.10	0.66	0.19	3.46	0.00				
Taxi type 3	1.33	0.30	4.38	0.00	-0.36	0.20	-1.79	0.07				
Security Info 2												
Security Info 3					-0.44	0.22	-2.03	0.04				
Individual Offer 2	-0.54	0.30	-1.82	0.07	-0.63	0.18	-3.53	0.00				
Individual Offer 3	-1.04	0.26	-3.95	0.00								

Appendix P. Final Discrete Choice Models of the Future Scenario: Commuting - High Time Pressure (own illustration; *Est.* = Estimate, *SE* = Standard Error, *z* = *z*-value, *p* = *p*-value; prohibitions of attributes are highlighted in orange).

Mode	Robo-Taxi				Shared Robo-Taxi				Public transport			
	Est.	*SE*	*z*	*p*	*Est.*	*SE*	*z*	*p*	*Est.*	*SE*	*z*	*p*
Intercept	-3.79	0.99	-3.81	0.00	0.18	1.02	0.18	0.86	Reference Level			
Individual-specific												
Age	-0.04	0.01	-3.45	0.00	-0.03	0.01	-2.45	0.01	Reference Level			
Gender												
Income	0.60	0.10	5.86	0.00								
Kids												
Alone					-0.44	0.23	-1.89	0.06				
Medium city					1.18	0.37	3.21	0.00				
Small city	-1.31	0.37	-3.53	0.00	0.64	0.32	2.02	0.04				
Town					0.72	0.33	2.20	0.03				
Village												
PT access	0.21	0.04	5.97	0.00	0.10	0.03	3.14	0.00				
Frq. info. commute												
Attitudes												
PT trust	-1.37	0.21	-6.47	0.00	-1.10	0.21	-5.18	0.00	Reference Level			
Robo-Taxi trust	0.66	0.18	3.75	0.00	0.50	0.16	3.05	0.00				
Hedonic motivation	0.72	0.11	6.80	0.00	0.41	0.09	4.39	0.00				
Tech. Intr.	0.56	0.17	3.29	0.00	0.43	0.15	2.84	0.00				
Alternative-specific												
Cost 2	-1.01	0.19	-5.20	0.00	-0.80	0.21	-3.86	0.00	-0.70	0.19	-3.71	0.00
Cost 3	-1.53	0.21	-7.24	0.00	-1.56	0.22	-7.16	0.00	-1.56	0.22	-7.20	0.00
Time 2	-0.71	0.20	-3.57	0.00	-0.85	0.20	-4.32	0.00	-0.67	0.20	-3.38	0.00
Time 3	-1.52	0.21	-7.15	0.00	-1.66	0.22	-7.48	0.00	-1.13	0.21	-5.52	0.00
Wait 2	-0.71	0.22	-3.19	0.00	-0.80	0.21	-3.85	0.00				

Mode	Robo-Taxi				Shared Robo-Taxi				Public transport			
	Est.	*SE*	*z*	*p*	*Est.*	*SE*	*z*	*p*	*Est.*	*SE*	*z*	*p*
Wait 3	-1.07	0.23	-4.75	0.00	-1.21	0.22	-5.61	0.00	-0.41	0.21	-1.98	0.05
Walk 2					-0.48	0.20	-2.45	0.01	-0.85	0.20	-4.30	0.00
Walk 3					-1.47	0.24	-6.19	0.00	-1.41	0.22	-6.41	0.00
Taxi type 2												
Taxi type 3												
Security Info 2												
Security Info 3												
Individual Offer 2												
Individual Offer 3												
Random effects												
Intercept	2.69	0.19	13.91	0.00	1.33	0.15	8.82	0.00	Reference level			
Cost 2					-0.66	0.20	-3.23	0.00				
Cost 3	0.42	0.25	1.69	0.09	0.66	0.20	3.29	0.00	-0.53	0.23	-2.29	0.02
Time 2	0.59	0.24	2.42	0.02	0.60	0.22	2.78	0.01	-0.88	0.23	-3.83	0.00
Time 3					0.78	0.21	3.63	0.00	0.52	0.22	2.33	0.02
Wait 2	-0.62	0.21	-2.90	0.00								
Wait 3	1.11	0.23	4.79	0.00	1.12	0.21	5.22	0.00				
Walk 2									0.39	0.23	1.70	0.09
Walk 3					1.64	0.28	5.82	0.00	-1.02	0.23	-4.51	0.00
Taxi type 2					-0.77	0.20	-3.78	0.00				
Taxi type 3					0.54	0.22	2.49	0.01				
Security Info 2	-0.76	0.26	-2.87	0.00								
Security Info 3					-0.38	0.22	-1.71	0.09				
Individual Offer 2	0.52	0.21	2.44	0.01	0.96	0.23	4.19	0.00				
Individual Offer 3					-0.73	0.23	-3.21	0.00				

Appendix Q. Final Discrete Choice Models of the Future Scenario: Leisure Time Trips - Low Time Pressure (own illustration; *Est.* = Estimate, *SE* = Standard Error, *z* = *z*-value, *p* = *p*-value; prohibitions of attributes are highlighted in orange).

Mode	Robo-Taxi				Shared Robo-Taxi				Public transport			
	Est.	*SE*	*z*	*p*	*Est.*	*SE*	*z*	*p*	*Est.*	*SE*	*z*	*p*
Intercept	-10.85	1.64	-6.63	0.00	-2.84	0.93	-3.05	0.00	Reference Level			
Individual-specific												
Age	-0.07	0.02	-4.37	0.00					Reference Level			
Gender	-0.80	0.37	-2.20	0.03								
Income	0.52	0.19	2.78	0.01								
Kids	2.18	0.48	4.49	0.00								
Alone	1.58	0.35	4.51	0.00								
Medium city	2.93	0.48	6.16	0.00								
Small city												
Town	1.57	0.42	3.75	0.00								
Village					1.84	0.33	5.52	0.00				
PT access	0.30	0.05	6.16	0.00								
Frq. info. leisure trips	-1.35	0.32	-4.24	0.00								
Attitudes												
PT trust					-0.72	0.17	-4.17	0.00	Reference Level			
Robo-Taxi trust	1.29	0.29	4.53	0.00	0.79	0.15	5.30	0.00				
Hedonic motivation	0.51	0.15	3.45	0.00	0.59	0.09	6.65	0.00				
Tech. Intr.	0.89	0.26	3.43	0.00								
Alternative-specific												
Cost 2	-1.59	0.29	-5.48	0.00	-1.39	0.21	-6.56	0.00	-0.77	0.21	-3.73	0.00
Cost 3	-3.96	0.46	-8.67	0.00	-2.83	0.24	-11.97	0.00	-2.90	0.25	-11.73	0.00
Time 2									-0.48	0.20	-2.39	0.02
Time 3	-0.78	0.31	-2.50	0.01	-0.75	0.20	-3.74	0.00	-0.94	0.21	-4.40	0.00
Wait 2	-1.79	0.34	-5.21	0.00								

Mode	Robo-Taxi				Shared Robo-Taxi				Public transport			
	Est.	*SE*	*z*	*p*	*Est.*	*SE*	*z*	*p*	*Est.*	*SE*	*z*	*p*
Wait 3	-1.51	0.36	-4.24	0.00	-0.49	0.20	-2.45	0.01	-0.45	0.21	-2.18	0.03
Walk 2									-0.53	0.21	-2.57	0.01
Walk 3					-0.52	0.20	-2.52	0.01	-1.33	0.22	-6.12	0.00
Taxi type 2					0.31	0.19	1.65	0.10				
Taxi type 3												
Security Info 2												
Security Info 3					0.42	0.18	2.26	0.02				
Individual Offer 2	-0.50	0.30	-1.65	0.10								
Individual Offer 3												
Random effects												
Intercept	4.05	0.35	11.61	0.00	1.34	0.13	10.52	0.00	Reference level			
Cost 2					0.39	0.21	1.85	0.06	-0.42	0.22	-1.89	0.06
Cost 3	2.03	0.41	4.91	0.00	1.57	0.27	5.80	0.00	1.13	0.23	4.92	0.00
Time 2	1.19	0.27	4.46	0.00								
Time 3	-0.92	0.27	-3.41	0.00					-1.00	0.24	-4.18	0.00
Wait 2	2.13	0.35	6.14	0.00								
Wait 3	1.59	0.35	4.49	0.00	-0.39	0.18	-2.13	0.03	-0.58	0.25	-2.35	0.02
Walk 2												
Walk 3									0.88	0.24	3.74	0.00
Taxi type 2	0.50	0.25	2.03	0.04								
Taxi type 3	2.32	0.31	7.45	0.00								
Security Info 2					-0.43	0.19	-2.26	0.02				
Security Info 3					0.89	0.20	4.43	0.00				
Individual Offer 2	-0.75	0.29	-2.59	0.01	-0.72	0.22	-3.29	0.00				
Individual Offer 3	1.20	0.24	4.90	0.00								

Appendix R. Final Discrete Choice Models of the Future Scenario: Leisure Time Trips - High Time Pressure (own illustration; *Est.* = Estimate, *SE* = Standard Error, *z* = *z*-value, *p* = *p*-value¸ prohibitions of attributes are highlighted in orange).

Mode	Robo-Taxi				Shared Robo-Taxi				Public transport			
	Est.	*SE*	*z*	*p*	*Est.*	*SE*	*z*	*p*	*Est.*	*SE*	*z*	*p*
Intercept	-8.52	1.30	-6.54	0.00	-2.76	1.03	-2.70	0.01	Reference Level			
Individual-specific												
Age					-0.02	0.01	-2.25	0.02	Reference Level			
Gender	1.50	0.27	5.60	0.00								
Income	0.39	0.10	3.77	0.00								
Kids												
Alone	1.10	0.30	3.63	0.00								
Medium city	1.66	0.38	4.37	0.00								
Small city	-2.44	0.49	-5.01	0.00	0.64	0.32	1.99	0.05				
Town	-1.26	0.42	-3.01	0.00								
Village												
PT access												
Frq. info. leisure trips												
Attitudes												
PT trust	-0.76	0.25	-3.08	0.00					Reference Level			
Robo-Taxi trust	1.13	0.20	5.49	0.00	0.34	0.17	1.99	0.05				
Hedonic motivation	0.83	0.12	6.65	0.00	0.36	0.10	3.68	0.00				
Tech. Intr.	0.43	0.20	2.14	0.03	0.50	0.16	3.23	0.00				
Alternative-specific												
Cost 2	-1.50	0.25	-5.98	0.00	-1.39	0.22	-6.40	0.00	-0.57	0.22	-2.62	0.01
Cost 3	-2.16	0.27	-7.97	0.00	-2.48	0.26	-9.63	0.00	-1.91	0.24	-8.07	0.00
Time 2	-0.56	0.23	-2.38	0.02	-0.90	0.21	-4.18	0.00	-0.51	0.21	-2.42	0.02
Time 3	-1.85	0.25	-7.33	0.00	-1.57	0.24	-6.61	0.00	-1.18	0.22	-5.33	0.00
Wait 2	-0.88	0.25	-3.44	0.00					-0.51	0.22	-2.28	0.02

Mode	Robo-Taxi				Shared Robo-Taxi				Public transport			
	Est.	*SE*	*z*	*p*	*Est.*	*SE*	*z*	*p*	*Est.*	*SE*	*z*	*p*
Wait 3	-1.08	0.26	-4.22	0.00	-0.49	0.22	-2.23	0.03	-0.75	0.22	-3.41	0.00
Walk 2					-0.75	0.21	-3.50	0.00	-0.93	0.22	-4.19	0.00
Walk 3					-1.41	0.24	-5.78	0.00	-1.30	0.23	-5.74	0.00
Taxi type 2												
Taxi type 3												
Security Info 2												
Security Info 3												
Individual Offer 2												
Individual Offer 3												
Random effects												
Intercept	4.01	0.29	13.61	0.00	1.04	0.13	7.89	0.00	Reference level			
Cost 2	0.88	0.27	3.20	0.00								
Cost 3	0.77	0.28	2.80	0.01	1.17	0.25	4.70	0.00	1.37	0.20	6.71	0.00
Time 2					-0.56	0.25	-2.24	0.03				
Time 3	-0.90	0.24	-3.69	0.00	-0.99	0.24	-4.12	0.00	-0.42	0.25	-1.68	0.09
Wait 2	-0.83	0.20	-4.18	0.00	-0.44	0.27	-1.63	0.10				
Wait 3	0.86	0.22	3.87	0.00	1.46	0.24	6.13	0.00	-0.48	0.23	-2.10	0.04
Walk 2												
Walk 3					-1.66	0.26	-6.38	0.00	-0.80	0.22	-3.61	0.00
Taxi type 2					-0.36	0.19	-1.87	0.06				
Taxi type 3	-0.96	0.27	-3.57	0.00								
Security Info 2												
Security Info 3	-1.19	0.27	-4.46	0.00								
Individual Offer 2					0.59	0.21	2.80	0.01				
Individual Offer 3					0.40	0.20	1.97	0.05				