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Identifying the Factors Affecting the Use and Adoption of Urban Air Mobility

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Abstract

Recently, technological advances have led to the development of new concepts for the operation of on-demand fully-automated vertical take-off and landing aircraft (VTOL) for intra-city passenger transportation, also called as urban air mobility (UAM). Despite a growing interest in UAM, several barriers obstruct its implementation, such as community acceptance. Although many studies focus on the acceptance of ground autonomous vehicles, only a few target users' perceptions of urban air mobility. The aim of this study is to identify the factors affecting the user's adoption and use of UAM. A survey was developed to assess perception in terms of stated time adoption, including choices such as the first five years of UAM's implementation, a time frame starting its sixth year, unsure, and never. The obtained results were evaluated using first exploratory factor analysis, followed by the development of choice models, including both multinomial logit models (MNL) and ordered logit models (OLM), where stated time adoption served as a dependent variable. Findings revealed the importance of safety and trust, affinity to automation, data concerns, social attitude, and socio-demographics in adoption. Factors such as time savings, costs of automation, and service reliability were strongly influential as well. There was also an indication that skeptical respondents, i.e. choosing "unsure", had similar behavior as late adopters. The summarized results helped in adapting the Technology Acceptance Model to be applied in an urban air mobility context. The findings provide meaningful insights with recommendations and policy implications.

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List of Abbreviations

AIC	Akaike information criterion
ADAS	Advanced driver-assistance systems
ASC	Alternative-specific constant
AV	Autonomous vehicle
BIC	Bayesian information criterion
CFA	Confirmatory factor analysis
DE	German language
EFA	Exploratory factor analysis
EN	English language
eVTOL	Electric vertical take-off and landing aircraft
FA	Factor analysis
IIA	Independence of irrelevant alternatives
IID	Independent and identically distributed
Min	Minutes
MNL	Multinomial logit
NL	Nested logit
ODM	On-demand mobility
OLM	Ordered logit model
PAV	Personal aerial vehicle
PEU	Perceived ease of use
PNA	Prefer not to answer
PT	Public transportation
PU	Perceived usefulness
SP	Stated preference
TAM	Technology acceptance model
UAM	Urban air mobility
VOT	Value of time
VTOL	Vertical take-off and landing aircraft
Y	Year of operation; e.g. Y1: first year of operation

1 Introduction

1.1 Urban Air Mobility

Transportation systems in urban environments are facing an increasing number of challenges. Some are old like congestion; others are more recent, including environmental impacts and urban sprawl resulting from land scarcity and housing affordability (Rodrigue, Comtois, and Slack 2016). Growing mobility demands imposes additional pressure on existing infrastructure and public transportation systems. As investing in new infrastructure does not seem to be a plausible solution, a shift towards sustainable transportation is emerging (Rodrigue, Comtois, and Slack 2016).

Modern patterns of mobility, such as car-sharing, are providing users with more efficient travel, characterized by a lower demand for parking spaces, lower vehicle ownership, but also reduced environmental impacts resulting from lower emissions (Baptista, Melo, and Rolim 2014). At the same time, autonomous vehicles promise safe and comfortable transportation, and most companies are expected to have launched fully autonomous vehicles in the coming decade (Bimbraw 2015). These patterns lead to a research interest in (ground) shared autonomous mobility (Fagnant and Kockelman 2014), and inevitably to the exploration of the third dimension: the skyscape.

Urban air mobility (UAM) is therefore introduced as the on-demand sharing mobility operated by fully-automated vertical take-off and landing aircraft (VTOL) for intra-city passenger trips (Airbus 2017). For instance Voom, an Airbus company, is providing on-demand helicopter booking in megacities like Mexico City and Sao Paolo. Technological advances in terms of battery storage, electrical power transmission and distributed propulsion systems allow the development of different concepts for short-haul passenger air trips, also called Personal Air Vehicles (PAV) (Shamiyeh, Bijewitz, and Hornung 2017). The introduction of this new generation of vertical take-off and landing vehicles, also called e-VTOL, promises to reduce problems of noise emissions, environmental impacts, but mostly congestion, contributing therefore to more efficient transport systems (Airbus 2017).

Manufacturers and service providers are already racing to win the skyscape. From giants in the aerospace industry like Airbus, to smaller and more recent air taxi companies like Lilium or Volocopter, the idea is the same: “Rethinking Urban Air Mobility” (Airbus 2017), “Reinventing Urban Air Mobility” (Volocopter 2018), or “The Aircraft for Everyone” (Lilium 2018). Airbus and Audi are already partnering to connect air and urban ground mobility services to provide seamless journeys with last mile connectivity (Airbus 2018). Uber Elevate or Uber Air Taxi is promising the launch of its services by 2023 in Dallas, Los Angeles, and a third international city (Uber Elevate 2018). Air mobility seems not to be a fiction anymore and the old dream of flying over cities might be, as Uber Air describes it, “Closer than you think” (Uber Elevate 2018). Uber Air Taxi mentions however several market feasibility barriers, notably vertiport infrastructure design, air traffic control, and certification process. Noise acceptance is mentioned as part of community acceptance (Uber Elevate 2016); still, little focus is given to acceptance in general, or the overall human factors that might hinder adoption and use.

1.2 Research Motivation

Similarly to ground autonomous vehicles, the required technology does not seem to be the only challenge. The application and introduction of UAM is constrained to many aspects, addressing regulations, infrastructure availability, air traffic control, environmental impacts, but also community acceptance (Vascik 2017). The aspect dealing with the human factors is therefore crucial for a better understanding of potential users' needs. Accordingly, these could be better cared for, resulting in a more successful market entry.

In this context, automation readiness indexes have been developed to compare market entries for driverless cars in different countries (KPMG 2018). Studies have also focused on user perception and adoption of ground and shared autonomous vehicles (Nees 2016, Kaan 2017, Bjørner 2015, Gaggi 2017, Merat, Madigan, and Nordhoff 2016). Despite some attempts to estimate the market volume for on-demand air mobility (Porsche Consulting 2018, Kreimeier and Stumpf 2017), very little was done to focus on community acceptance in relation to the time-frame adoption. Research in that area rather focused on a system-level analysis of UAM feasibility (Vascik 2017) or on users' preferences for transportation modes in a future involving UAM (Fu 2018). More generally, models in the literature (refer to Section 2.2.2) were developed to understand why people use a technology or not. The most renown perhaps is the Technology Acceptance Model, developed to investigate the use of information systems, particularly computer technology (Davis, Bagozzi, and Warshaw 1989). However, to the knowledge of the author, these models have not been adapted to the use of urban air mobility.

The need to understand UAM's perception and adoption outside the scope of a mode choice, focusing on the intrinsic motivation of its adoption and use, acts therefore as a research motivation to study the factors associated with it.

1.3 Objectives and Research Questions

The main objective of this work is therefore to **identify the factors affecting the adoption and use of UAM**. This means to extract the most influential factors associated with respondents' intended time adoption of UAM.

The identified factors could help relevant stakeholders better address the challenges of UAM implementation in relation to its potential users. Manufacturers and service providers could thereby appropriately care for the needs of different classes of users. Other stakeholders, such as authorities, would also benefit from these factors by setting some guidelines or more stringent regulations if required.

As these factors are associated with a mode that is not yet available, a **Stated Preference survey** presenting realistic case scenarios of UAM is a prerequisite for any behavioral modeling. These scenarios or examples only aim at giving respondents an idea about UAM services and their main characteristics including time and cost. Another important objective would therefore be to **design a suitable survey to extract the relevant factors.**

The goal of this survey is not to present mode choice options, but rather transparent examples of expected use cases of UAM. The factors in this survey are therefore only related to the decision-maker (in terms of attitudes, socio-demographics, or other parameters) and have no variability among the stated choices (time adoption).

This leads us to the following research questions associated with the study:

- Can a suitable survey design help identifying the factors affecting the time adoption of UAM?
- Can **Exploratory Factor Analysis (EFA)** be used to understand latent constructs in UAM adoption?
- Can factors obtained from EFA be meaningful in new model estimations?
- Can stated time preferences be modeled using **Discrete Choice Modeling (Multinomial Logit, Ordered Logit, and Nested Logit models)**?
- Can the obtained factors be used to adapt the current **Technology Acceptance Model (TAM)** to be more suitable for UAM use?

The research questions above all act as methodological tools to answer, in line with the main objective, the overall **research question**: What factors affect the adoption and use of UAM?

1.4 Expected Contributions

In line with our main objectives and research questions, our thesis is expected to contribute in the following:

- Theoretical contributions:
  - Using intended time adoption as the dependent variable following a behavioral modeling approach, such as ordered logit models for instance.

    To the best of the author's knowledge, OLMs are usually used with scaled-dependent variables regarding a mode choice or an attitudinal statement, also known as Likert scale answer options, ranging from weak to strong agreement (1 to 5, for instance). Although a study used OLM for time adoption, it didn't integrate in one variable several time adoptions as answer options, but rather developed several models, each for a time-frame with a Likert scale dependent variable as answer option (Efthymiou, Antoniou, and Waddell 2013).

    In UAM adoption, forecasting future values of adoption is not plausible with time-series, as UAM is a future mode that does not yet exist. Observing current patterns is therefore not possible, but might be by looking at patterns of ground autonomous vehicles. Still, this can only be achieved in the future when these new modes are integrated in existing systems.

- Proposing an adapted Technology Acceptance Model for the context of urban air mobility.

- Methodological contributions:
  - Proposing a methodology including several steps to extract the relevant factors in UAM adoption, including problem identification, and consistent literature review. In this methodology, the results of each step mostly serve as input for the next one.
  - Using Exploratory Factor Analysis for dimensionality reduction and latent constructs extraction
  - Using the results of the factor analysis to build an MNL for adoption, laying the ground for an OLM, and potentially an NL model.
  - Proposing a framework for future work including the use of a nested model and a nested ordered logit model to model adoption.

- Practical contributions:
  - Providing useful suggestions on survey design
  - Discussing the factors affecting the adoption of urban air mobility, followed by recommendations based on the thesis findings.

1.5 Thesis Framework

The thesis framework is summarized in Figure 1.

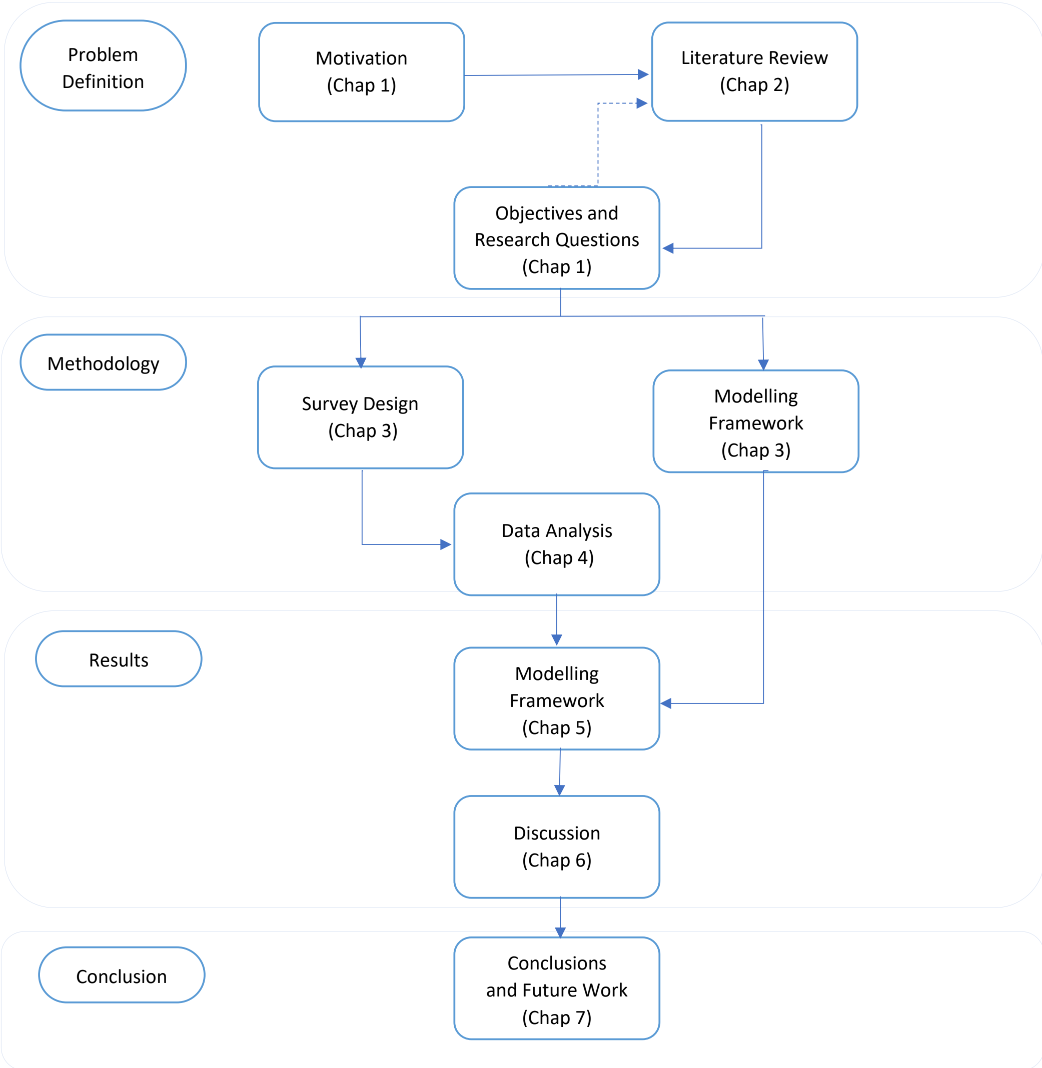

Figure 1: Thesis framework

1.6 Report Structure

In line with the defined objective and research problems, and following the thesis framework, this report will be organized as follows. The literature review will first be presented, including an overview of UAM, acceptance studies in automation, analysis methods in modeling, and the traditional TAM model. After that, the methodology for our work is detailed, comprising both the experimental design and the analysis methods. Later, the data analysis section reveals the outcome of the survey, including statistical findings and interesting insights, partially qualitative. Thereafter, the modeling framework elaborates on the different methods used, followed by a discussion of the findings and the implications they have on the different levels. Finally, a conclusion including recommendations, limitations, but also insights for future work is given.

2 Literature Review

This chapter presents a summary of the literature review that enables the survey design in Section 3.2. As we aim to identify the factors influencing the adoption and use of UAM, a better understanding of UAM is first required, followed by an extensive review of studies tackling user acceptance. These mostly include **user acceptance of ground autonomous vehicles** and **technology acceptance** through the Technology Acceptance Model (TAM). This chapter also includes relevant analysis methods used in acceptance studies. The overall aim is to summarize the factors and project them to UAM acceptance.

For practical reasons, the term "autonomous vehicles" will be used to refer to autonomous ground vehicles. Otherwise, the word urban air mobility or on-demand air mobility would be mentioned to refer to autonomous air vehicles.

2.1 Urban Air Mobility (UAM)

Urban air mobility is meant as the on-demand sharing mobility operated by fully-automated vertical take-off and landing aircraft (VTOL) for intra-city passenger trips (Airbus 2017). Advances in terms of electric power transmission and distributed propulsion systems facilitate the development of a broad range of personal air vehicle configurations, with different operational capabilities, design focus and system complexity (Shamiyeh, Bijewitz, and Hornung 2017). Among these for instance, the CityAirbus concept for up to four passengers, or Volocopter's two-seated model 2X.

The demand for this mobility pattern has been investigated and related to the area of its implementation. For instance, Silicon Valley was found to be the ideal early adopter for on-demand civil VTOL operations (Antcliff, Moore, and Goodrich 2016). Mostly, this was due to good weather, high housing prices complemented with high incomes, but also the number of hyper commuters (those who commute two or more hours per day) who would benefit from this mode to reduce their time in congestion by lowering up to six times their trip time (Antcliff, Moore, and Goodrich 2016).

In Germany, the market share for on-demand air mobility services has been estimated as 19% or 235 million trips, based on a transport model and a choice model, assuming specific passenger costs (Kreimeier and Stumpf 2017). More generally, the passenger market for VTOL is expected to be around 23 000 aircraft by 2035, a worth of $32 Billion (Porsche Consulting 2018).

Still, barriers remain for the market entry of on-demand air transportation, such as certification process, performance and reliability, air traffic control, cost and affordability, safety, environmental impacts like emissions and noise, and ground infrastructure availability (Uber Elevate 2016, Vascik 2017). These factors have been summarized into four main components: aircraft system, certification and law, social acceptance, and infrastructure (Porsche Consulting 2018).

As a solution for the ground infrastructure challenge, vertiport prototypes have been studied to optimize land use, site selection, and community acceptance (Cohen 1996). More recently, a study has focused on a GIS-based analysis for ground infrastructure selection for urban air mobility (Fadhil 2018).

System integration of personal air transport concepts into urban mobility modeling is also a topic of interest (Straubinger and Rothfeld 2018). Agent-based simulation has been used to model urban air mobility (Rothfeld et al. 2018a) and an initial analysis of urban air mobility transportation performance has been investigated (Rothfeld et al. 2018b).

In addition to transport modeling, choice modeling has been applied in the context of UAM. A study from the Georgia Institute of Technology collected responses from 2,500 high-income workers in different areas of the US to better predict demand for eVTOL; in other terms, to see whether commuters intend to use these vehicles or not. A Munich case study also aimed at understanding passenger adoption through choice modeling in a UAM environment (Fu 2018).

Finally, besides transportation and choice modeling, understanding the implication of urban air mobility on the inhabitants and the changes on the city is necessary (Straubinger and Verhoef 2018).

2.2 Acceptance Studies

Different obstacles still face automation, including liability, and social acceptance (Forrest 2018). In the following section, we discuss the most relevant findings on factors affecting the acceptance of autonomous vehicles (mostly ground), then summarize them in Table 1, and try to project them to UAM in an adapted TAM for UAM.

2.2.1 Factors in acceptance

Trust in automation
Studies on the acceptance of robotics and autonomous car-sharing systems have outlined the importance of human factors in trusting these systems. These include **reliability**, **safety** (Merat, Madigan, and Nordhoff 2016), and **perceived locus of control** or situation management (Choi and Ji 2015).

Perceived reliability of automation
A study focusing on the acceptance of self-driving cars found that idealized performance expectations increase initial acceptance, but might hinder long-term trust in case of performance failure. Therefore, realistic expectations are noted to be crucial in autonomous vehicles acceptance, notably in terms of the user's supervisory role. This study therefore mentions perceived reliability as an influential factor for user acceptance (Nees 2016).

Perceived safety
Safety is a crucial factor in gaining trust. In urban areas in particular, passenger security especially during the night has been noted as essential for the implementation of AVs (Piao et al. 2016). The user's feeling of safety could therefore depend on the vehicle's interior (Merat, Madigan, and Nordhoff 2016), but might also be hindered by cyber-security concerns (Kyriakidis,

Happee, and Winter 2015).

Locus of control

The locus of control or situation management also impacts trust, which in turn greatly influences the intention to use, a major component of the basic Technology Acceptance Model (Choi and Ji 2015). In a study focusing on autonomous driving in Germany, 90% of the respondents stated that they would feel safer if they were able to intervene or control the vehicle at any time, or at least in case of emergency (Deloitte Analytics Institute 2017). Control has also been associated with feeling more independent (Gaggi 2017) and proved to positively impact the user's perceived ease of use (Rödel et al. 2014).
Overall, users have to be aware and convinced of the benefits of the new technology in order to be able to trust it and use it thereafter. Manufacturers' reputation could be a competitive factor in gaining this trust (Deloitte Analytics Institute 2017). Real-life tests for AVs and a higher transparency in demonstrating the new modes could also lead to a higher trust through an increased user awareness (Bjørner 2015; Choi and Ji 2015).

Ethical concerns

Social acceptance could be a major obstacle to the implementation of AVs (Forrest 2018). Legislation must therefore clearly address accidents or failures in order to alleviate liability concerns (Deloitte Analytics Institute 2017), but also the **loss of jobs** induced by automation. Still, concerns remain regarding terrorism, crime, or cyber-security in general. Data concerns, such as data protection, data use, or privacy in broader terms, are major factors in the acceptance of automation (Kyriakidis, Happee, and Winter 2015).

Perceived usefulness

A higher perception of the benefits of automation helps gaining trust to use the technology, which is reflected in a higher perceived usefulness. By taking over the driving task, automation provides the driver with benefits on a **personal level**, allowing him or her to perform different activities, but also taking over unpleasant tasks such as parking (Gaggi 2017) or driving unpleasant roads, for which users might be willing to pay more (Deloitte Analytics Institute 2017).

By decreasing congestion and improving road safety, automation creates **social benefits** (Kaan 2017) by reducing the number of road crashes. Finally, it contributes to improved mobility for mobility-impaired users (Clements and Kockelman 2017). Social benefits are also accompanied with **environmental ones**, due to the use of electric vehicles (mostly), reducing thereby fuel consumption, leading to a more sustainable transportation (Bjørner 2015). These advantages lead to a higher perceived usefulness, resulting in a higher user acceptance.

It is important to note that some benefits are only related to ground autonomous vehicles and therefore don't apply to UAM, as users are not expected to operate flying vehicles.

Perceived ease of use

Ease of use in terms of effort expectancy in the case of autonomous vehicles, or ease of access for dependents or mobility-impaired users (Merat, Madigan, and Nordhoff 2016) is influential in the intention to use autonomous vehicles.

In the case of UAM; this factor would be translated in the booking and boarding processes, as these are the only tasks needed from the user, since he or she is not expected to take control of the flying vehicle at any point.

Trip purpose
The trip purpose plays a role in behavioral intention. For instance, users might opt to use autonomous vehicles for leisure trips, or after alcohol consumption (Connected Automated Driving EU 2017). Also, they might decide to use autonomous vehicles if the intended trip is unpleasant (Deloitte Analytics Institute 2017).

Value of time:
The value of time, like in any transportation choice model, plays a crucial role in the adoption of shared autonomous vehicles (Krueger, Rashidi, and Rose 2016) . More recently, research has also focused on the value of time reliability (Abir, Burris, and Spiegelman 2017), which could be associated with the perceived reliability factor presented above.

Costs of automation
The price of automation in driverless cars is an influential factor affecting their acceptance (Rychel 2016,Merat, Madigan, and Nordhoff 2016). Also for on-demand air mobility, passenger costs highly impact behavioral intention. In a study estimating the market volume of thin-haul on demand mobility services in Germany, a high sensitivity to automation pricing was found (Kreimeier and Stumpf 2017).

Social behavior
The willingness to share the ride with strangers is a factor in the acceptance of shared autonomous vehicles as it might cause psychological and social discomfort for the users (Merat, Madigan, and Nordhoff 2016). In this case for instance, users would avoid choosing the middle seat in a shared vehicle.
The perceived fun of driving or driving enjoyment can also play an important role for autonomous vehicles (Bjørner 2015). This factor can also be related to the cultural aspect. For instance, driving enjoyment might play a higher role in Germany (DE 2017).

Vehicle and operation characteristics
Vehicle and operation characteristics also have an impact on the intention to use, as mentioned in studies on autonomous and shared autonomous vehicles. These include comfort (Rychel 2016, Rychel 2016), vehicle cleanliness (Merat, Madigan, and Nordhoff 2016), but also also service in terms of availability in different weather conditions (Merat, Madigan, and Nordhoff 2016).

Cultural differences
Acceptance and adoption vary **globally**. In industrialized countries for example, automated vehicles might face higher skepticism compared to emerging countries like India or China (Rychel 2016). As in the former accident rates are lower due to higher measures of safety, people might be more reluctant to automation as they are not necessarily convinced of the benefits of it. Also, in more developed countries, users are less likely to be comfortable with their data being shared

or used (Kyriakidis, Happee, and Winter 2015). In that perspective, Germany for instance implemented laws for testing and developing driverless vehicles, but also for protecting the data used during the ride (Reuters 2017). Moreover, research on UAM has targeted the city of Ingolstadt, as part of the "Urban Air Mobility Initiative", supported by the European Commission. Still, despite the government's initiatives and advances in technology, Germany lags behind in consumer acceptance. (KPMG 2018).

Socio-demographic impact

Perception of automation is also influenced by socio-demographic factors, such as age and gender, as mentioned in several studies (Rödel et al. 2014, Kyriakidis, Happee, and Winter 2015, Payre, Cestac, and Delhomme 2014). Women were found to have lower intention to use autonomous vehicles, possibly due to the effect of sex on anxiety rather than on pleasure (Hohenberger, Spörrle, and Welpe 2016). Accordingly, ads focusing on reducing anxiety for women could be a plausible solution for reducing the differences between the sexes. Age also plays a role in automation and young (Deloitte Analytics Institute 2017) multimodal (Krueger, Rashidi, and Rose 2016) travellers were found to be more likely to adopt shared autonomous vehicles.

Technology awareness and previous experience with automation

Technology awareness have been found to have a positive impact on autonomous vehicles acceptance. For instance, having heard of Google cars (Bansal, Kockelman, and Singh 2016) or autonomous vehicles (Schoettle and Sivak 2014) positively influenced the adoption time or the intention to use. In the same way, previous experience with advanced driver-assistance systems (ADAS) was found to positively impact automation.

The factors mentioned in this section are summarized in Table 1, along with their references. This table will be later used to develop the adapted UAM TAM, and to build the survey, by projecting the relevant factors to UAM.

Table 1: Table of factors

Factors	References
Perceived reliability of automation	Nees 2016; Kaan 2017; Merat, Madigan, and Nordhoff 2016; Deloitte Analytics Institute 2017; Choi and Ji 2015; Hohenberger, Spörrle, and Welpe 2016; Rödel et al. 2014
Perceived vehicle's safety	Rychel 2016; Gaggi 2017; Kaan 2017; Merat, Madigan, and Nordhoff 2016; Deloitte Analytics Institute 2017; Kyriakidis, Happee, and Winter 2015; Kyriakidis, Happee, and Winter 2015; Hohenberger, Spörrle, and Welpe 2017
Perceived locus of control	Gaggi 2017; Nees 2016; Merat, Madigan, and Nordhoff 2016; Connected Automated Driving EU 2017; Deloitte Analytics Institute 2017; Becker and Axhausen 2017; Rödel et al. 2014; Choi and Ji 2015
Data concerns	Reuters 2017; Gaggi 2017;Kaan 2017; Merat, Madigan, and Nordhoff 2016; Becker and Axhausen 2017; Kyriakidis, Happee, and Winter 2015
Loss of jobs concerns	Kaan 2017; Kyriakidis, Happee, and Winter 2015; KPMG 2018
Perceived usefulness	Gaggi 2017; Kaan 2017; Merat, Madigan, and Nordhoff 2016; Connected Automated Driving EU 2017; Deloitte Analytics Institute 2017; Nees 2016; Bjørner 2015; Choi and Ji 2015; KPMG 2018, Payre, Cestac, and Delhomme 2014,Hohenberger, Spörrle, and Welpe 2017; Clements and Kockelman 2017
Perceived ease of automation	Nees 2016; Kaan 2017; Merat, Madigan, and Nordhoff 2016; Bjørner 2015; Rödel et al. 2014
Trip purpose	Kaan 2017;Connected Automated Driving EU 2017; Deloitte Analytics Institute 2017; Becker and Axhausen 2017; Payre, Cestac, and Delhomme 2014
Value of time	Gaggi 2017; Kaan 2017;Connected Automated Driving EU 2017; Deloitte Analytics Institute 2017;Bjørner 2015; Krueger, Rashidi, and Rose 201
Costs of automation	Rychel 2016; Gaggi 2017;Nees 2016; Kaan 2017;Deloitte Analytics Institute 2017; Becker and Axhausen 2017; Krueger, Rashidi, and Rose 2016; Kyriakidis, Happee, and Winter 2015; Piao et al. 2016
Willingness to be with a stranger	Kaan 2017; Merat, Madigan, and Nordhoff 2016;Deloitte Analytics Institute 2017
Perceived fun of driving	Rychel 2016; Nees 2016; Kaan 2017; Bjørner 2015; Hohenberger, Spörrle, and Welpe 2016; Rödel et al. 2014; Payre, Cestac, and Delhomme 2014
Operation characteristics	Merat, Madigan, and Nordhoff 2016; Clements and Kockelman 2017
Perceived comfort and cleanliness	Rychel 2016; Kaan 2017; Merat, Madigan, and Nordhoff 2016; Clements and Kockelman 2017
Socio-demographics	Rychel 2016; Merat, Madigan, and Nordhoff 2016; Krueger, Rashidi, and Rose 2016; Kyriakidis, Happee, and Winter 2015; Hohenberger, Spörrle, and Welpe 2016; Rödel et al. 2014; Payre, Cestac, and Delhomme 2014; Becker and Axhausen 2017
Technology and/or automation awareness	Kaan 2017; Becker and Axhausen 2017; Clements and Kockelman 2017; Rödel et al. 2014;Payre, Cestac, and Delhomme 2014; Nordhoff, Van Arem, and Happee 2016; Merat, Madigan, and Nordhoff 2016; Deloitte Analytics Institute 2017; KPMG 2018

2.2.2 Technology Acceptance Models (TAMs)

Technology acceptance has been explored long before automation and researchers have developed models to understand why people use a technology or not. The most renown perhaps is the Technology Acceptance Model (TAM, Figure 2 below), developed to investigate technology use of information systems, particularly computer technology (Davis, Bagozzi, and Warshaw 1989). The main idea is that the attitudes towards using a technology depends on two main variables: the perceived usefulness (PU) and the perceived ease of use (PEU), where PEU reinforces PU. PEU and PU are both subject to external variables. In this model, the behavioral intention to use is impacted by the attitude towards the technology and the perceived usefulness. Finally, the behavioral intention can be related to the actual system use.

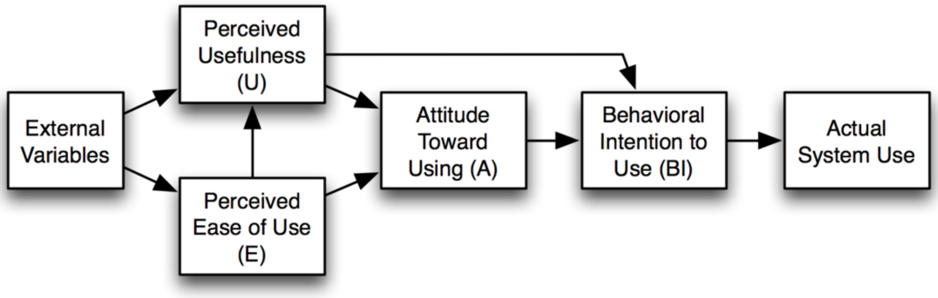

Figure 2: Technology Acceptance Model (TAM, Davis, Bagozzi, and Warshaw 1989)

A second TAM was later developed, with additional variables grouped into social influence and cognitive processes (Venkatesh and Davis 2000), impacting the perceived usefulness of the technology. This model is shown in Figure 3.

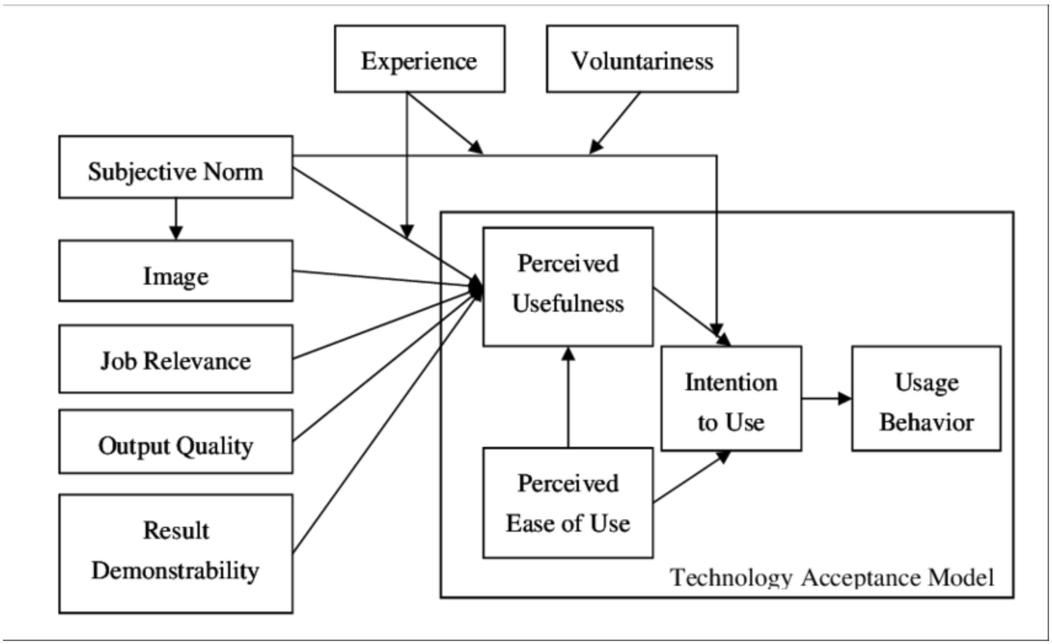

Figure 3: Technology Acceptance Model 2 (TAM2, Venkatesh and Davis 2000)

A further revision extended the TAM into the Unified Theory of Acceptance and Use of Technology (UTAUT, Venkatesh et al. 2003), and a later revision into TAM 3 (Venkatesh and Bala 2008). The UTAUT and TAM3 are shown in Figures 4 and 5, respectively.

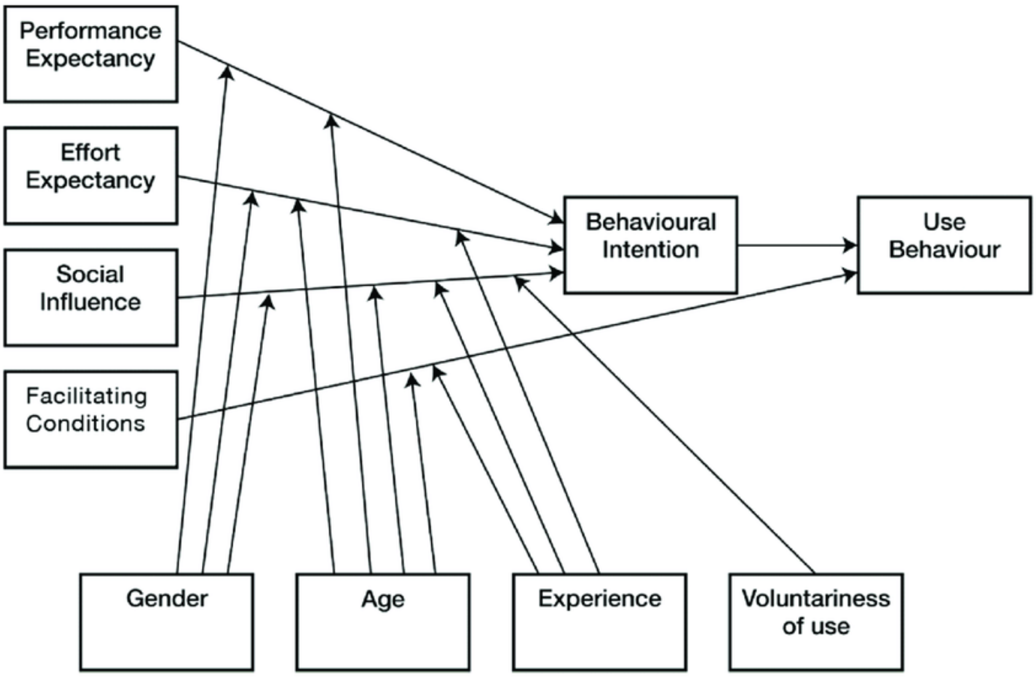

Figure 4: Unified Theory of Acceptance and Use of Technology (UTAUT, Venkatesh et al. 2003)

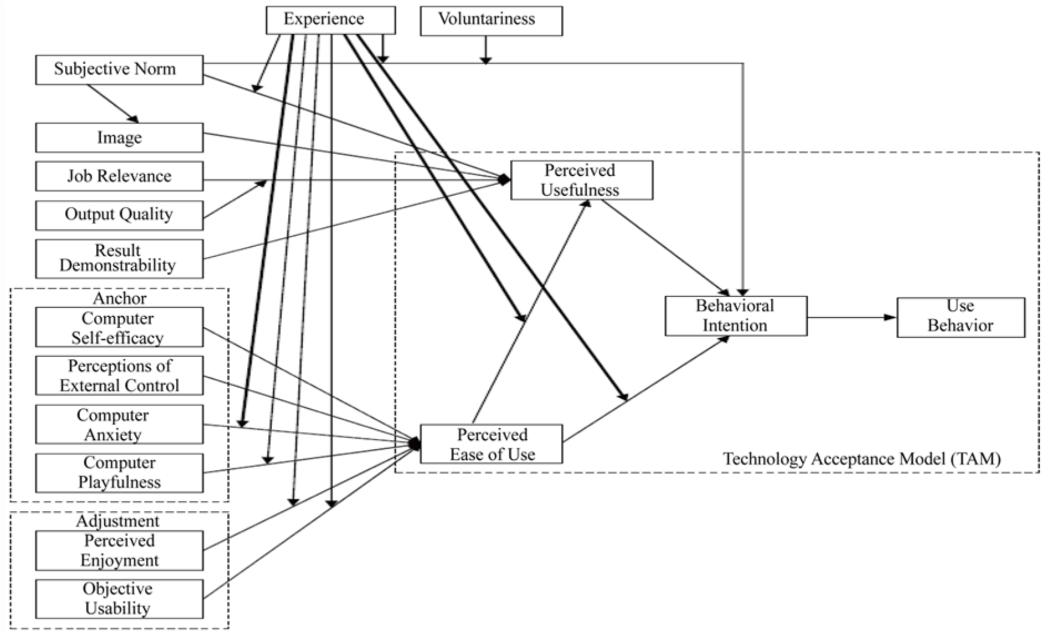

Figure 5: Technology Acceptance Model 3 (TAM3, Venkatesh and Bala 2008)

The technology acceptance model has been the interest of many researchers and several studies have tried to understand its development over time (Lee, Kozar, and Larsen 2003). The role of moderating factors has been found crucial in such models(Sun and Zhang 2006); for instance, the moderating effects of gender and self-efficacy in the context of mobile payment adoption (Riad et al. 2014).

More recently, a study at the University of St. Gallen in Switzerland developed an adapted TAM for personal autonomous mobility, focusing on road vehicles (Jenkins and Linden 2018). The main additions in this model could be relevant to be applied to autonomous VTOL, or UAM.

2.3 Analysis Methods

2.3.1 Factor Analysis (FA)

Factor analysis is a statistical method that aims to describe a set of observed variables in terms of a lower number of latent (unobserved) factors, by looking at their maximum common variability and the proportion of the overall data set variance they explain. In transportation data analysis, this method has been used to reduce the number of variables (Washington, Karlaftis, and Mannering 2010).

There are two types of factor analysis: the Exploratory Factor Analysis (EFA) and the Confirmatory Factor Analysis (CFA). The former is a subset of Structural Equation modeling and aims as its name indicate at exploring the latent factors behind the observed variables, to better reveal the structure and patterns of the data. The latter goes from an already existing theory and a hypothesis on the structure and aims at verifying it. In the following part, the focus is rather on EFA as exploratory approach will be more interesting for our analysis, as detailed in Chapter 3.

For a given observation and a set of p random observable variables, x_1,...,x_p with means μ_1,...,μ_p respectively, the latent unobserved factors F_1,...,F_k can be found by solving the set of linear equations:

$$x_i - \mu_i = l_{i1}F_1 + l_{ik}F_k + \epsilon_i \tag{1}$$

where,

- l_{ij} is constant representing the factor loading of factor j in variable i
- i $\in$ 1,...,p
- j $\in$ 1,... ,k
- k is the number of unobserved or latent factors in the factor analysis
- k $<$ p
- ϵ_i is the random error term associated with x_i, with mean zero and finite variance

In matrix notation, this equation is expressed as follows:

$$(X - \mu)_{p\times 1} = L_{p\times k}F_{k\times 1} + \epsilon_{p\times 1} \tag{2}$$

For n observations, the above matrix notation is translated in the below, where $L_{p\times k}$ is constant across all observations:

$$(X - \mu)_{p\times n} = L_{p\times k}F_{k\times n} + \epsilon_{p\times n} \tag{3}$$

The solution for these equations would give the factor and loading matrices F and L, respectively. As there are $p+k$ unknown but only p equations, some restrictions are needed. In an orthogonal model, the factors and their loading are unique, and the following assumptions are satisfied:

- F and ϵ are independent
- E(F) = 0
- COV(F) = I, the identity matrix
- COV(ϵ) = Ψ, the diagonal matrix

Exploratory Factor Analysis has been used in several studies focusing on public transit user satisfaction (Tyrinopoulos and Antoniou 2008), vehicle sharing adoption (Efthymiou, Antoniou, and Waddell 2013) or technology acceptance for several concepts including e-commerce and e-shopping (Ahn, Ryu, and Han 2004, Shih 2004). It is often used in combination with other statistical models like behavioral modeling, or structural equation modeling (Van der Heijden 2004). A study on the adoption of vehicle sharing system used factor analysis to extract the perceived car and bike ownership characteristics in order to better understand latent correlation between them. The reduced number of variables helped build ordered logit models to better predict vehicle-sharing adoption (Efthymiou, Antoniou, and Waddell 2013).

EFA consists of several essential steps. First, the factors extraction method is chosen. After that, the preferred number of factors to be retained is determined according to different methods. Then, a rotation method is chosen and applied to allow a better visualization of the retained factors. Factor loadings are thereafter extracted for each factor. Finally, factor scores are computed from the obtained loads (Costello and Osborne 2005).

The most common extraction method is the **Maximum Likelihood Estimation (MLE)** which assumes that the data is relatively normally distributed (Costello and Osborne 2005). Otherwise, principle axis factors is recommended. However, MLE is overall better as it doesn't inflate the results since it still explains the shared variance, whereas the principle axis factors method assigns all communalities as one.

The suggested **number of factors** usually follows the Kaiser-Guttman criterion which retains the variables having an eigenvalue greater than one (Kaiser 1960). Other methods include the scree test, Velicer's MAP criteria, and the parallel analysis method (Costello and Osborne 2005, Velicer and Jackson 1990, Hayton, Allen, and Scarpello 2004). The former is usually preferred as it is available in most software packages.

The rotation method depends on the factors' correlation. If the factors are not correlated, orthogonal methods are applied; most commonly varimax is utilized. Otherwise, oblique methods are used, the most common one being oblimin. There are also other rotation methods beyond those listed above, and the package GPArotation in R offers many options for that (Bernaards and Jennrich 2005). After rotation, factor loadings are obtained. These indicate the loading or weight of each variable in a specific factor. A high factor loading means that the variable highly explains the variance in the extracted factor. The variables that do not or poorly load in all the factors are considered less important in explaining the overall variance of the variables and are not retained as explanatory factors in the data set's architecture.

Finally, **factor scores** are computed, taking into account the factor loadings calculated, by computing for example a weighted average of these.

Factor Analysis (FA) vs Principle Component Analysis (PCA):
The main difference between both methods is that the former is used to uncover latent factors causing observed variables to vary/covary, whereas the latter only aims at reducing the data set dimensionality without exploring the data set's pattern. For a given variable, the FA displays the shared variance (made up of the unique variance and the error variance). Compared to the PCA, it avoids the inflation of estimates of variances accounted for.

2.3.2 Discrete Choice Modeling (DCM)

Discrete choice modeling is a widely used method in revealing user preferences for a given choice that uses the principle of utility maximization. This means that each individual will choose the alternative having the highest utility, which in turn is based on attributes related to the alternative and the decision-maker (Ben-Akiva, Lerman, and Lerman 1985).

For a an alternative i and an individual q,the utility is a combination of a systematic element V_{iq} and a random component ϵ_{iq} (Louviere, Hensher, and Swait 2000), as shown in Equation 4 below:

$$U_{iq} = V_{iq} + \epsilon_{iq} \tag{4}$$

where,

- U_{iq} is the utility of alternative i for individual q
- V_{iq} is the systematic component of alternative i for individual q
- ϵ_{iq} is the random error component associated with V_{iq}

V_{iq} is a combination of components exclusively associated with the attributes of the alternative (varying for the same individual across different alternatives), of the decision-maker (constant for the same individual across different alternatives), and the interactions between attributes of the alternative and characteristics of the decision-maker. The systematic component V_{iq} also includes an alternative-specific constant for the given alternative i (Koppelman and Bhat 2006). V_{iq} can be written in terms of its explanatory observed variables or attributes (Ortuzar and Willumsen 2011):

$$V_{iq} = \beta_{1i}X_{1iq} + \beta_{2i}X_{2iq} + \cdots + \beta_{ki}X_{kiq} \tag{5}$$

where,

- β_{1i}, β_{2i}, $\cdots\beta_{ki}$ are the unknown parameters to be estimated, that are constant for the individual but may vary across alternatives.
- X_{1iq}, X_{2iq}, $\cdots\mathrm{X}_{kiq}$ are the k independent variables including all attributes of alternative i for individual q: decision-maker and alternative related.

For a given utility, the alternative-specific constant (ASC) captures the effect of factors that are not part of the model. By adding this constant, the unobserved or remaining error term is bound to a mean of zero (Train 2009). As only the differences in utility matters, one alternative can be normalized to zero by setting its ASC to zero. Therefore, for i alternatives, the model can at most have i-1 ASCs.

Individual q will choose alternative i over j if and only if the utility of i is greater than that of j; in other terms, if $U_{iq} > U_{jq}$.

This leads to the following equations (Louviere, Hensher, and Swait 2000):

$$V_{iq} + \epsilon_{iq} > V_{jq} + \epsilon_{jq} \tag{6}$$

$$V_{iq} - V_{jq} > \epsilon_{jq} - \epsilon_{iq} \tag{7}$$

The difference between the error terms cannot be calculated, but rather the probability that $V_{iq} - V_{jq}$ is greater than that of ϵ_{jq} - ϵ_{iq} (Louviere, Hensher, and Swait 2000). A random utility model is therefore generated due to the random error term, which is assumed to follow a given probability distribution.

In other terms, the probability P_{iq} that individual q chooses alternative i is as follows (Ben-Akiva, Lerman, and Lerman 1985):

$$P_{iq} = P(U_{iq} \geq U_{jq}) \tag{8}$$

Considering a specific probability distribution for the error term, the equation above can be solved and the β coefficients can be estimated using the Maximum Likelihood Estimation method (Ben-Akiva, Lerman, and Lerman 1985).

Note: To add a qualitative independent variable, it is important to set one of the levels of this variable as a base case, and thereafter add the other levels as binary variables (0 or 1). Therefore, for K levels of a given attribute, at most k-1 binary variables can be added to the model; otherwise, the variables would be redundant.

Depending on the probability distribution of the error term, there are different types of discrete choice models (Ben-Akiva, Lerman, and Lerman 1985). A common assumption that the error term is normally distributed (Koppelman and Bhat 2006) leads to the formulation of probit models. However since they can be difficult to solve, logit models based on a logistic distribution of the error term are more commonly used.

Logistic regression model is commonly used in regression analysis, where independent variables are explored in terms of their relation to the dependent variables they explain (Hosmer Jr, Lemeshow, and Sturdivant 2013). In logit models, the discrete outcome variable is binary and the resulting model called binary logit model. Several other models following logistic regression are used in practice, and explained in the following section.

Multinomial Logit Models (MNL):

Multinomial logit models (MNL) are logit models with more than two dependent variables or two unordered outcomes. The main assumptions followed in this model are the Independence-from-Irrelevant Alternatives (IIA) and Independent and Identically Distributed (IID) variables. IIA states that choosing one alternative over the other does not dependent or is not affected by the presence or absence of other alternatives (Louviere, Hensher, and Swait 2000). IIA also means that for different alternatives, the random error terms ϵ_{iq} are independent and identically distributed. Based on the above properties and the extreme value type one (EV1) distribution, the multinomial logit model (MNL) is translated in the following (Train 2009):

$$P_{iq} = \frac{e^{Vjq}}{\sum_{j=1}^{J} e^{Vjq}} \tag{9}$$

where,

- $P_{iq}$is the probability of choosing alternative i by individual q
- $V_{iq}$is the systematic component of the utility of alternative i for individual q

- $V_{jq}$is the systematic component of the utility of alternative j for individual q

Multinomial logit models have been widely used in transportation research. For instance, MNL models have been used in pedestrian crossing behavioral analysis (Kadali and Vedagiri 2012) or long ago in passenger's choice for airport(Ashford and Benchemam 1987). In air mobility, MNL models were used to model VTOLs as touristic mobility modes in sicily, Italy (Amoroso et al. 2012).

There are however several limitations to the MNL models. Often, their basic assumptions are violated due to the nature of the dependent variable. For instance, if outcomes are ordered or in case alternatives share some similarities, other models could be used, such as ordered or nested models.

2.3.3 Ordered Logit Models (OLM)

Ordered logit models are extensions of the logistic regression models and are applied to more than two ordered responses or dependent variables (McCullagh 1980). They are mostly applied in user preference studies, where respondents are asked to rate their satisfaction in a scaled outcome, often ranked in a Likert scale (Likert 1932). In Athens, Greece, OLMs were used to model user satisfaction of transit systems (Tyrinopoulos and Antoniou 2008) or the adoption of new mobility patterns, such as vehicle-sharing (Efthymiou, Antoniou, and Waddell 2013).

For ordered outcomes, OLMs can relax the assumptions of the independence of irrelevant alternatives (Ben-Akiva, Lerman, and Lerman 1985). In such models, threshold values, also known as intercepts or cutoff values, are estimated between the different ordered outcomes.

The order of an observation can be modeled by defining a latent variable Z, corresponding to the exact unobserved dependent variable, represented as follows (Washington, Karlaftis, and Mannering 2010):

$$Z = \beta X + \epsilon \tag{10}$$

where,

- X is the vector of independent variables
- β is the vector of parameters to estimate
- ϵ is the error term

Although the exact value of Z cannot be determined, an estimate of the categories of responses is found, based on the observed ordered data y (stated dependent variable):

$$\begin{aligned} y = 1 \text{ if } z \leq \mu_0 \\ y = 2 \text{ if } z \leq \mu_0 \leq \mu_1 \\ y = 3 \text{ if } z \leq \mu_1 \leq \mu_2 \\ y = \ \cdots \\ y = I \text{ if } z \geq \mu_{I-1} \end{aligned}$$

where,

- μ are the estimate parameters corresponding to the cutoff or threshold values for the different ordered outcomes
- I is the highest ordered outcome

OLMs result in estimates for both β and μ parameters. For each individual, the probability of the I ordered outcomes is estimated assuming specific probability distributions (Washington, Karlaftis, and Mannering 2010). For two response levels, the model is simply the binary logit model (Harrell 2015).

Proportional Odd Models (POM):
The proportional odd models is the most commonly used ordered logit model and is based on cumulative probabilities (Harrell 2015).
For k ordered responses and a vector of X explanatory independent variables, the probability that the latent variable Z is greater than the dependent variable Y is given as:

$$P(Z \geq Y/X) = \frac{1}{1 + \exp[-(\beta X + \alpha_y)]} \tag{11}$$

where, j=1,2,...,k

In this model, β estimates are assumed to be independent of the alternative Y and the cut-off levels. Similarly, no interaction between X variables is assumed. This model is fitted using the Maximum Likelihood Estimation with a likelihood function dependent on the difference between the logistic model probabilities (Harrell 2015).

2.3.4 Nested Logit Models (NL)

Nested models have been used in different areas of transportation research, such as parking choice modeling (Hunt and Teply 1993) or traditional transportation mode choice (Forinash and Koppelman 1993).

Following logistic probability distribution, nested logit models (NL) are used when the alternatives can be grouped into subsets, called nests (Train 2009). Alternatives within a nest share a higher degree of similarity than those outside the nest. The nested logit model therefore partially relax MNL constraints such as IIA and IID, where IIA only holds within the nest.

The utility of alternative i for individual q is a combination of a nest component that is constant across alternatives within the nest, and a variable component that is variable for alternatives within a nest. The utility in a nested model is expressed in Equation 12(Train 2009):

$$U_{iq} = W_{kq} + Y_{iq} + \epsilon_{iq} \tag{12}$$

where,

- W_{kq} only depends on variables describing nest k and is constant across alternatives within this nest
- Y_{iq} depends on variables describing alternative i
- ϵ_{iq} is the error term of alternative i for individual q

The probability of choosing $i \in B_k$ is the product of the probability that an alternative within B_k is chosen and the conditional probability that i is chosen given B_k. This probability can be expressed as follows in Equation 13:

$$P_{iq} = P_{iq|B_k} P_{qB_k} \tag{13}$$

Equation 13 can be rewritten as follows:

$$P_{qB_k} = \frac{\exp(W_{kq} + \lambda_k I_{kq})}{\sum_{l=1}^{K} exp(W_{lq} + \lambda_l I_{lq})} \tag{14}$$

$$P_{iq|B_k} = \frac{\exp(Y_{iq|\lambda_k})}{\sum_{j \in B_k} exp(Y_{jq}|\lambda_k)} \tag{15}$$

where,

- $I_{kq} = ln \sum_{j \in B_k} \exp^(Y_{jq}|\lambda_k)$
- λ_k represents the degree of independence in the unobserved utility among the alternatives in nest k
- I_{kq} is the inclusive utility
- k is the given nest
- I represents other nests

2.3.5 Maximum Likelihood Estimation (MLE)

The maximum likelihood estimation is a statistical tool used for several analysis methods, to estimate the model parameters given a set of observations (Harrell 2015). It can be applied assuming that the explanatory model variables are independent of the unobserved components of the utility (Train 2009). Given that the choices of individuals for an alternative are independent of each other, the likelihood function can be expressed as follows:

$$L(\beta) = \prod_{q=1}^{Q} \prod_{i} (P_{iq})^{y_{iq}} \tag{16}$$

where,

- β is a vector with the estimate parameters of the model
- P_{iq} is the probability that individual q chooses alternative i
- y_{iq} is equal to one if individual q chooses i and zero otherwise

The aim is to maximize the likelihood function in order to maximize the probability of Y_i being one, meaning the probability of success. Due to the complexity of the likelihood function, it is easier to therefore maximize its logarithm (Louviere, Hensher, and Swait 2000), as shown below:

$$L(\beta) = \sum_{q=1}^{Q} \sum_{i} y_{iq} \ln(P_{iq}) \tag{17}$$

Maximizing the above equation is translated into setting its derivative with respect to the variable parameters to zero.

$$\frac{dL(\beta)}{d\beta} = 0 \tag{18}$$

Using the linear parametrization function of the utility from Equation 5 and the logit probabilities formula, we obtain the following:

$$\sum_{q} \sum i(y_{iq} - P_{iq})X_{iq} = 0 \tag{19}$$

Solving this equation, the estimate values maximizing the log likelihood function can be obtained.

2.3.6 Statistical Tests

Utility estimates: The significance of utility estimated obtained from the maximum likelihood method can be achieved using t-tests, which are ratios of mean parameters to their standard errors. For an estimate to be significant, its t value must be more than 1.96 in order to be 95% confident that the mean is different from zero (Louviere, Hensher, and Swait 2000); in other terms, the null hypothesis of its zero mean can be rejected.

Goodness-of-fit Tests: In assessing the model performance, the likelihood ratio index is often used, similar to R^2 in regression analysis (Train 2009) and calculated as follows:

$$\rho^2 = 1 - \frac{\bar{\beta}}{L(0)} \tag{20}$$

In the above equation, the ratio is between the final and the initial log likelihood (Train 2009). Everything else being the same, the model with the highest rho-squared value ρ^2 is a better fit for the data. The limitation of this tool however is that it always improves by adding more variables, regardless of their meaning or significance (Koppelman and Bhat 2006). An approach to overcome this problem is to improve the rho-squared value by taking into account the degrees of freedom K. The corresponding equation becomes:

$$\bar{\rho}^2 = 1 - \frac{L(\bar{\beta}) - K}{L(0)} \tag{21}$$

To test whether removing a variable improves the overall model or not, the likelihood ratio test can be applied, as shown in Equation 22. The null hypothesis in this case is that the restricted model improves is true.

$$-2(L(\bar{\beta}_R) - L(\bar{\beta}_U))\ \chi_{K,\alpha^2} \tag{22}$$

This test can only be used if one model is nested from the other, meaning that it can be obtained from the other by adding linear restrictions on the parameter. Otherwise, a non-nested ratio test is used (Bierlaire 2003). The Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC) can also be used to assess the model performance, where lower values represent better model fits (Burnham and Anderson 2004).

3 Methodology

In this chapter, the methodology of this work is described, consisting of the proposed Technology Acceptance Model (TAM), the survey design, and the analysis methods, including the exploratory factor analysis and the framework for specifying the models. After that, built hypotheses are listed, according to which the main objective and research problems were answered.

3.1 Proposed Technology Acceptance Model

The findings of the literature indicate the need for an adapted model to represent UAM adoption. A proposed UAM TAM model was therefore developed, and is presented in Figure 6.

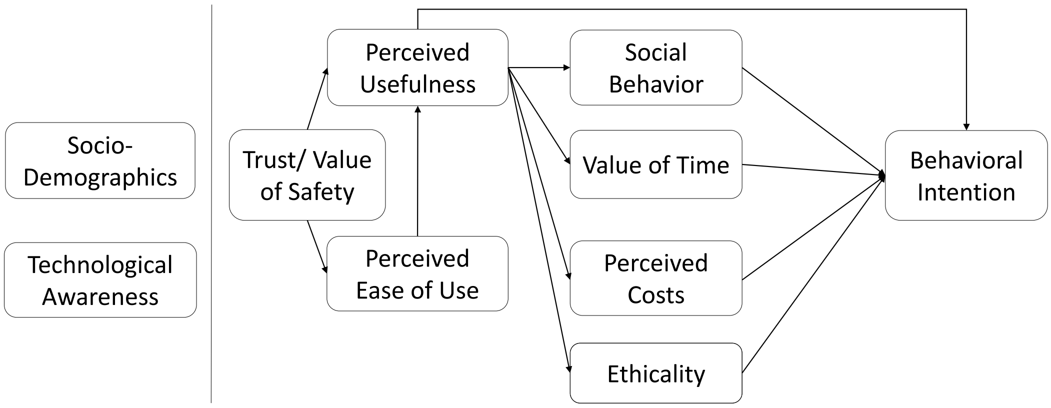

Figure 6: Proposed Technology Acceptance Model for UAM (*own illustration*)

This model is based on both the TAM and the UTAUT (Figures 2, 4). The basic factors of perceived usefulness (PU) and perceived ease (PEU) of use remain from the original TAM. PU and PEU also relate to performance expectancy and effort expectancy as mentioned in the UTAUT, through the perceived benefits of automation, and the booking and boarding processes of UAM, respectively. Similarly to the previous established models, PEU impacts PU, which directly influences the behavioral intention.

Social behavior or social attitude is meant as the social influence, and includes attitudes towards automation, affinity to social media, etc. Other constructs such as the value of time, perceived costs and ethical concerns (regarding data use or the loss of jobs due to automation) are added as facilitating (or inhibiting) conditions to behavioral intention.

An important added construct, inspired from the TAM for autonomous mobility is trust. This key factor is a base for both PU and PEU and is in turn influenced by several factors. Many factors impact trust, and although it is latent non-observable construct, four main components affecting are mentioned it: the perceived reliability of automation, the perceived vehicle's safety, the perceived locus of control, and the previous experience with automation. These are summarized in Figure 7.

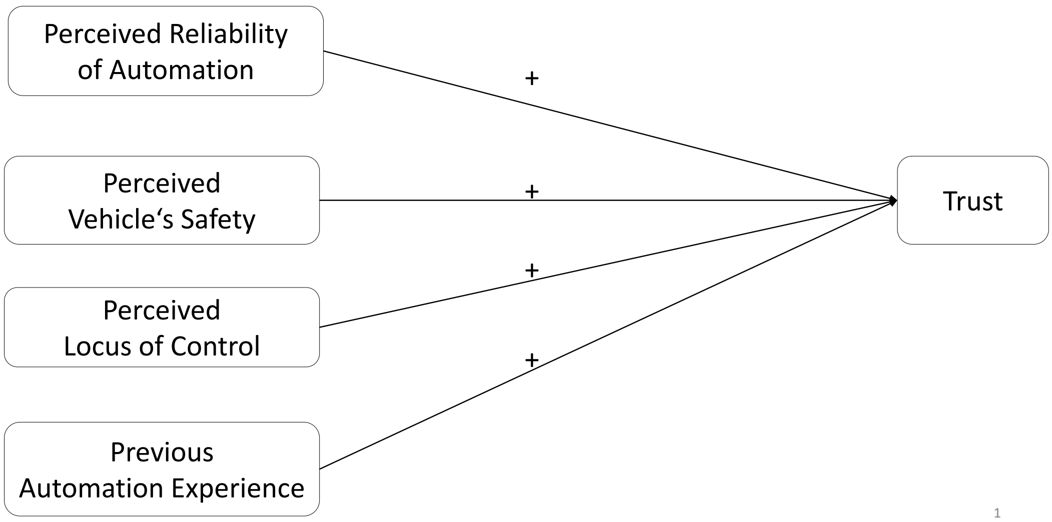

Figure 7: Factors affecting trust in UAM (*own illustration*)

Finally, socio-demographic variables (including age, gender, previous experiences, income) and technology awareness act as overarching factors influencing the behavioral intention of using UAM.

The proposed model will be at least partial validated in this thesis. As it is not easy to assess many of the mentioned variables, even less for UAM, it would be interesting to see if this model has at least the right direction, and could be used for further research investigation. It is important to mention that use behavior has not been added to this model as UAM is not yet available; therefore, there is no way to know whether the people will actually use the model or not. Also, in our study, we not only focus on the use, but also the time adoption, which cannot be reflected in this model.

3.2 Survey Design

This section describes the designed survey, which is the starting point of the methodology and the main source for the data analysis. It includes the survey structure and survey methodology and presents the assumptions taken in building it. The full survey is available in Appendix A.

3.2.1 Survey structure

As UAM does not yet exist, a stated preference (SP) survey was designed. The survey was structured using the main findings of the literature, and relying mostly on the table of factors (Table 1) presented in Chapter 2. Accordingly, 31 questions (or question groups[1]) were formulated and grouped in four main parts. The required time for completion was around 10 to 15 minutes. The reasoning behind each part's formulation is described in details in the following.

- **Introduction:** The authors and main objectives of this study were introduced; anonymity and data use statements were also given.

[1]A question consisted sometimes of a matrix including several agreement statements, focusing on one attribute for instance.

- **Part 1:** This part included six questions focusing on users' commute behavior and their awareness of automation. In the first four questions, respondents were asked about their commute time and commute mode, and whether they owned a driver's license and (if yes) had access to a car. The answer options for these questions were categorical and numerical. After that, public transportation satisfaction was assessed. This was done using a five-point Likert scale question with answer options ranging from very dissatisfied (1) to very satisfied (5).

  Automation-related statements involved agreement statements on automation, also using a five-point Likert scale, with answer options ranging from 'strongly disagree' to 'strongly agree'. Such statements included enjoyment and trust of automation (of systems like Siri or Alexa for instance), previous experience with advanced driver-assistance systems (ADAS), and the perceived usefulness of such systems.

  Notes:

  1. *Most agreement statements were five-point Likert scale questions, ranging from 'strongly disagree' to 'strongly agree', unless otherwise stated.*
  2. *All questions in this part were mandatory and multiple choice with only one answer option, unless otherwise stated.*
  3. *For Likert scale questions, we first looked into the possibility of removing the neutral answer option, as mentioned in some studies (Garland 1991), in order to avoid the bias of having more 'neutral' answers from respondents who would otherwise choose different answer options. Other sources stated on the other hand that removing the neutral option might affect the respondents' judgments and lead to risk aversion (Nowlis, Kahn, and Dhar 2002). We decided therefore to keep the traditional Likert scale, including a neutral answer option.*

- **Part 2:** In this part, UAM was introduced as a future mobility service operated by vehicles with the following properties:

  - Fully-automated VTOL (vertical take-off and landing aircraft) without any pilot assistance (Shamiyeh, Bijewitz, and Hornung 2017, Vascik 2017).
  - Electrically-powered vehicles, addressing thereby noise concerns (Shamiyeh, Bijewitz, and Hornung 2017; Cohen 1996).
  - On-demand online booking using the service's website or application, assuming very high availability (Shamiyeh, Bijewitz, and Hornung 2017, Vascik 2017).
  - 4-seat capacity: the vehicle can be booked for up to four passengers, including one wheelchair seat. This assumption was done based on the economic model of Uber Elevate (Uber Elevate 2016).
  - Possibility to ride-pool: by sharing the UAM flight with other passengers, users are expected to save money (Uber Elevate 2016). As UAM business models are not yet defined, the survey does not include the amount saved by sharing the ride.
  - Operating speed around 150 km/h (Holden and Goel 2016).

- Boarding time is assumed to be 5 minutes (an approximation for both boarding and de-boarding times. A study conducted by Porsche Consulting suggests 3 minutes for boarding, and 3 minutes for de-boarding (Porsche Consulting 2018); this total of 6 minutes was approximated as only 5 minutes boarding time, for simplification purposes and assuming a fast and efficient process.
- Vertiports access and egress: 'Helipad' infrastructures distributed around the city, (i.e. at rooftops) and used for take-off and landing of VTOLs.
- Vertiports are assumed to be integrated with existing public transportation (PT) systems (Cohen 1996).

To better describe UAM properties, an illustration was drawn to explain the process from origin (O) to destination (D), with taxi as a benchmark, as shown in Figure 8.

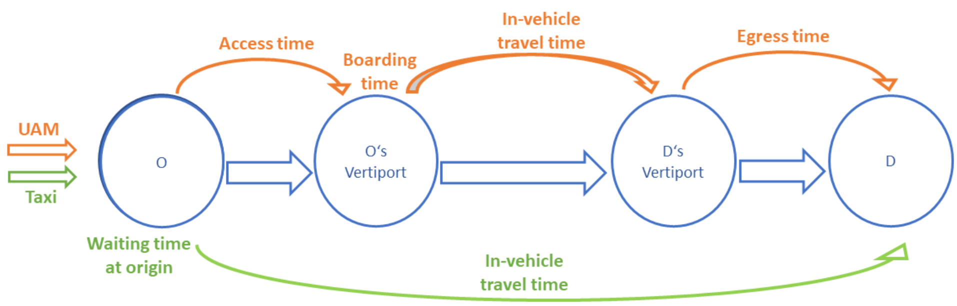

Figure 8: UAM process (*own illustration*)

For this part, it was essential to introduce some scenarios to familiarize the respondents with the topic. As most respondents were expected to come from Munich, the examples were built around realistic scenarios of this region. Also, they were cases where PT required at least one hour of travel time, with a necessary transfer in the center. Therefore, PT was not attractive for these cases, and the focus was on a comparison between Taxi and UAM, as it was a rather comparable mode in these cases. Accordingly, and since the aim of the study is not a mode choice, other modes' characteristics were not given in the scenarios.

Providing respondents with realistic properties based on the current knowledge in this field aims at giving potential users a better insight on UAM, to be able to asses their perception and identify the relevant factors. The presentation of the scenarios is illustrated in Figure 9 below.

To better illustrate the use of UAM, two scenario **examples** are provided, where UAM could be used (in the region of Munich for example), **hypothetically starting 2030.**

Notes for both examples:

1. *The public transportation option requires more than an hour (in vehicle) from origin to destination, via a necessary transfer in the center of Munich.*
2. *We are only giving travel times and fares for taxis, as a benchmark for the UAM option.*
3. *Taxi ranges (for time and fares) are given depending on road traffic.*

Example 1: A trip from **Munich Airport** to **Dachau:**

	UAM	TAXI
Trip Duration	• 15 min **access time** • 5 min **boarding time** • 13 min **in-vehicle travel time** • 5 min **egress time**	• 5 min **waiting time** • 28-40 min **in-vehicle travel time**
Trip Fare	• 90 €	• 53-69 €

Example 2: A trip from **Planegg** to **Taufkirchen:**

	UAM	TAXI
Trip Duration	• 8 min **access time** • 5 min **boarding time** • 8 min **in-vehicle travel time** • 12 min **egress time**	• 5 min **waiting time** • 30-55 min **in-vehicle travel time**
Trip Fare	• 53 €	• 40-52 €

Figure 9: Survey scenarios

This part contained eight questions. In the first one, the respondents were asked to rank some factors according to their importance for UAM adoption. The following questions were five-point Likert scale questions on the perceived usefulness of UAM, and on ethical, and safety concerns. Ethical concerns included data use, cyber-security, and the loss of jobs induced by automation. Safety concerns tackled the importance of service reliability, in-vehicle surveillance cameras, and service provider's reputation. This group of questions also assessed the requirement for an operator on the ground, and to override the system in case of emergency, in order to address the perceived importance of "locus of control" in automation.

In the case of UAM, is is not expected that the user overrides the vehicle in case of emergency; however, the possibility of having an operator to override the system and the human factor associated with being able to communicate with that person contributes to that "locus of control".

Cost considerations were assessed by also using agreement statements. These targeted the willingness to use UAM for prices comparable to taxis', the importance given to costs, and the perception of given costs, i.e. if they were reasonable based on the scenarios. After that, perception of travel time savings was tackled. This included the importance of time savings in adoption, and the sensitivity to different time savings, like 5, 10, or 20 min.

These agreement statements were followed by questions on intended purpose of use like 'daily commute', 'business travel', 'leisure', and 'other', and intended time-frame adoption, including answer options ranging from the first, the second or third, the fourth or fifth, the sixth or more years of implementation, to 'never', or 'unsure'. The stated time adoption is crucial to develop the behavioral models, as it will be the dependent variable related to the explanatory independent variables.

- **Part 3:** This part included behavioral and attitudinal questions on different concepts. The familiarity and frequency of use of different services was first tested using five-point scaled answers. These included sharing services (Airbnb, DriveNow/car2go, Uber, BlaBlaCar) and social media platforms (Facebook, WhatsApp, Instagram, Twitter). Also, comfort of use of online services (online, banking, shopping) was assessed in a similar way.

  Social behavior was also assessed by looking at respondents' willingness to share a ride with strangers ('very unwilling 'to 'very willing'), driving enjoyment of cars and environmental attitudes (agreement statements on environmental matters). Finally, respondents' personal experiences were taken into account by considering previous crashes they might have had, and looking at their comfort with flying ('very uncomfortable' to 'very comfortable'). Since these are personal, and potentially sensitive questions, both included 'prefer not to answer' as an option.

- **Part 4:** This part on socio-demographics included questions on age, gender, household size, disability in household, education level, main occupation, household income, and current residence location (city and country). All these questions had 'prefer not to answer' as an answer option.

  As stated preference studies are susceptible to anchoring bias (McFadden 2001), socio-demographic questions were asked in the end, so that people would not be biased in answering them according to what they think would be consistent with their choices, adjusting thereby their answers to what they would otherwise not have answered. Placing these questions in the end can also overcome stereotype threat (Steele 1995), where people try to avoid the confirmation of any stereotype they feel threatened by. Such stereotypes might include socio-demographic factors, such as gender, income groups, or even social aspects like technology awareness.

3.2.2 Survey methodology

- **Sample Selection:** The survey goal was to assess UAM adoption in the region of Munich. For this, and assuming a representative random sample, a sample size of 300 respondents was required for a 95% level of confidence. However, due to limitations in time and resources, the survey was conducted online (as will be later explained) and gathered diverse responses outside the region of Munich. Still, as the research was based in Munich, a lot of respondents were Munich or more generally German residents. A later motivation would be to assess the difference between the respondents based on their place of residence.

- **Sampling Procedure**

  1. **Pilot Survey:** A pilot survey was conducted on the 6th of July 2018, as a first step in assessing the survey design. This study was part of a discussion workshop in which ten employees of Bauhaus Luftfahrt e.V., a Munich-based aviation research

institute, participated to give feedback and advice on the survey structure. The aim of this study was to therefore have external insights on the survey, to potentially avoid confusion or biases among the respondents. As a result, the relevant learnings were taken into consideration and incorporated in the survey. Still, the results of this pilot study were not used in the analysis and/or development of models.

2. **Survey Running:** The survey was conducted online using LimeSurvey PRO (limesurvey.org) and was publicly available for two months starting the 18th of July 2018. It was available in both English and German and distributed among various groups. These included local university groups, choirs, community groups, student dormitories, companies, etc. The survey was further distributed based on the researchers' personal social networks, using mailing lists and social media platforms such as Facebook and Linkedin. An observed advantage was the heterogeneity among these groups, and their willingness to share and forward the survey to other people, further diversifying the pool of respondents. Starting from Munich, the distribution target was thereafter expanded to other locations as it was available online and in English as well.

   Notes:

   (a) *The authors are aware that the distribution method does not lead to a perfectly random sample; however, it is used due to the limited resources allocated for this research.*

   (b) *Although offline methods such as flyers could be beneficial in reaching a wider sample, these would still require internet access to enter the survey link. Alternatives such as pen-and-paper surveys also risk being tedious, and inefficient, especially in the scope of 10-15 minutes survey.*

   (c) *Research was done to identify the most suitable platform. For our study, LimeSurveyPro was assessed as the most suitable one as it was both friendly and powerful, and provided a high cost-benefit value.*

3.3 Modeling Framework Definition

This section presents an overview of the thesis's modeling framework. Two main analysis methods were used in reaching our objectives. First, exploratory factor analysis was performed to reduce the dimensionality of major parts of the survey and to better understand the underlying patterns behind some variables. Second, discrete choice models were used based on factor analysis results. This method was often used in perception studies as an alternative to developing hybrid class models; it was for instance used in assessing public transport user satisfaction (Tyrinopoulos and Antoniou 2008), and in identifying factors for the adoption of vehicle sharing systems (Efthymiou, Antoniou, and Waddell 2013).

3.3.1 Exploratory Factor Analysis (EFA)

As mentioned above, exploratory factor analysis was the first analysis method used and had two main objectives: dimensionality reduction and latent variables identification. EFA was applied to parts 2 and 3 of the survey, as both included Likert scale questions that could be easily converted to same-scale numerical data.

In this study, EFA was applied using R statistical software (R Core Team 2013). Particularly, **psych** library package (Revelle 2018) was used and the function *factanal*, to apply the **Maximum Likelihood Estimation** as a factor extraction method. The suggested **number of factors** was obtained from both Kaiser-Guttman method and the scree test. Usually, they yielded to more or less the same results. As the factors were assumed to be uncorrelated, varimax **orthogonal rotation** was used.

"Cleanest" factor structures include only item loadings above 0.30, with no or few item cross-loadings, and no factors with fewer than three items (Costello and Osborne 2005). Accordingly, loadings less than 0.3 were removed to reduce the noise in the data, and the factor analysis was run again. The process was repeated several times until satisfactory results were reached. Factors were expected to explain at least 10% of the variables' variance (Costello and Osborne 2005). Although there are several rules of thumb for factor loadings thresholds, these were rather assessed according to personal judgment on their importance and meaning. Finally, factor scores were computed using *factor.scores* and the "component" method, which is basically a weighted sum of the factor loads. The obtained factor scores and their interpreted meanings could thereafter be used in the subsequent analysis methods, simplifying thereby the analysis process. Since the variables used were ordinal (Likert scale results), polychloric correlation using *polychlor* was preferred (Revelle 2018). However, as no major difference was observed by applying it, it was not used in the subsequent analysis.

3.3.2 Behavioral modeling

Behavioral or choice modeling was the second analysis method of this thesis. In an aim to identify the factors affecting the adoption and use of UAM, factor analysis results were used in building several choice models with the stated time-adoption as a dependent variable. The choices were therefore the given options ranging from immediate adoption (Y1), to later adoption (Y2-Y3, Y4-Y5, Y6+), non-adoption (Never), or uncertainty (Unsure). The independent variables were the results of the survey parts, retained or not from the EFA. For categorical variables like socio-demographics, binary variables were created to assess the impact they have on the models. As time outcomes were ordered, the main goal was to use ordered models to assess adoption. A preliminary step was therefore to develop MNL models to get first insights on influential and relevant factors.

MNL models: Using the stated time outcome as a dependent variable, MNL were first developed by setting the first year as a base case, and using only generic variables. Accordingly, respondents' behavior was assessed in terms of early adoption. Models were built first by using all survey variables, in what is called a "saturated model" method. After simplifying and eliminating the highly insignificant variables, the approach was reversed. "Empty models" were developed, adding one by one the significant variables. These models were then optimized using alternative-specific explanatory variables, with the advantage of observing patterns of attribute estimates across different alternatives or time frames.

OLM models: Insights obtained from the developed MNL models were used in OLM, with the stated time adoption as a dependent variable as well. For ordered models, there is only one latent (ordered) variable to estimate, but also several cut-off values acting as boundaries for the latent variable. Therefore, the retained independent variables from the MNLs were in general those who had clear estimate patterns across the alternatives. Different ordering cases ranked the "unsure" alternative between different time groups (as part of non-adopters, or between late and non-adopters). On the other hand, the rest of the alternatives followed clear time frame patterns (Y1, Y2, Y3, Y4, Y5 Y6, Never) and had therefore only one way of being ordered.

NL models: Nested logit models were also developed with different nesting options, such as first five year adopters, first three year adopters, or first year adopters. Results from MNL and OLM models were incorporated in these models. However, these models couldn't be estimated, probably due to the lack of attribute variability among the different alternatives.

The modeling framework of the thesis is summarized in Figure 10.

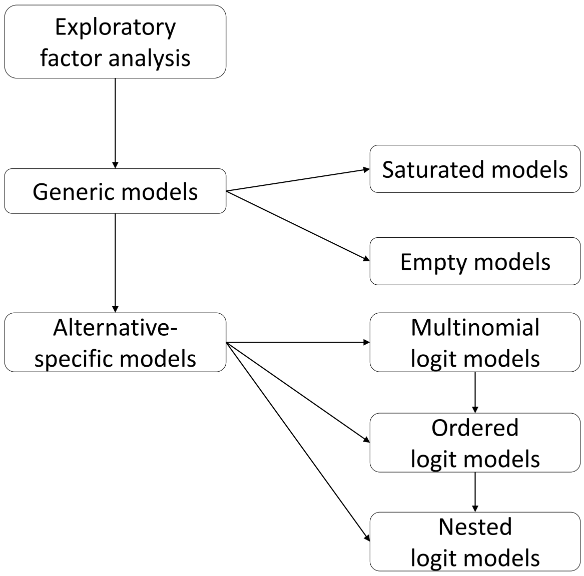

Figure 10: Modeling Framework

3.4 Built Hypotheses

As a basis for the models to build, and based on previous literature and related works, we came up with the hypotheses listed below, organized as demographic-related, attitudinal-based, and model-related. These will be discussed in the following chapters.

3.4.1 Demographics-related hypotheses

Demographic variables significantly impact UAM adoption.

- Hypothesis 1: Gender impact: Females are more likely than males to be late adopters of UAM.
- Hypothesis 2: Age impact: Very Young respondents are more likely to be early adopters than older ones.
- Hypothesis 3: Main occupation impact: Fully-employed respondents are more likely to be early adopters compared to students, part-time, or non-employed.
- Hypothesis 4: Cultural impact: Cultural differences influence the adoption of UAM; Respondents answering the survey in German are more likely to be late adopters, or unsure about their intended UAM time adoption, than the ones answering it in English.
- Hypothesis 5: Income impact: Higher income respondents are more likely to be early adopters compared to low income respondents.
- Hypothesis 6: Education impact: Respondents with a higher level of education are more likely to be early adopters than those having a lower level of education.

3.4.2 Attitude-related hypotheses

- Hypothesis 7: Car users are more likely to be early adopters compared to those commuting with other modes of transportation.
- Hypothesis 8: Technological awareness, including the affinity to automation, is very likely to be associated with early adoption.
- Hypothesis 9: Safety concerns, including the importance of locus of control, are related to late UAM adoption.
- Hypothesis 10: Data concerns, and concerns regarding the loss of jobs induced by automation, are likely associated with late UAM adoption.
- Hypothesis 11: Social behavior, including environmental awareness, sharing perception, and affinity to social media and online services contribute to early adoption of UAM.
- Hypothesis 12: Higher public transportation satisfaction is more likely related to later or uncertain adoption of UAM.
- Hypothesis 13: Higher value of time savings is likely to be related to earlier adoption of UAM.
- Hypothesis 14: Positive perception of proposed UAM costs is more likely associated with earlier UAM adoption.

3.4.3 Model-related hypotheses

- Hypothesis 15: UAM adoption can be modeled with an ordered logit model.
- Hypothesis 16: UAM adoption (including unsure respondents) can be nested according to different nesting options.

4 Data Analysis

This chapter presents a preliminary data analysis of the survey, including the summary statistics of the responses, a detailed analysis of the outcomes, and a qualitative analysis of the respondents' comments.

4.1 Summary Statistics

The survey generated 250 responses, after which only 221 were retained due to missing answers in the remaining ones. As mentioned in Chapter 3, the study was conducted online and gathered responses from all over the world, with a focus on the Munich region. In the coming chapters, we will therefore analyze the entire data as one sample, and test for the significance of the place of residence. Still, as Munich constitutes a subsample for the data (97 out of 221), the summary statistics of the entire sample and the major subsample (Munich) are presented in Table 3, in addition to the latest Munich Census for reference (Statistische Ämter des Bundes und der Länder 2014).

The main findings of the sample distribution (Table 3) can be summarized as follows.

1. Both samples are well distributed in terms of gender, occupation, household size, and household incomes.

2. Both samples have an overrepresentation of the age category 25-34 and of higher level of education; conversely older age categories were underrepresented for both samples; this might be due to the online method of survey distribution.

3. PT as commute mode was overrepresented for Munich subsample.

4. In general, and for later analysis, missing values representing very small percentages of the sample size (less than 5%) were recoded using mean or median values (such as PNA values for gender, occupation, education). However, for household income, PNA was a category on its own as it represented about 20 % of the sample size.

5. Some categories were combined together if they made sense, and when they represented only a very small percentage of the sample size.

6. Age categories 0-17 and 18-24 were combined together in one category, for less than 24 years old. Similarly, 55-64 and 65+ were combined.

7. Occupation categories were reassigned to full-time, part-time, student, other.

8. Education categories were reassigned to bachelor or lower (high school, apprenticeship, bachelor), master, and doctorate levels.

9. Car as driver or passenger categories were merged into one category (car).

Moreover, as we are interested in the time adoption of UAM, the distribution of the outcomes for this dependent variable is of great interest and shown in Table 2 below.

Table 2: Distribution of survey outcomes

Outcome	Frequency (%)
Y1	22.17
Y2-Y3	36.65
Y4-Y5	14.03
Y6+	2.71
Never	3.17
Unsure	21.27

The outcome distributions show an overall enthusiasm about UAM as around 60% express their interest in adopting the service in the first three years of its implementation. Still, the percentage of immediate adopters (Y1) is about half that of second and third year adopters (Y2-Y3). Despite a relatively low percentage of late (Y4-Y5, Y6+) and non-adopters (Never), a non-negligible amount of respondents remains skeptical (Unsure).

Table 3: Summary of sample and subsample characteristics

		Total sample (N=221) Percentage (%)	Munich subsample (N=97) Percentage (%)	2011 Census
Gender	Female	43.0%	51.6%	48.6%
	Male	56.1%	47.4%	51.4%
	PNA	0.9%	1.0%	-
Age[2]	0-17	0.5%	-	-
	18-24	19.5%	23.7%	9.2%
	25-34	45.7%	56.7%	21.7%
	35-44	19.0%	16.5%	22.4%
	45-54	9.5%	16.5%	22.2%
	55-64	5.0%	-	16.8%
	65+	0.9%	-	7.7%
Main occuption	Full-time employed	57.9%	46%	87.1%
	Part-time employed	9.1%	8%	
	Student	28.1%	42%	2.9%
	Unemployed	0.5%	1%	2.2%
	Self-employed	2.3%	1%	7.8%
	Retired	0.9%	-	
	PNA	1.4%	1%	
Education	High School	8.6%	6%	34.1%
	Apprenticeship	2.7%	1%	40.7%
	Bachelor	26.7%	26%	22.7%
	Master	47.5%	52%	
	Doctorate	13.1%	13%	2.5%
	PNA	1.4%	2%	-

[2] Census values for age are based on different age categories and are therefore best-fit values for the survey classes.

Continuation of Table 3

		Total sample (N=221)	Munich subsample (N=97)	2011 Census
Household size	1	43.0%	61%	50.0%
	2	29.9%	28%	29.0%
	3	10.4%	5%	11.0%
	4	9.9%	2%	7.0%
	5+	4.1%	-	3.0%
	PNA	2.7%	4%	-
Disability in household	Yes	1.8%	2%	-
	No	97.3%	98%	-
	PNA	0.9%	-	-
Household income[3]	<500 €	7.2%	13.4 %	
	500-1000 €	8.6%	13.4%	
	1000-2000 €	11.3%	10.3%	
	2000-3000 €	14.0%	16.5%	
	3000-4000 €	10.9%	6.2%	
	4000-5000 €	10.9%	7.2%	
	5000-6000 €	4.9%	3.1%	
	6000-7000 €	5.4%	30.9%	
	>7000 €	6.3%	21.7%	
	PNA	20.4%	3.1%	
Main commute mode[4]	Car as a driver	33.9%	14.0%	31.0%
	Car as a passenger	1.8%	-	
	Public transportation	40.7%	63.0%	28.8%
	Bike	15.4%	20.0%	14.7%
	Walk	5.9%	1.0%	25.5%
	Other	2.3%	2.0%	

[3]No census values for income levels
[4]The given values are trip distribution percentages (MVG 2011)

4.2 Analysis of Outcomes

4.2.1 Factors ranking

Factors ranking resulting from the second part of the survey gave the following insights. The majority of respondents (more than 50 %) ranked safety as the most important factor in UAM adoption. The following ranked factors were less decisive, representing each about 20 % of the respondents.

The factors ranking mostly highlight the importance of safety in automation. This finding is confirmed by many studies on safety and automation, as described in the literature (see Chapter 2). Also, a strong indication towards the importance of UAM costs, trip duration, on-time reliability, and operation characteristics were also given. In terms of less important factors, trip purpose seem to be a less significant factor, and vehicle characteristics, boarding process and booking experience somewhat not as significant either.

4.2.2 Adoption and attitudes of different demographics

In this subsection, stated UAM time adoption is represented for the different demographics or attributes of interest, in order to have preliminary insights of their impacts on adoption. Most figures represent distributions for all 221 outcomes. However, for some demographics, graphs were generated excluding categories representing less than 5% of the sample size, as it wouldn't be convenient or representative to observe their distribution.

Note: Although categories Y6+ and Never represent together around only 5% of the sample size, these were shown in the below graphs as part of the different demographics' choice sets.

Adoption by gender:
The analysis of the adoption choices by gender shows significant differences for male and female respondents. Figure 11 shows that females have a lower tendency of being early adopters, and a higher of being "unsure" about their adoption time. This initial finding goes with Hypothesis 1, and will be further investigated in the models.

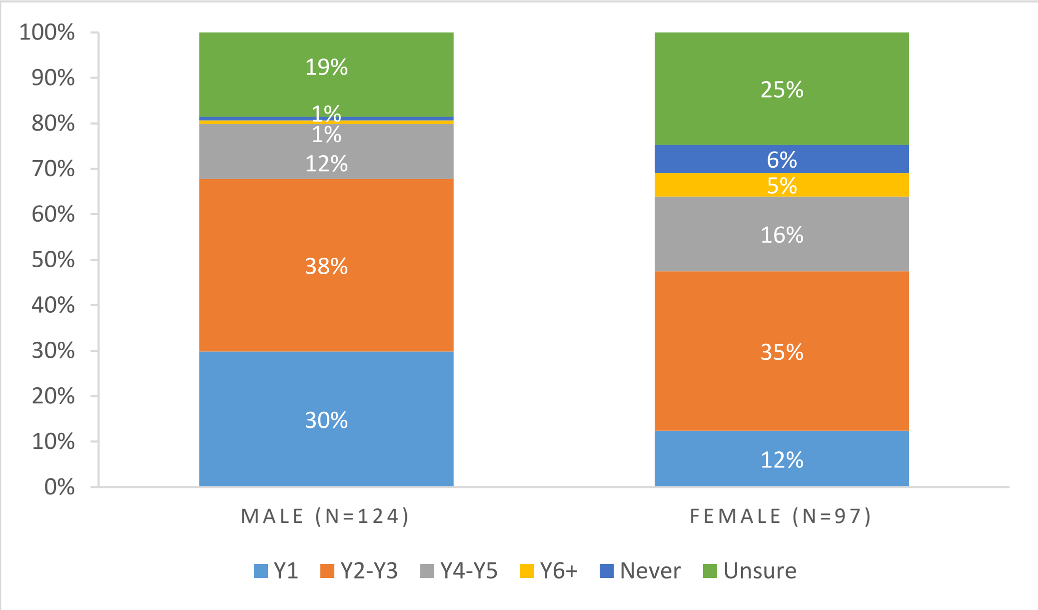

Figure 11: UAM adoption by gender (N=221)

Adoption by age:
Figure 12 shows that younger people (0-24 years old) have a higher tendency of being late adopters (Y4-Y5) and a lower of being early adopters (Y1), which is contrary to common expectation, and to the previously formulated Hypothesis 2. Conversely, middle-aged adults (35-44 years old) seem to be very interested in UAM, and more ready to use it during its initial stages.

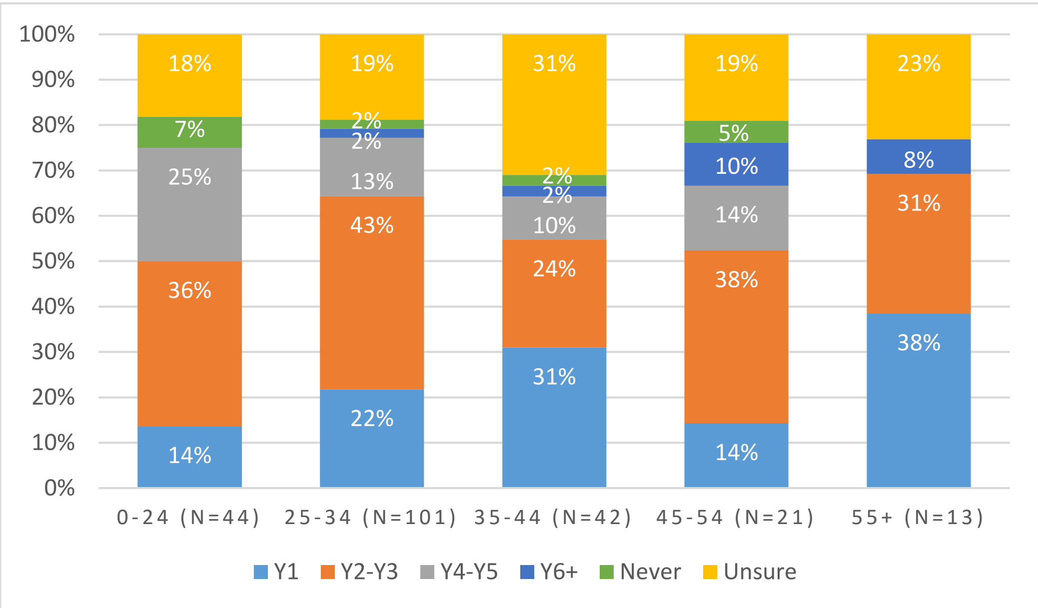

Figure 12: UAM adoption by age (N=221)

Adoption by occupation:
Figure 13 shows that respondents working full-time have a tendency to be early adopters, and

those working part-time a pattern in being "unsure"; this finding should be looked at more carefully as part-time employment only represents about 10% of the total sample size. Still, overall there is an indication in favor of Hypothesis 3.

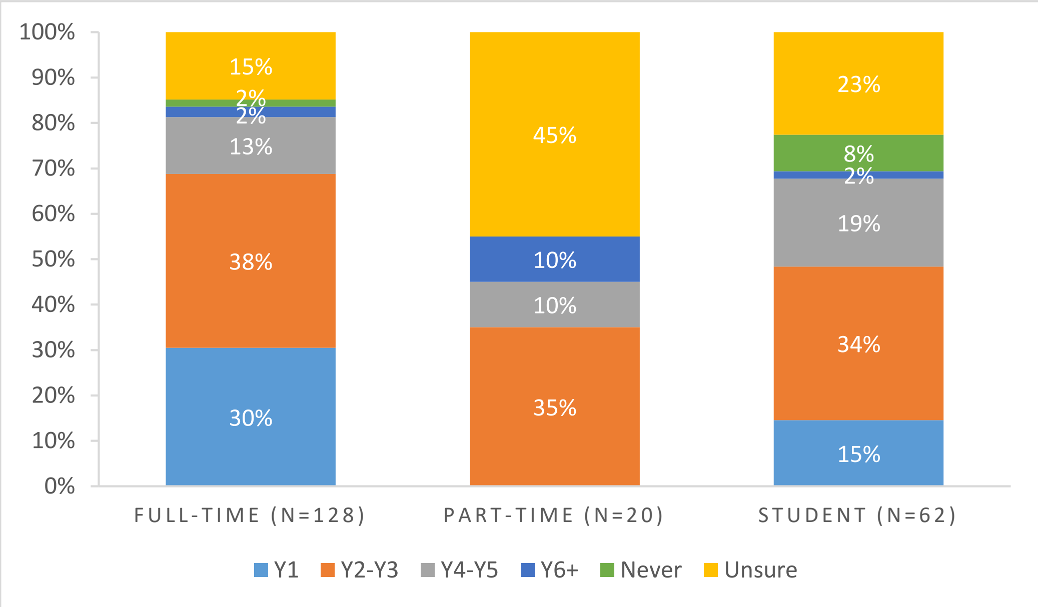

Figure 13: UAM adoption by occupation (N=210)

Adoption by income:
Despite being not conclusive, Figure 14 shows a pattern in which higher income levels share higher percentages of early adoption (Y1) compared to lower income levels.

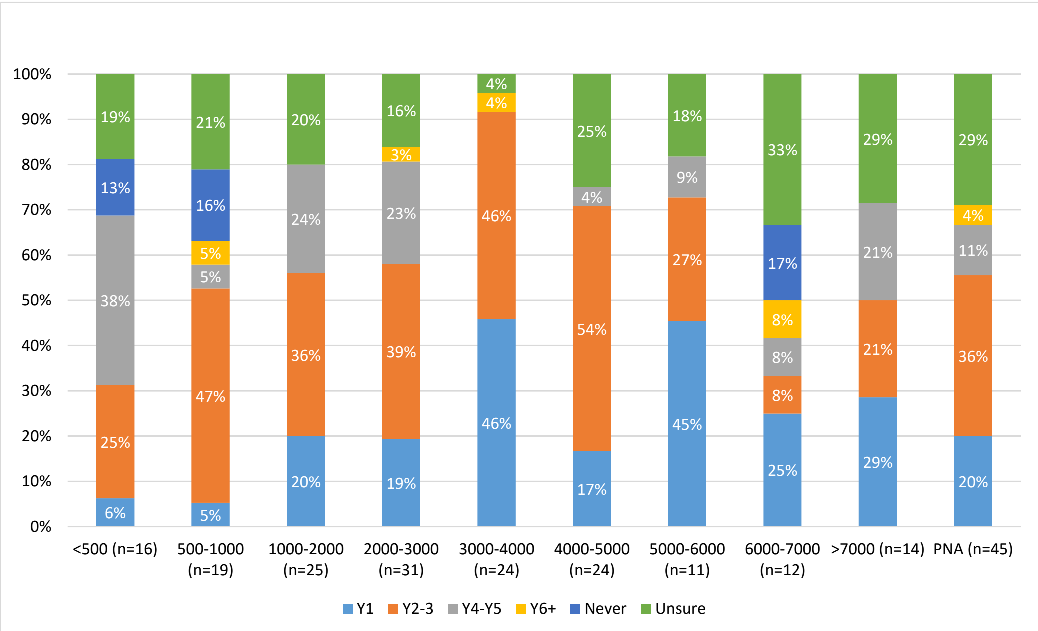

Figure 14: UAM adoption by income (N=221)

Adoption by survey language:
Figure 15 shows an interesting finding related to the respondents' cultural aspect, revealed by the starting language of the survey: German (DEU) or English (EN). There is a clear pattern in which respondents answering in German have a higher tendency to be uncertain about their intended time adoption, accompanied with less enthusiasm about early adoption (Y1) as revealed by the small percentage for this category. These findings reveal the importance of the cultural aspect in adoption, are in favor of Hypothesis 4, and can be related to a study on consumer's preferences in Germany, in which Germany ranked rather low in consumer acceptance of automation (Krueger, Rashidi, and Rose 2016).

An interesting comparison with adoption based on the place of residence shows no major differences between Munich and non-Munich residents, as shown in Figure 33. Respondents residing in Munich do not necessarily share the same cultural backgrounds, and might therefore have very different behavioral intentions; on the other hand, language seems to be a more uniting cultural aspect.

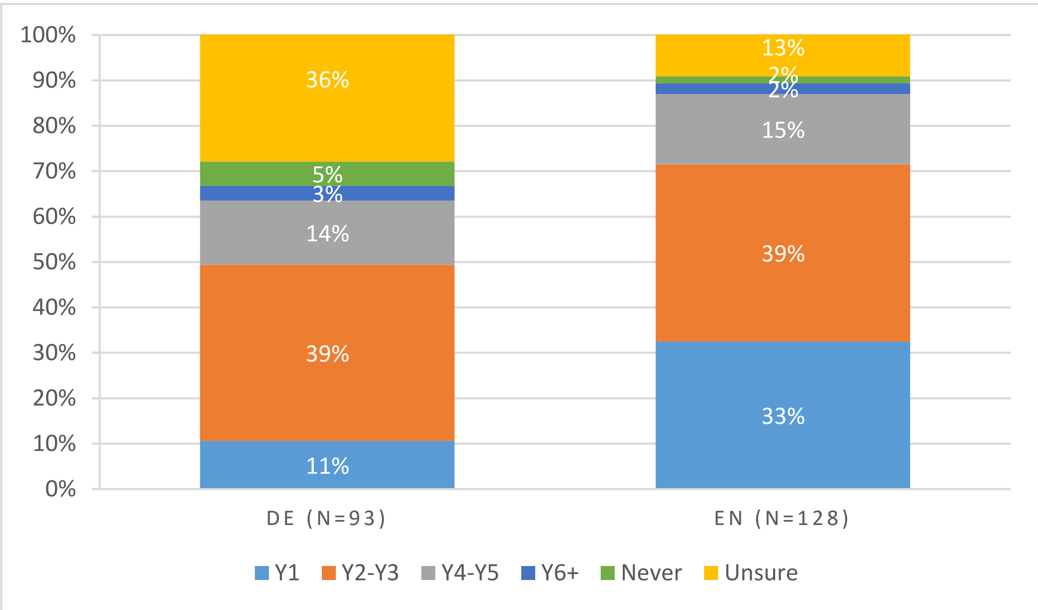

Figure 15: UAM Adoption by survey language (N=221)

Adoption by trip purpose:
Figure 16 shows that there are no significant differences in adoption behavior for the stated UAM purposes. The only notable differences seen in the last category "other"cannot be really taken into consideration as this category represents only 10 % of the total sample size.

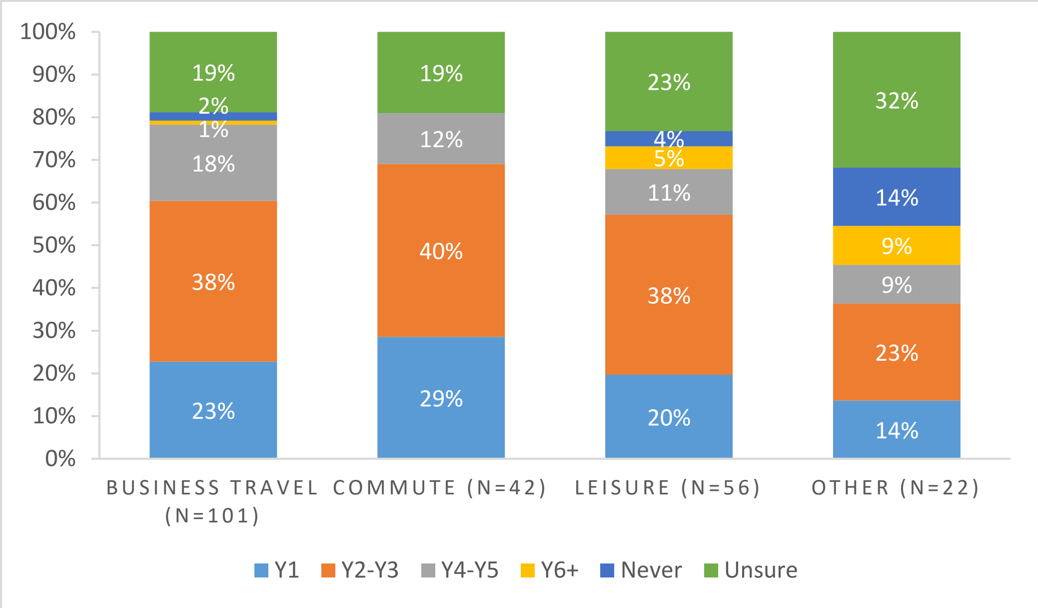

Figure 16: UAM adoption by stated UAM purpose (N=221)

Attitudes towards automation, safety, and data concerns:
Different demographics have different attitudes towards automation, safety, and data concerns. In the below, some interesting findings are revealed to compare the attitudes by gender, or survey starting language. Figure 17 shows an overall higher affinity to automation by male respondents, due to higher enjoyment and trust of automation[5], more experience in advanced driver assistance system, and higher perception of usefulness of such systems and of UAM.

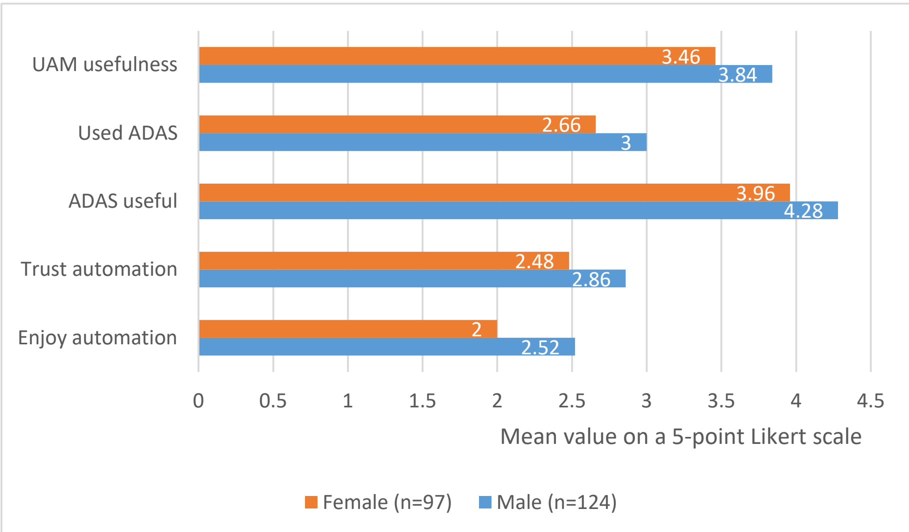

Figure 17: Attitudes by gender towards automation (N=221)

[5]Enjoyment and trust of automation was mentioned in the survey in the form of automated systems like Siri, or Alexa

In terms of trust and concerns, females seem to accord a higher level of importance to service reliability as a prerequisite for trust, to the loss of jobs due to automation, and to cyber-security in the context of UAM, as shown in Figure 18. However, there seems to be a similar level of concern with males regarding data sharing.

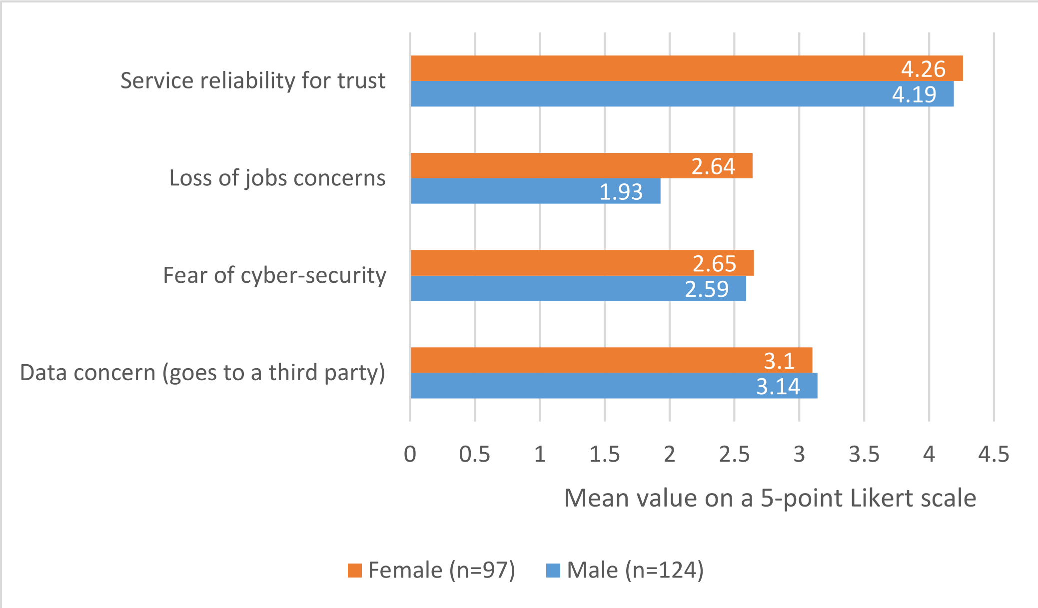

Figure 18: Attitudes by gender towards trust and data concerns (N=221)

Figure 19 shows higher safety requirements by females in terms of in-vehicle camera expectations[6] and more stringent requirements of an operator on the ground[7] and to override the vehicle in case of emergency. Also, this figure reveals a generally lower flying comfort stated by females.

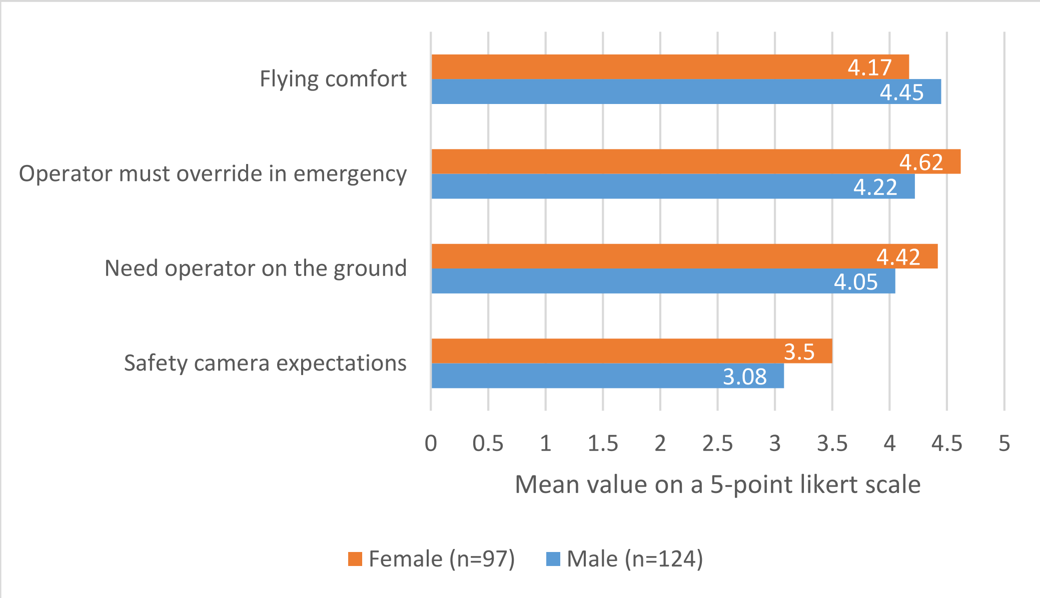

Figure 19: Attitudes by gender towards safety (N=221)

In terms of trust and concerns, females seem to accord a higher level of importance to service reliability as a prerequisite for trust, to the loss of jobs due to automation, and to cyber-security in the context of UAM, as shown in Figure 18. However, there seems to be a similar level of concern with males regarding data sharing. The overall attitude findings support the evidence of a generally lower enthusiasm towards automation for females compared to their male counterparts.

Figures 20 and 21 show attitudes of respondents according to the language in which they filled the survey (DEU for german, EN for english). The former shows an overall higher affinity to automation for respondents who filled the survey in English. The latter however shows higher concerns of respondents who filled the survey in English, including data concerns and fear of cyber-security, potentially hindering them from using UAM.

The findings above could explain the observations in Figure 15, in which filling the survey in German was associated with a lower level of early adoption, and a higher level of uncertainty.

[6] Corresponding survey statement: In order for me to feel safe, I would expect UAM's vehicles to be equipped with surveillance cameras

[7] Corresponding survey statement: I should be able to talk to an operator on the ground at any time

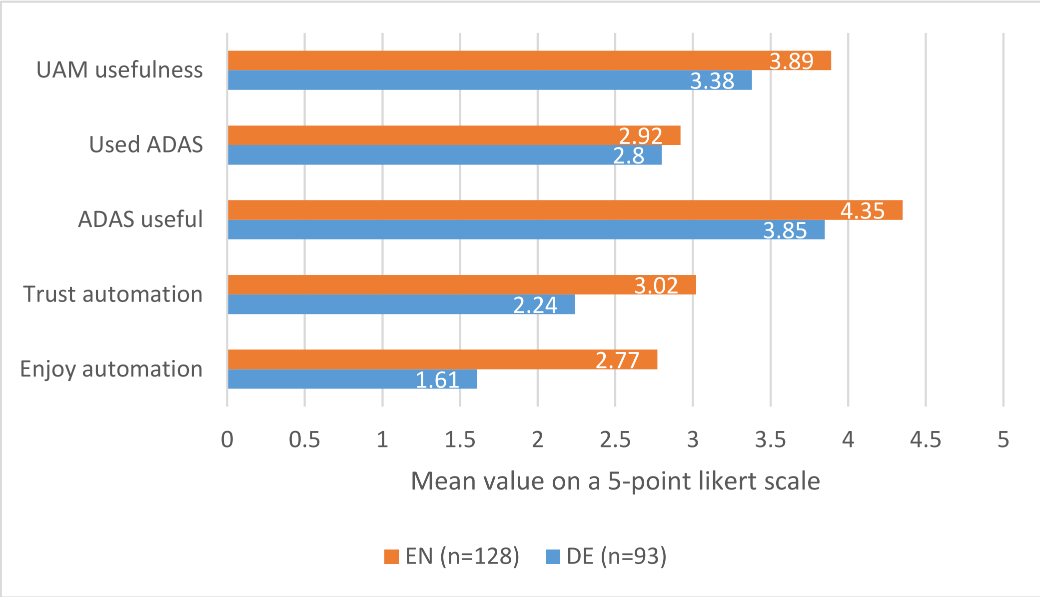

Figure 20: Attitudes by language towards automation (N=221)

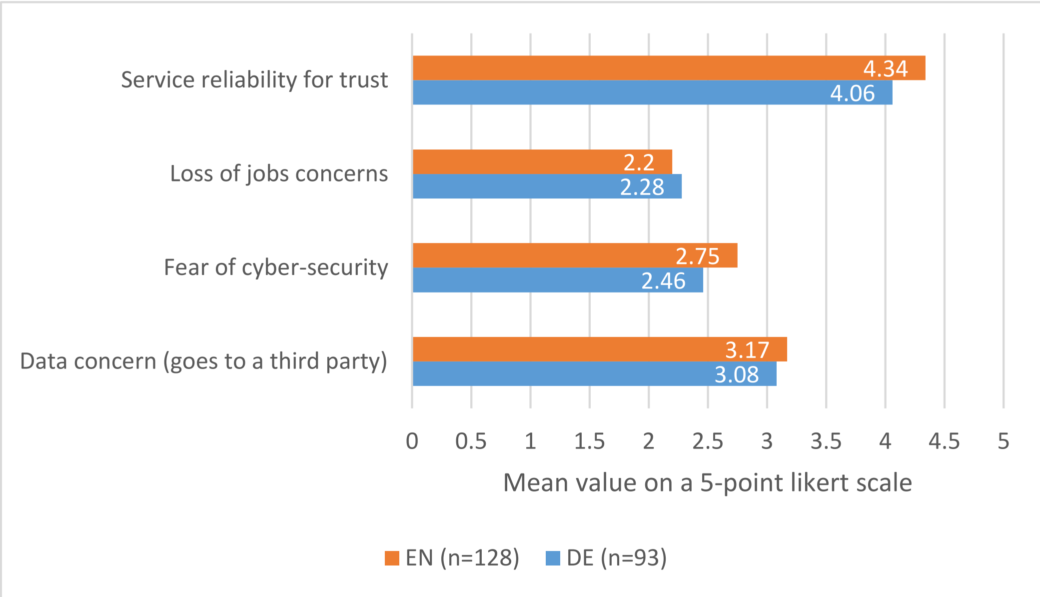

Figure 21: Attitudes by language towards trust and data concerns (N=221)

Figure 22 shows the attitudes towards safety according to the respondents' level of education. It is interesting to note that doctorate level respondents seemed to have less concerns about data, loss of jobs due to automation, in addition to lower safety camera expectations. Also, they seemed to be more experienced in using ADAS. These findings could indicate a higher affinity to automation by these respondents.

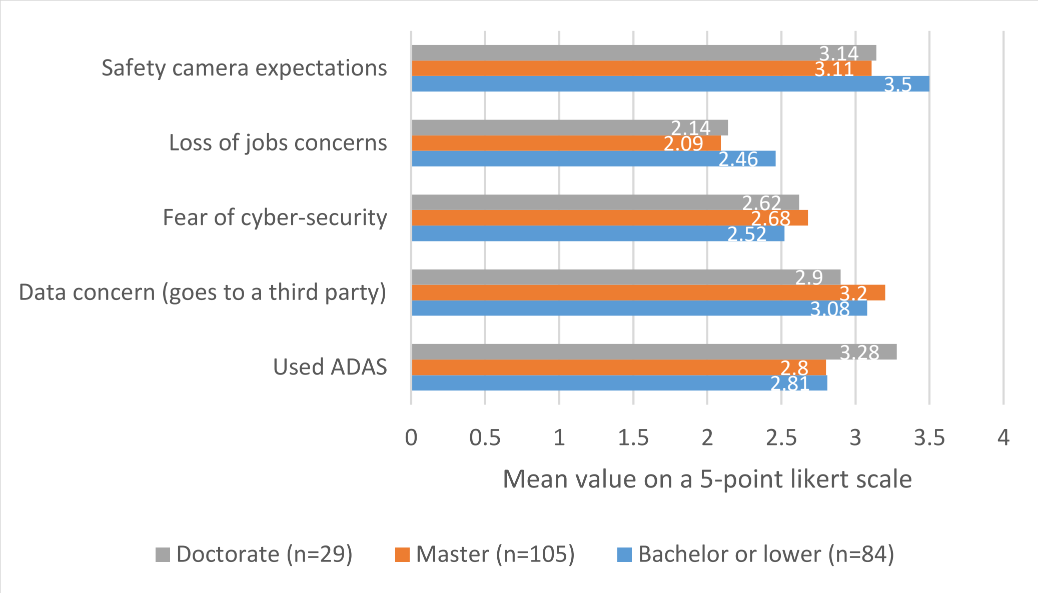

Figure 22: Attitudes by education level towards safety (N=218)

4.2.3 Qualitative analysis

In this section, a qualitative analysis of the survey is presented through a careful examination of the comments section. Among the 221 respondents, 41 have left comments in the optional comment section, making up about 19% of the total number of respondents. The main findings from these comments are summarized in the following.

1. **Skepticism** about the following was noted:

   - **Environmental impacts.**
     Environmental concerns were cited as crucial aspects in UAM adoption and use. More transparency about the environmental impacts of UAM were inquired by respondents, particularly concerning the energy to be used for these vehicles. Respondents also indicated their interest in using UAM if it were more environmentally friendly than taxis.
   - **Noise and visual pollution.**
     There was a notable skepticism about **noise pollution**. **Visual pollution** was concerned with the unwillingness to hear and see flying vehicles all day long, and/or to be watched from above. This was compared by one respondent to the NIMBY (Not In My Backyard) effect. Accordingly, the altitudes at which the vehicles would fly were expected to be defined.
   - **Economic impacts.**
     Concerns were noted due to the loss of jobs resulting from automation, the slow decrease of car economy, the resulting monopoly of UAM service providers, leading to a subsequent increase in service prices, and the downturn of the economy on the long run. Respondents were also worried that UAM might become a tool for "rich people to show off".

- **Safety and automation**.
  The takeover function was mentioned as a placebo effect; respondents were skeptical about the takeover time that "would mostly exceed fault-tolerant time of the system". There was a higher perceived (safety) risk compared to ground vehicles as users are not able to alight whenever they want. Safety standards were expected to be confirmed and incident-free operation to be proven.
- **Purpose of use.**
  As the scenarios compared UAM with taxis, the former would only be considered in very seldom occasions in which taxis would be used. A considerable time reduction and similar (or ideally cheaper) price ranges were expected.
- **Privacy concerns** if UAM were integrated with social media platforms
- **Congestion reduction.**

2. **System integration** was highly desired. UAM were expected to work closely with the existing and future systems
3. **Information sharing** inside the vehicles was deemed as crucial.
4. **Time and costs** were assessed as significant parameters.
5. **On-demand availability** was mentioned as an important consideration, with a high frequency of about only a few minutes.

However, **positive comments and encouragements** were also noted besides the skepticism. Respondents also gave specific examples of how and when they would use UAM, or why not, and expressed their interest in the results of the survey. The following deductions were therefore made:

- Better awareness and public information should be given regarding the aspects of UAM. For that, the business models should first be well defined, to better know the service's impacts. Still, more transparency should allow the people to better understand these models. Environmental impacts, noise, and visual pollution effects are to be addressed carefully, and then shared with the public. Also, time and cost uncertainties are to be better cared for.
- Automation and safety considerations are primary concerns.
- Benefits perception and usefulness are to better be proved through a demonstration of potential time and cost reduction, higher efficiency, and the purpose of use.
- Integration with existing systems, such as PT is essential

The data analysis in this section served as a preliminary understanding of the built hypotheses, and the general directions of the research findings. Based on the general adoption behaviors, and the attitudes of the different demographics, better models can be specified in Chapter 5, leading to recommendations with strong policy implications.

5 Modeling Framework Results

This section presents the modeling framework of this work, including the model specifications. Following the methodology discussed in Chapter 3, an exploratory factor analysis was first conducted, after which models were built, taking the results of the former as input variables. In this section, the results are also interpreted in terms of their meaning, and significance; however, a more elaborate discussion is conducted in Chapter 6, where insights and applications are provided for relevant stakeholders, such as policy-makers and aircraft manufacturers.

5.1 Exploratory Factor Analysis (EFA)

This subsection presents the results of the Exploratory Factor Analysis, conducted on parts 2 and 3 of the survey, as explained in Chapter 3.

5.1.1 Exploratory factor analysis on part 2

The exploratory factor analysis on this part initially included 20 variables. After several runs during which variables adding noise were removed, results revealed four factors, presented in Table 4. The obtained factors shared a 55% cumulative variance and were able to cluster 11 of variables into the following: value of time savings, affinity to automation, data concerns, and safety concerns.

The **value of time savings** is a cluster of the three variables related to time savings of 5, 10, and 20 min, giving a higher factor loading for travel time savings of 10 min, compared to both 5 and 20 min. In other terms, the attitude towards 10 min savings causes the highest variability between these variables.

The second factor related to **automation affinity** clusters the users' attitudes towards automation, including their enjoyment and trust of automated systems (like Alexa or Siri) and their perceived usefulness of UAM.

The third factor clusters **data concerns** including the fear of cyber-security and the concern of data being shared to a third party. The former seems twice as important as the latter in capturing the meaning of this latent variable.

Finally, the fourth factor groups **safety-related** attitudes including the need for an operator on the ground, an operator to override the system in case of emergency, and in-vehicle safety cameras. For this factor, the first variable (operator on the ground) is twice as important as each of the second and third.

To summarize, the obtained factors reduce the dimensionality of the variables, while providing valuable insights on latent variables shedding the light on the value of time savings, the affinity to automation, and data and safety concerns.

Table 4: Factor analysis on part 2

Loadings:				
	Factor 1	Factor 2	Factor 3	Factor 4
Travel time savings 5min	0.78			
Travel time savings 10min	0.98			
Travel time savings 20min	0.6			
Enjoy automation		0.79		
Trust automation		0.78		
UAM is useful		0.5		
Fear of cyber-security			0.99	
Fear that data goes to a third party			0.47	
Operator on the ground				0.8
Operator to override				0.49
In-vehicle safety cameras				0.42
Interpretation	**Value of time savings**	**Affinity to automation**	**Data concerns**	**Safety concerns**
	Factor 1	Factor 2	Factor 3	Factor 4
SS loadings	2	1.63	1.26	1.21
Proportion Var	0.18	0.15	0.11	0.11
Cumulative Var	0.18	0.33	0.44	0.55

5.1.2 Exploratory factor analysis on part 3

In this part, the factor analysis initially included 17 variables. Similarly to the previous factor analysis, results from this one cumulatively account to 55 % of the total variance. These clustered 10 variables into four factors: affinity to online services, environmental awareness, affinity to social media, and affinity to sharing.

The **affinity to online services** is simple to understand and comes as a combination of perception, in terms of comfort, of several online tools, such as online booking, banking, and shopping.

Environmental awareness comes as a second factor to explain concerns about global warming and willingness to spend on more environmental products. Interestingly this factor loads twice as much in the former attitude than in the latter.

The third factor, **affinity to social media**, clusters the use of social media platforms like Facebook and Instagram. The loading of this factor is twice as much in Instagram. A potential explanation might be that Instagram has less users than Facebook, resulting in a higher explanatory power of the data variability.

Finally, the fourth factor addresses the **affinity to sharing**, by clustering the familiarity and use of BlaBlaCar, Airbnb, and the user's willingness to share a ride with a stranger. The loading for this factor is about the same for the different variables, with a slightly higher loading for BlaBlaCar.

Based on the initial answers of the Likert scale questions targeting these variables, this factor analysis reduces the data dimensionality, and extracts four highly explanatory factors that describe the users' social behavior in terms of their environmental awareness, and their affinity towards social media, online services, and sharing.

Table 5: Factor analysis on part 3

Loadings:				
	Factor 1	Factor 2	Factor 3	Factor 4
Online booking	0.81			
Online banking	0.86			
Online shopping	0.65			
Concerned about global warming		0.99		
Spend on environmental products		0.5		
Instagram			0.99	
Facebook			0.43	
BlabBlaCar				0.67
Airbnb				0.5
Willingness to share				0.5
Factor interpretation	**Affinity to online services**	**Environmental awareness**	**Affinity to social media**	**Affinity to sharing**
	Factor 1	Factor 2	Factor 3	Factor 4
SS loadings	1.93	1.28	1.24	1.06
Proportion Var	0.19	0.13	0.12	0.11
Cumulative Var	0.19	0.32	0.45	0.55

5.2 Behavioral Modeling

In this section, the model specifications using behavioral modeling are presented, in addition to the rational for their choices. As discussed in Chapter 3, the aim is to develop models to be able to extract the relevant factors in the adoption and use of UAM.

5.2.1 Public transportation satisfaction model

Before developing UAM adoption models for the entire sample, it was interesting to develop an ordered logit model for the satisfaction of Munich residents. With the subsample of 97 respondents living in Munich, models were developed with public transport satisfaction (five-point Likert scale) as a dependent variable (Table 6). Although the findings presented very significant cut values for the three models shown, mostly with a 99% confidence level, the explanatory attributes were not as significant. Still, there is an indication that some variables are important in the model, with about 90 % significance. Higher commute times (above 90 min) were associated with a lower PT satisfaction. The same pattern was observed for high income levels. Conversely, working part-time for instance had the opposite effect, and was related to a higher PT satisfaction.

Table 6: PT satisfaction OLM for Munich

Variables Description	Model 1)		(Model 2)		(Model 3)		(Model 4)	
PT satisfaction								
Female	0.270	(0.69)	0.358	(0.89)	0.256	(0.64)		
Main mode of transport: car	-0.611	(-1.14)	-0.739	(-1.34)	-0.788	(-1.46)	-0.831	(-1.55)
Income levels: 3000-7000 €	-0.734	(-1.51)	-0.819	(-1.60)	-0.797	(-1.61)	-0.807	(-1.63)
Commute time: > 90 min	-0.858	(-1.69)	-0.940	(-1.83)	-0.847	(-1.63)	-0.834	(-1.61)
Age: <24 years old			-0.463	(-0.88)				
Age: >45 years old			0.562	(0.61)				
Education level: doctorate or higher					0.843	(1.43)	0.787	(1.34)
Occupation: part-time employment					1.119	(1.52)	1.200	(1.66)
Very dissatisfied | dissatisfied	-3.269***	(-5.99)	-3.370***	(-5.95)	-3.169***	(-5.77)	-3.299***	(-6.43)
Dissatisfied | neither dissatisfied nor satisfied	-1.743***	(-4.55)	-1.838***	(-4.47)	-1.628***	(-4.17)	-1.758***	(-5.24)
Neither dissatisfied nor satisfied | satisfied	-0.945**	(-2.70)	-1.031**	(-2.72)	-0.806*	(-2.24)	-0.941**	(-3.22)
Satisfied | very satisfied	1.729***	(4.43)	1.673***	(4.07)	1.998***	(4.72)	1.854***	(5.23)
Observations	97		97		97		97	
Pseudo R^2	0.027		0.032		0.049		0.048	

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

5.2.2 Multinomial Logit Models (MNLs)

Initial models with Stata:
First models were estimated with **Stata 13**[8] (StataCorp. 2013), including all six categories (Y1, Y2-Y3, Y4-Y5, Y6+, Never, Unsure) as dependent variables. These models failed however to estimate coefficients for Y6+ and Never, as both categories represented a small percentage of the sample size (about 5% combined). An MNL excluding these two categories was therefore estimated with Y1 as a base case.

In estimating these models, two approaches were followed. First, a saturated model combining all the variables was estimated by progressively removing the insignificant variables. Based on initial saturated model results, the most important factors could be determined. The model was then built the other way around, starting from an empty one, then progressively adding the meaningful variables. The ones with very low significance were immediately removed; the highly significant ones (above 95 % significance level or 90% according to importance) were kept. Also, other variables that were important for the hypotheses were added at other points of the estimation, to be certain that they were not removed in vain. Moreover, these models assumed early adoption (Y1) to be the base case. After several runs, the final MNL model was estimated (Table 14 in Appendix D) and gave great insights on important factors, summarized as follows.

- For uncertain respondents:
  - Respondents filling the survey in German are significantly more likely to be unsure about their adoption time.
  - Higher affinity to automation is less likely related to uncertainty.
  - Higher data concerns is more likely related with uncertainty.
  - Full-time employment is significantly less associated with uncertainty.
- For Y2-Y3:
  - Safety concerns seem to be significantly associated with this category.
  - Data concerns, PT satisfaction, and previous crashes with injuries seem to be positively related to this group.
  - Automation affinity and higher level of education seem to be negatively related with this group.
- For Y4-Y5:
  - High income respondents and respondents with higher affinity to automation are significantly less likely to be UAM adopters in years 4 to 5.
  - Higher data concerns and (surprisingly) higher value of time savings are significantly more likely to be adopters of this category.

[8] The initial choice of Stata was motivated by the *meologit* function for multilevel ordered models.

However, all variables were present in all outcomes, and to the knowledge of the author, specifying different utilities for each outcome was not possible in the *mlogit* function. Although the results were plausible, these could be improved by removing the noise of insignificant variables across some alternatives. The next step was therefore to specify the utility for each alternative using **Python Biogeme** (Bierlaire 2003).

Notes:

1. *Although some variables were not retained in Stata's final MNL, they were tested later in Biogeme due to their expected importance according to the literature or the data analysis.*

2. *A comparison between both models from Stata and Biogeme is not possible as in the former the variables are present in all outcomes, whereas in the latter the variables are alternative-specific; in addition, both built models have different base cases.*

Alternative-specific models with Python Biogeme:
In the following, we elaborate on important models that helped in the development of the final one, and label them as models 1 to 5 (for convenience only), even if in reality more models were estimated. The results of the first two are presented in Appendix D, and of the last three in this section. The model specifications for all presented models are given in Appendix C.

MNL Model 1:
The initial model in Python Biogeme included all outcomes. After specifying attributes for outcomes Y6+, and Never, the resulting model gave estimate values with very large standard errors, and t-values of zeros, as seen in Table 17 of Appendix D. In other terms, the model was not correctly specified. This was most probably due to the very small sample size categories for Y6+ and never.

To overcome this, the utilities of both outcomes (y6+ and never) were specified as only alternative-specific constants, meaning that they were set as base alternatives.

MNL Model 2:
After adding attributes in the relevant alternatives and after several iterations, Model 2 was estimated, as shown in Table 18 of Appendix D. This model gives the following insights:

- ASC estimates for Never and Unsure are very similar and highly significant. This might be an indication that both categories could be merged into one.

- There is a clear pattern of alternative-specific estimates for the affinity to automation, previous crashes with injuries, and female respondents.

    1. Automation is positively and strongly influential in adoption and has a higher impact for earlier adoption. Estimates of automation therefore decrease in an observable pattern from Y1, Y2-Y3, Y4-Y5 to unsure. This high influence of automation goes in the direction of Hypothesis 8, in which a higher automation awareness was assumed to be associated with early adoption.

2. There is also a pattern for female respondents; this time however in the opposite direction. Estimates for the female attribute were negative across different alternatives and highly significant. This observation goes in the direction of Hypothesis 1, stating that females are more likely to be late adopters than males (or less likely to be early adopters).
3. Previous crashes with injuries also negatively influence adoption, in a similar decreasing pattern starting from year 1, though less consistent than the previous patterns.
4. German as a starting language, doctorate (or higher) level of education, higher income levels, and data concerns are significantly negative in Y1, validating hypotheses 4, 5, and 6 on cultural, education, and income impacts on automation.
5. Full-time respondents are significantly more likely to be early adopters (Y1, and also Y2-Y3 with less significance), validating Hypothesis 3.
6. Higher values of time savings are positively and strongly correlated with outcome Y4-Y5 and safety concerns estimates are significantly negative for years 1 and years 4 and 5.
   These findings are yet to be investigated in future models as they might not be very intuitive.

Overall, the patterns in alternative-specific estimates indicate that an ordering of the alternatives might be plausible, but also that the "unsure" category is likely to be ordered after years 4 and 5.

MNL Model 3:
Based on the last model shown in Table 18, newer models were built by combining both categories Y6+ and never into one with the same alternative-specific constant, but also by adding variables of interest to be tested. Also, variables that were part of the factor analysis but weren't clustered into any group were added in this model, as these hadn't been considered by previous models.

Keeping only significant (or relevant) estimates, Model 3 was obtained as shown in Table 7. In this model, some alternative-specific estimates were combined provided that the overall model performance was improved. This was generally tested with statistical tests, such as the log-likelihood ratio test. Compared to Model 2 in Table 18, Model 3 combined estimate values for the affinity to automation and previous crashes; both attributes had one estimate for year 1 and one estimate for years 2 to 5 and unsure respondents. Also, full-time employment estimates were combined for years 1 to 3.

Moreover, the addition of new parameters (from variables that did not load in the factor analysis) resulted in the following new insights.

- Thinking first about cost in UAM adoption[9] is strongly significant for years 2 to 5. In other terms, people who are more sensitive to cost (or who give it a higher importance in the decision process) are more likely to adopt UAM in later years than in the first year of its implementation.

[9] Corresponding survey statement: I would first think about cost when deciding whether or not to use UAM.

Table 7: Adoption MNL Model 3

Parameter number	Description	Coeff. estimate	Robust Asympt. std. error	t-stat	p-value
1	ASC Y6+ or Never	9.41	2.19	4.31	0.00
2	Affinity to automation Y2-Y5 and Unsure	0.682	0.441	1.55	0.12
3	Affinity to automation Y1	1.02	0.450	2.26	0.02
4	Cost first Y2-Y5	0.330	0.133	2.48	0.01
5	Cost as taxi Y1	0.370	0.204	1.81	0.07
6	Previous crashes with injuries Y2-Y5 and Unsure	-2.01	1.04	-1.94	0.05
7	Previous crashes with injuries Y1	-2.59	1.19	-2.18	0.03
8	Starting language German unsure	1.37	0.368	3.72	0.00
9	Starting language German Y1	-0.570	0.513	-1.11	0.27
10	Data concerns Y1	-0.398	0.135	-2.95	0.00
11	Doctorate Y2-Y3	-1.48	0.553	-2.67	0.01
12	Female respondents Unsure	-3.00	1.16	-2.60	0.01
13	Female respondents Y1	-3.27	1.20	-2.73	0.01
14	Female respondents Y2-Y3	-3.20	1.16	-2.77	0.01
15	Female respondents Y4-Y5	-2.99	1.18	-2.53	0.01
16	Full-time employment Y1-Y3	0.773	0.322	2.40	0.02
17	High income: 3000-7000 €Y4-Y5	-1.18	0.681	-1.73	0.08
18	PT commute mode Y4-Y5	1.04	0.432	2.41	0.02
19	Service provider reputation Y1, Unsure	0.787	0.151	5.22	0.00
20	Safety concerns Y1 and Y4-Y5	-0.257	0.0922	-2.79	0.01
21	Affinity to social media Y1-Y5, Unsure	0.524	0.251	2.09	0.04
22	TT important for UAM Y2-Y3	0.436	0.168	2.59	0.01
23	Value of time savings Y4-Y5	0.503	0.0910	5.52	0.00
24	WhatsApp affinity Y1, Y4-Y5, and Unsure	0.436	0.274	1.59	0.11
25	WhatsApp affinity Y2-Y3	0.756	0.287	2.64	0.01

Summary statistics

Number of observations = 221

Number of excluded observations = 0

Number of estimated parameters = 25

$$\mathcal{L}(\beta_0) = -355.686$$
$$\mathcal{L}(\hat{\beta}) = -238.182$$
$$-2[\mathcal{L}(\beta_0) - \mathcal{L}(\hat{\beta})] = 235.008$$
$$\rho^2 = 0.330$$
$$\bar{\rho}^2 = 0.260$$

- Willingness to use UAM if its price is in the range of a taxi's is strongly correlated with early adoption (Y1)[10]. This might be due to respondents' strong belief that costs will be in that range starting UAM's first year of implementation (based on their personal beliefs or the given scenarios in the survey).
- Commuting with public transportation has a positive correlation with late adoption (Y4-Y5). This might be related to the behavior of PT commuters and their satisfaction with this mode.
- The importance given to the service provider's reputation[11] has a significant positive influence on early adoption, but also on skepticism regarding UAM as this attribute is strongly and positively significant for uncertain respondents as well. This might indicate a difference in the beliefs of respondents regarding the service provider's reputation. A reasonable assumption is that both groups would adopt UAM if the service provider were highly reputable. The first group (Y1) implies that the corresponding respondents already expect UAM to be operated by reputable providers, whereas the second (Unsure) indicates a skepticism regarding the service provider's reputation due to a lack of public information about it. The respondents of this group would therefore probably wait until they are certain that UAM would be operated by highly reputable service providers.
- Affinity to social media seems to have an overall positive impact on UAM adoption, as this generic variable is positive and strongly significant for all outcomes, except the base case of extremely late or non-adopters (Y6+/Never).
- Importance given to travel time savings is positively and significantly correlated to rather early adoption (Y2-Y3).
- Affinity to WhatsApp services is also strongly and positively influential in adoption.

  It is interesting to observe that affinity to WhatsApp is significant even when considering affinity to social media. This might indicate that WhatsApp use might have a different implication than the use of other platforms, like Facebook or Instagram, as they might be less popular or more controversial in terms of data sharing.

  In subsequent iterations, estimates for both the affinity to automation and previous crashes were merged across alternatives. The overall models resulted however in worse performance and Model 3 was kept.

MNL Model 4:
In Model 4, estimates for female respondents were merged as follows: one estimate for years 1 to 3 and one estimate for years 4 to 5 and uncertain respondents. This was motivated by highly significant and close estimate values for these groups. The resulting model is shown in Table 8.

[10]Corresponding survey statement: I would be willing to use this service as long as its price is in the same range as that of a taxi.

[11]Corresponding survey statement: The service provider's reputation is very important for gaining trust to use UAM

Table 8: Adoption MNL Model 4

Parameter number	Description	Coeff. estimate	Robust Asympt. std. error	t-stat	p-value
1	ASC Y6+ or Never	9.40	2.18	4.32	0.00
2	Affinity to automation Y2-Y5 and Unsure	0.681	0.441	1.54	0.12
3	Affinity to automation Y1	1.02	0.449	2.27	0.02
4	Cost first Y2-Y5	0.331	0.131	2.53	0.01
5	Cost as taxi Y1	0.373	0.204	1.83	0.07
6	Previous crashes with injuries Y2-Y5 and Unsure	-2.01	1.04	-1.94	0.05
7	Previous crashes with injuries Y1	-2.59	1.19	-2.18	0.03
8	Starting language German unsure	1.37	0.366	3.73	0.00
9	Starting language German Y1	-0.577	0.505	-1.14	0.25
10	Data concerns Y1	-0.400	0.134	-2.98	0.00
11	Doctorate Y2-Y3	-1.47	0.543	-2.71	0.01
12	Female respondents Y1-Y3	-3.22	1.15	-2.80	0.01
13	Female respondents Y4-Y5 and Unsure	-3.00	1.14	-2.63	0.01
14	Full-time employment	0.771	0.323	2.39	0.02
15	High income: 3000-7000 €Y4-Y5	-1.18	0.662	-1.78	0.07
16	PT commute Y4-Y5	1.04	0.428	2.44	0.01
17	Service provider reputation Y1, Unsure	0.786	0.149	5.28	0.00
18	Safety concerns Y1 and Y4-Y5	-0.260	0.0866	-3.01	0.00
19	Affinity to social media Y1-Y5 and Unsure	0.524	0.251	2.09	0.04
20	TT important for UAM Y2-Y3	0.435	0.167	2.60	0.01
21	Value of time savings Y4-Y5	0.505	0.0891	5.67	0.00
22	WhatsApp affinity Y1, Y4-Y5 and Unsure	0.436	0.273	1.60	0.11
23	WhatsApp affinity Y2-Y3	0.758	0.286	2.66	0.01

Summary statistics

Number of observations = 221

Number of excluded observations = 0

Number of estimated parameters = 23

$$\begin{aligned}
\mathcal{L}(\beta_0) &= -355.686 \\
\mathcal{L}(\hat{\beta}) &= -238.193 \\
-2[\mathcal{L}(\beta_0) - \mathcal{L}(\hat{\beta})] &= 234.986 \\
\rho^2 &= 0.330 \\
\bar{\rho}^2 &= 0.266
\end{aligned}$$

Compared to Model 3 in Table 7, Model 4 presents a nested model, with only two additional restrictions on the female attribute coefficients. A first indication of the model performance can be obtained by looking at the statistical AIC and BIC tests[12]. Both estimator values decreased from Model 3 to Model 4, indicating a higher performance of the latter[13]. Also, the improved rho-squared value improved from Model 3 to Model 4, increasing from 0.260 to 0.266.

Still, applying the nested log-likelihood test (Equation 22) could give a higher indication on the model improvement since one model is nested from the other; in particular, Model 4 is obtained from Model 3 by applying two restrictions on the female estimates. To test whether the restriction assumptions can be rejected or not, the following null hypotheses are formulated.

$$H_0 : \beta_{Females(Y1)} = \beta_{Females(Y2-Y3)}$$

$$H_0 : \beta_{Females(Y4-Y5)} = \beta_{Females(Unsure)}$$

Model 3 in this case is unrestricted with 25 parameters and Model 4 is restricted with 23 parameters. Applying the ratio test using final log-likelihood values for these models, two degrees of freedom (the difference between the number of parameters), and 95% confidence level, the following is obtained.

$$-2(-238.193 - (-238.182)) \sim \chi_{2,0.05}$$

$$0.022 \sim 5.991$$

As the ratio test is much lower than the chi-squared value, the null hypothesis can definitely not be rejected. This is equally true for lower confidence intervals; in fact, this hypothesis can only be rejected for a 1% confidence interval with a chi-square value of 0.02. Not being able to reject the null hypothesis doesn't necessarily mean that it can be accepted. However, since the restricted model can only be rejected with a very low confidence level, and since it leads to a model simplification, there is a strong indication that it performs better; Model 4 is therefore assessed as better than Model 3.

Estimates of both models (Model 3 and Model 4) are very similar, with about the same level of significance. Combining the estimates for females resulted in negative and highly significant values, indicating once more the impact of gender on adoption.

MNL Model 5:
The specifications of Model 5 are given in Appendix C. Compared to Model 4, Model 5 (Table 9) presents a nested model with similar findings and three parameters less. The first one is lost by further combining female parameter estimates, the second by combining parameters related to the affinity to use WhatsApp, and the third simply by removing German as a starting value for Y1 as it didn't show a significance in Model 4.

When comparing the performance of Model 5 with that of Model 4 using the AIC and BIC estimators, the following can be noted. The AIC increases from Model 4 to Model 5, but the BIC decreases[14]. These findings show some inconsistency, as both estimators are expected to move in

[12] Not shown in this report, but obtained in the output files of Biogeme

[13] AIC (Model 3) = 526.363, BIC (Model 3) = 611.317, AIC (Model 4) = 522.386, BIC(Model 4) = 600.544

[14] AIC (Model 4) = 522.386, BIC (Model 4) = 600.544, AIC (Model 5) = 525.185, BIC(Model 5) = 593.148

Table 9: Adoption MNL Model 5

Parameter number	Description	Coeff. estimate	Robust Asympt. std. error	t-stat	p-value
1	**ASC Y6+ or Never**	9.27	2.16	4.29	0.00
2	Affinity to automation Y2-Y5 and Unsure	0.638	0.423	1.51	0.13
3	**Affinity to automation Y1**	1.01	0.431	2.34	0.02
4	**Cost first Y2-Y5**	0.399	0.129	3.09	0.00
5	Cost as taxi Y1	0.374	0.203	1.85	0.06
6	Previous crashes with injuries Y2-Y5 and Unsure	-1.97	1.03	-1.91	0.06
7	**Previous crashes with injuries Y1**	-2.54	1.17	-2.16	0.03
8	**Starting language German unsure**	1.39	0.334	4.17	0.00
9	**Data concerns Y1**	-0.395	0.129	-3.06	0.00
10	**Doctorate Y2-Y3**	-1.40	0.563	-2.49	0.01
11	**Female respondents Y1-Y5 and Unsure**	-3.05	1.13	-2.71	0.01
12	**Full-time employment Y1-Y3**	0.829	0.304	2.73	0.01
13	High income: 3000-7000 €Y4-Y5	-1.19	0.661	-1.81	0.07
14	**PT commute Y4-Y5**	0.958	0.424	2.26	0.02
15	**Service provider reputation Y1, Unsure**	0.730	0.148	4.95	0.00
16	**Safety concerns Y1 and Y4-Y5**	-0.319	0.0872	-3.66	0.00
17	**Affinity to social media Y1-Y5 and Unsure**	0.534	0.251	2.13	0.03
18	**TT important for UAM Y2-Y3**	0.622	0.145	4.30	0.00
19	**Value of time savings Y4-Y5**	0.514	0.0874	5.88	0.00
20	WhatsApp affinity Y1-Y5 and Unsure	0.504	0.276	1.83	0.07

Summary statistics

Number of observations = 221

Number of excluded observations = 0

Number of estimated parameters = 20

$$\begin{aligned}\mathcal{L}(\beta_0) &= -355.686\\ \mathcal{L}(\hat{\beta}) &= -242.593\\ -2[\mathcal{L}(\beta_0)-\mathcal{L}(\hat{\beta})] &= 226.186\\ \rho^2 &= 0.318\\ \bar{\rho}^2 &= 0.262\end{aligned}$$

the same direction, i.e. decrease in case of improvement. The improved rho-squared value also decreases from Model 4 to Model 5, from 0.266 to 0.262.

By performing the log-likelihood ratio test (with three degrees of freedom) for Models 4 and Model 5, Model 5 was found to have a greater performance than Model 4, as it simplified it by three parameters but decreased its log-likelihood value by only four points. Most estimates of Model 5 were significant to the 95 % level of confidence. Only a few were significant to the 90 % level of confidence. Finally, only affinity to automation for years 2 or more had a lower significance level. However, removing this parameter resulted in a worse performing model. Therefore, Model 5 was kept as shown in Table 9 and considered as the most performing MNL model for adoption.

In Table 9, parameters that are significant to more than 95 % level of confidence are represented in Bold.

The generalized findings of this section are summarized in the following.

- There is a significantly high and positive alternative-specific constant for respondents stating a very late or non-adoption (Y6+, Never). This constant may include attributes that are characteristic of this group of people and that are likely to be latent.
- There is a significantly positive contribution of affinity to automation for UAM adoption, mostly for early adoption.
- The importance of cost consideration in UAM adoption mostly affects later adoption.
- The importance of UAM prices being scaled to taxis' is notable for immediate adoption.
- Previous crashes with injuries negatively impact the adoption and use of UAM, mostly early adoption.
- Choosing to fill the survey in German (compared to filling it in English) is highly associated with skepticism on UAM.
- Data concerns, including the fear of cyber-security or of data sharing, are highly significant and negatively impact early adoption.
- Higher levels of education negatively impact adoption in the second and third years of implementation.
- Gender plays a crucial role in adoption, with females being less prone to adoption than their male counterparts.
- Full-time employment significantly and positively contributes to adoption in the first three years.
- Higher income level respondents are less likely to be late adopters of UAM.

- Higher importance given to the service provider reputation plays a significant and positive role in adoption, notably for immediate and uncertain adoption.
- Travel time savings are decisive in UAM adoption for the second and third years, and the value of time savings positively contributes to adoption for the fourth and fifth years.
- Higher affinity to social media, and to WhatsApp services positively and significantly impact adoption.

5.2.3 Ordered Logit Models (OLMs)

In this part as well, an initial OLM was estimated with Stata and is included in Table 15 of Appendix D.

Ordered models were built based on prior expectations resulting from estimates of the multinomial logit models; particularly, the patterns in attributes like gender, affinity to automation, and previous crashes. These also suggested that "unsure" respondents were rather ordered with late ones. Two ordered models were accordingly proposed.

- Case one: this model included the following ordered categories: Y1; Y2-Y3; Y4-Y5; Unsure; Y6+/Never (clustered in one category as in the previous models).
- Case 2: this model included one category less than case 1, by combining "unsure" and Y6+ and Never, resulting in the following ordered categories: Y1; Y2-Y3; Y4-Y5; Unsure, Y6+ and Never.

Case 1:
An initial model estimation OLM Model 1 is presented in Table 19 of Appendix D. Findings are discussed below with respect to their significance.

- Highly insignificant attributes were eliminated. These included level of education, high income, cost importance, PT as a commute mode, service provider's reputation, safety concerns, affinity to social media and to WhatsApp, and the value of time savings. A possible reason for their insignificance compared to MNL models is the assumption in multinomial models that alternatives are independent and unordered.
- Meaningful, but not very significant attributes were kept for subsequent iterations and tested in terms of their influence on the overall model improvement. These included previous cash experience and German as a survey language, which were associated with rather late adoption as indicated by the negative values of their estimates. Also, female estimates and travel time importance were associated with a rather late adoption.
- Highly significant values included the affinity to automation, data concerns (both significant at the 99 % level of confidence, with t-values greater than 2.58), cost as taxi, and full-time employment (both significant at the 98 % confidence level, with t-values higher than 2.33). The meaning of these estimates and their significance goes with previous findings obtained from MNL models. Higher affinity to automation, willingness to use UAM services if

their prices were in the range of taxis, and full-time employment (negative estimates) are associated with rather early adoption. Conversely, higher data concerns (positive estimate) are associated with later adoption.

- Cutoff values between the different orders are strongly significant, indicating that the ordering of the adoption alternatives is rather plausible.

After several iterations in which variables were removed and the overall model improvement was tested, OLM Model 2 was obtained as the final model for Case 1, as shown in Table 10 below.

Note: In tables 10, 11, and 19, cutoff values were calculated based on the model output values, which included the first cutoff value (au_1), and the differences (δ_2, δ_3, δ_4) between the subsequent cutoff values. Accordingly, the given statistical values for the standard error, t-stat, and p-value correspond to the statistics for the differences between the cutoffs.

Table 10: Adoption OLM Case 1 Model 2

Parameter number	Description	Coeff. estimate	Robust Asympt. std. error	t-stat	p-value
1	Affinity to automation	-0.261	0.0787	-3.32	0.00
2	Cost as taxi	-0.411	0.139	-2.95	0.00
3	Starting language German	0.603	0.311	1.94	0.05
4	Data concerns	0.262	0.0753	3.48	0.00
5	Full-time employment	-1.04	0.263	-3.96	0.00
6	Y1 | Y2-Y3	-4.69	0.855	-5.48	0.00
7	Y2-Y3 | Y4-Y5	-2.65	0.204	9.96	0.00
8	Y4-Y5 | Unsure	-1.843	0.135	5.97	0.00
9	Unsure | Y6+/Never	0.357	0.302	7.30	0.00

Summary statistics

Number of observations = 221

Number of excluded observations = 0

Number of estimated parameters = 9

$$\begin{aligned}
\mathcal{L}(\beta_0) &= -389.123 \\
\mathcal{L}(\hat{\beta}) &= -284.865 \\
-2[\mathcal{L}(\beta_0) - \mathcal{L}(\hat{\beta})] &= 208.515 \\
\rho^2 &= 0.268 \\
\bar{\rho}^2 &= 0.245
\end{aligned}$$

Table 10 represents the final OLM model for UAM adoption with five ordered categories: Y1, Y2-Y3, Y4-Y5, Unsure, Y6+ and Never. The highly significant cut values indicate that adoption is indeed ordered and people who are unsure display a behavior that is ranked between late (Y4-Y5) and extremely late or non-adopters (Y6+ or Never). This was rather expected from the patterns observed in MNL models. Also, the significant parameters in this model are the highly significant ones from the previous OLM. Affinity to automation, full-time employment, and cost as taxi are associated with an early adoption. Similarly, data concerns and starting language

German (with a lesser degree of significance) are strongly correlated with a later adoption.

These findings go with the hypotheses formulated in Chapter 3, and will be discussed in details in Chapter 6.

Case 2:
In this case, the fourth ordered category was a combination of uncertain (Unsure) and extremely late to non-adopters (Y6+ or Never). Based on the results from Case 1, this model was built to test for the significance of the ordered categories. The results of this model are shown in Table 11 below.

Table 11: Adoption OLM Case 2

Parameter number	Description	Coeff. estimate	Robust Asympt. std. error	t-stat	p-value
1	Affinity to automation	-0.237	0.0771	-3.07	0.00
2	Cost as taxi	-0.405	0.148	-2.74	0.01
3	Starting language German	0.685	0.320	2.14	0.03
4	Data concerns	0.269	0.0761	3.53	0.00
5	Full-time employment	-1.09	0.267	-4.08	0.00
6	Y1 | Y2-Y3	-4.45	0.892	-4.98	0.00
7	Y2-Y3 | Y4-Y5	-2.41	0.205	9.92	0.00
8	Y4-Y5 | Unsure/Y6+/Never	-1.602	0.135	5.98	0.00

Summary statistics
Number of observations = 221
Number of excluded observations = 0
Number of estimated parameters = 8

$$\mathcal{L}(\beta_0) = -356.517$$
$$\mathcal{L}(\hat{\beta}) = -255.646$$
$$-2[\mathcal{L}(\beta_0) - \mathcal{L}(\hat{\beta})] = 201.741$$
$$\rho^2 = 0.283$$
$$\bar{\rho}^2 = 0.260$$

Compared to Case 1, Case 2 presents similar values for the relevant parameters, with close estimates in terms of value and significance. This model also presents very significant cutoff values between the ordered categories and indicates that uncertain respondents can be combined with extremely late and/or non-adopters. In other terms, respondents showing some skepticism regarding their time-frame use of UAM are more likely to use it at a later stage, or not to use it at all.

In both cases, uncertain adopters are associated with rather late adoption; the only difference is that one case considers uncertainty as part of non-adoption and the other regards it as one degree less. However, due to the difference in the nature of the data between these models, as the first case provides five outcomes for the dependent variable compared to four in the second, a likelihood ratio test is not possible. Deciding on the best performing model could be done by looking at the estimator values or by assessing models based on their importance.

In case 1, the AIC and BIC values are 587.731 and 618.314, respectively. In case 2, these values are 527.293 and 554.478. This could indicate that case 1 model has a better performance than that of case 2. However, the rho-squared values for case 1 and case 2 models are 0.268 and 0.260 respectively. The higher rho-squared value in case 1 model suggests that this model performs better, a finding that contradicts that of the other estimators. Therefore, and as a log-likelihood ratio test isn't feasible in this case, assessing both models is best done by personal judgment on the overall benefits of each. As the only difference between both is the clustering of the outcomes, one could argue that case 1 is better, as it ranks the unsure between late adopters and non-adopters. Case 1 provides more information and prevents the loss of information that could result from merging the last three categories.

Notes:

1. *For both models, the estimates of the third cut-off value δ_3 are smaller than those of other cut-offs, meaning that the margin between Y2-Y3 and Y4-Y5 is smaller that of other range categories. In other words, this range is rather sensitive and an increase in utility could result in a fast switch to another outcome category.*

2. *As both models have different initial log-likelihood values, using statistic estimator values to compare them isn't technically correct.*

3. *In case 2, merging unsure respondents with late and non-adopters might result in a loss of information, as the latter category represents a very small percentage of the sample size.*

4. *Overall, as both models have more or less the same meaning, deciding on the number of ordered categories depends on personal judgment and preference: parsimony vs. richness.*

5.2.4 Nested Logit Models (NLs)

For nested models, Stata was first used as well, with the aim of building a nested ordered logit model, where one of the nests would be ordered. However, models built could not generate any results, and gave a warning of lack of within-case variability. This might be due to the nature of the data, in which all attributes (like affinity to automation or socio-demographics for instance) were related to the decision-maker only and therefore constant across alternatives.

Another attempt using Python Biogeme was done by specifying alternative-specific utilities and included several nesting options. Each of these cases had two nests.

- Case 1: in the first five years with nest alternatives including : Y1, Y2-Y3, Y4-Y5; not in the first five years including alternatives: Unsure, Y6+/ Never.
- Case 2: in the first three years or early adopters: Y1, Y2-Y3; not in the first three years or late to non-adopters: Y4-Y5, Y6+, Never/Unsure.

- Case 3: in the first year or immediate adopters: Y1; rest of adopters: Y2-Y3, Y4-Y5, Unsure, Y6+/Never.

NL Case 1:
In this case, we first built a model with very few parameters to test for the correctness of the nest specification, and set the first five years to one for reference.

NL Case 2:
In this nesting, the first three years were clustered in a group and set to one for reference. We tried in this model to include more relevant parameters obtained from the MNL and OLM results that were previously discussed.

NL Case 3:
In this case, the first year represented one nest that served as a reference.

The outputs for all cases are given in Tables 20, 21, and 22 of Appendix D. It is notable that the models could not be estimated, as observed by the extremely high values of standard error for the nest estimates or the zero t-test estimates (as highlighted in the tables). This means that the models were not correctly specified, or that nesting was not possible.

Overall, the results of this section, from both Stata models (where attributes are generic) and Biogeme models (where utilities are specified) give an indication that nesting might not be possible for our model, due to the nature of our data. To overcome this, the survey must have been designed with variability across the different alternatives, by specifying for instance different attributes like time and cost for different time-schemes. This would however only apply for the specified years of implementation (Y1 to Y5), as it is not possible to specify attributes of the service for outcomes such as “unsure”, or “never”.

6 Discussion

This chapter discusses the findings of this thesis and relates them to the research problems and objectives stated in the introduction, the proposed UAM TAM model, and the hypotheses formulated in the methodology. The main aim of this discussion is to translate the findings to a higher level, in terms of policy implications, but also research directions.

6.1 Discussion of Main Results

The main findings of this study can be divided into two components: the direct findings from the survey statistics, and the model findings obtained from the different analysis methods.

6.1.1 Survey findings

The survey outcomes displayed in Table 2 show a general **enthusiasm** for UAM (about 37% for Y2-Y3 and 22 % for Y1). Still, outcomes share a high percentage of “unsure” respondents, indicating a high level of **skepticism**. The results are complemented by the free comments given at the end of the survey, as discussed in Section 4.2.3. These mentioned concerns on environmental **impacts** including noise and visual effects, safety and privacy concerns, purpose of use, economic impact, and congestion reduction. Moreover, respondents expressed the importance of time and costs, on-demand availability, in-vehicle information sharing, and system integration of UAM.

Results of factors ranking in UAM adoption indicated that **safety** was the factor of utmost importance in using UAM (as stated in the survey). A high indication for the importance of trip cost, trip time, service reliability and operation characteristics was also observed.

The survey results indicated a high impact of socio-demographic factors on adoption and attitudes. **Females** expressed a much lower interest in immediate UAM adoption (Figure 11), expressing overall lower trust and perceived usefulness of automation, and greater security and safety concerns and expectations (Figures 17, 18, and 19).

Younger respondents seemed to be less enthusiastic about an early adoption of UAM and mentioned a higher interest in later adoption (Figure 12). On the other hand, both **fully-employed** and **higher income** respondents expressed a greater interest in early adoption (Figures 13, 14). **Cultural** impact was observed through the survey language, which seemed to also have an impact on automation; respondents filling the survey in German expressed a lower interest in early adoption and a higher skepticism observed through a higher degree of uncertainty (Figure 15). This finding is complemented by the attitudes of those respondents (Figure 20). This is interesting when compared to the impact of the place of residence (Munich or Germany), which was less influential than the survey language (Figures 33, 34).

Respondents commuting with **public transportation** showed a rather lower enthusiasm towards early adoption, as they were more uncertain and expressed their interest in a rather late UAM adoption (Figure 32). Moreover, respondents with previous crash experiences were less enthusiastic about UAM, opting for rather later adoption levels (Figure 30). Higher **safety camera** expectations were noted among respondents with lower levels of education, in particular those at a bachelor or lower level of education, compared to their counterparts (Figure 22).

6.1.2 Model findings

In the following, we summarize the model findings that are not part of the tested hypotheses (to be discussed in Section 6.2).

The factor analyses were useful in clustering attitudes, helping in exploring the data and revealing latent patterns. For instance, affinity to automation included the **enjoyment, trust of automation, and perceived UAM usefulness**. Data concerns associated **fear of cyber-security** and **concerns of data being shared to third parties**. Moreover, safety concerns grouped the perceived importance of **in-vehicle safety cameras**, and **operators on the ground** for both communication at anytime, and **emergency intervention**. Other factors resulting from the factor analysis were rather straightforward, like environmental concerns, and affinity to social media, online services, and sharing.

Models revealed interesting findings on the importance of the **service provider's reputation** in gaining trust to adopt UAM. Also, **safety concerns** were found to play an inhibiting role in early and late adoption. Finally, **value of time savings** was highly significant in late adoption. As some of these findings might be counter-intuitive, their occurrence might be due to respondents' **prior expectations and judgments on service properties**. For instance, respondents may already believe that the service provider will be reputable (early adoption), or might be skeptical about it (unsure). In the same way, respondents might be skeptical about actual time savings of UAM, and therefore as they value this factor, decide to adopt UAM later on, waiting for the service to improve its performance. This was also observed for respondents who are highly sensitive to cost. As they give a high importance to cost in UAM adoption, they might believe that the service costs would decrease a few years after its implementation. Moreover, safety concerns might hinder late UAM adoption as users might believe that safety would only need a few years to be proven; waiting for too long would therefore not be needed. The survey also revealed that public transportation commute is associated with later UAM adoption, and that previous crash experiences (with injuries) might hinder early UAM adoption.

Finally, the ordered models gave meaningful insights regarding "unsure" respondents, in which these were found to have similar or close (one degree less) behavioral intentions as late adopters.

6.2 Hypotheses Results and UAM TAM

6.2.1 Hypotheses results

In the following, the results of the hypotheses presented in Chapter 3 are given, and then summarized in Table 12.

Hypothesis 1: The data analysis, but more importantly the MNL models strongly (with a

99% confidence level) indicate that females are less likely than their male counterparts to be early adopters of UAM, as shown by MNL Models 3 to 5 (Tables 7, 8, 9). This finding is also supported, to a lesser extent (only 85 % confidence level), by the OLM Model (Case 1) shown in Table 19. This hypothesis is accordingly validated.

Hypothesis 2: The data analysis goes in the opposite direction of this hypothesis as younger respondents (< 24 years old) were on the contrary more skeptical about UAM. This finding is also supported by the OLM model in Table 15, with a 90% level of significance. This hypothesis is therefore rejected.

Hypothesis 3: This hypothesis is supported by the data analysis, the MNL model (Table 9), and the OLM models (Tables 10, 19) with a very high level of significance (more than 99 %). The hypothesis associating full-time employment with early adoption is therefore confirmed.

Hypothesis 4: This hypothesis is supported by the data analysis, the MNL and the OLM models, with a very high level of significance. The cultural impact hypothesis is accordingly accepted.

Hypothesis 5: The MNL Model (Table 9) shows a strong indication of high income being negatively associated with late adoption (to a 90% significance level). This however doesn't necessarily means that higher income people are more likely to be early adopters. Therefore, this hypothesis is partially validated.

Hypothesis 6: The MNL model indicates that doctorate level respondents are less likely to be Y2-Y3 adopters. However, this doesn't mean that they will be early adopters. Also, as doctorate level respondents represent about only 13 % of the sample size, this finding has to be carefully examined. Still, there is an indication from the data analysis that master level respondents (compared with bachelor or lower) have a higher interest in early adoption (Figure 29). This however might be due to the fact that bachelor level respondents are young; age might be the influential factor in this case. This hypothesis can neither be rejected nor validated.

Hypothesis 7: Car as a commute mode isn't a significant parameter in any of the developed models, and was eliminated after developing the very first saturated models. Compared to PT, car users showed a higher interest in early adoption (Y1), as shown in Figure 32. Still, the findings are not conclusive and this hypothesis can neither be accepted nor rejected.

Hypothesis 8: Affinity to automation is a high explanatory variable retained in the factor analysis of part 2 of the survey. Automation attitude was proved to be highly influential (positive contribution) in early adoption. This was demonstrated by the different models: MNL, OLM, with very high levels of significance. This hypothesis is therefore validated.

Hypothesis 9: Safety concerns, including locus of control importance, is a significant factor retained from the factor analysis, sharing a high proportion of the data variability. This factor is negatively and significantly associated with immediate adoption, but also with years 4 to 5; respondents with higher levels of concerns were less likely to adopt UAM in these categories.

This hypothesis is accordingly partially validated.

Hypothesis 10: Data concerns are strongly associated with late UAM adoption as shown by the OLM models (but also by the MNL models through a negative impact on early adoption). However, no strong indication is correlated with the concerns of loss of jobs induced by automation. This might be due to the fact that this attribute is more relevant for ground autonomous vehicles, where automation would replace a whole industry involving bus or truck drivers for instance; in the aviation sector however, a lower number of jobs could be affected. As a result, this hypothesis is partially validated.

Hypothesis 11: Environmental awareness, sharing perception, and social media are all retained from the factor analysis. The first two didn't show a strong significance in any of the models. The third one however, showed a positive strong indication towards UAM adoption. This hypothesis is therefore partially validated.

Hypothesis 12: Table 14 indicates that a higher PT satisfaction is more likely to result in later adoption (Y4-Y5) compared to immediate adoption (Y1 base case). However, this parameter wasn't retained in any of the final MNL and OLM models. This hypothesis is therefore neither validated, nor rejected.

Hypothesis 13: Value of time savings is represented in our study with two attributes: value of time savings (retained from the factor analysis), and the importance of time savings in UAM adoption. Both attributes gave positive and strong estimates for Y4-Y5, and Y2-Y3, respectively. Still, these estimates are not sufficient to either accept or reject this hypothesis.

Hypothesis 14: A positive perception of UAM costs, through a higher willingness to adopt it if its prices were in the same ranges as taxis', is positively and strongly correlated to early adoption (Y1), as shown by the final MNL and OLM models. This hypothesis is therefore validated.

Hypothesis 15: Two ordering models were developed for UAM adoption, where unsure respondents were either merged with non-adopters, or described as one order below them. The developed models resulted in significant parameters, but most importantly significant cutoff values for the ordered categories. This hypothesis is therefore validated.

Hypothesis 16: Nest values couldn't be estimated for the developed nested models, possibly due to the lack of variability across alternatives. Therefore, the hypothesis has to be rejected[15].

The hypotheses results are summarized in Table 12

[15] This is of course only in the context of our data and does not mean that UAM adoption can never be estimated with NL models

Table 12: Summary of hypotheses results

Hypothesis	Validated	Rejected	Neither validated nor rejected
1	✔		
2		✖	
3	✔		
4	✔		
5	✔ (partially)		
6			o
7			o
8	✔		
9	✔ (partially)		
10	✔ (partially)		
11	✔ (partially)		
12			o
13			o
14	✔		
15	✔		
16		✖	

6.2.2 UAM TAM validation

In the following, we aim at relating the discussed findings with the proposed UAM TAM model, given in Figure 6 of Chapter 2.

The model analyses showed a strong indication of **socio-demographic** impacts and **technological awareness** as overarching parameters in UAM adoption. This study showed the importance of gender, occupation, and cultural aspects in UAM adoption. Also, the importance of age, income levels, and education was observed; however, with less significance. Moreover, technological awareness proved to positively contribute to UAM adoption in terms of affinity to automation, which itself was related to the enjoyment, trust of automation, and perceived UAM usefulness (factor analysis result).

Trust and safety were found as key components in UAM adoption. The majority of respondents mentioned safety as a number one factor in UAM adoption. Trust was shown to be highly associated with perceived in-vehicle safety that could be enhanced by adding in-vehicle surveillance cameras. Also, locus of control was influential as operators (both at any time and in emergency cases) were perceived as necessary. Moreover, previous experience with automation (through automation trust) and service reliability were crucial in trusting UAM use, and noted among the five first influential factors for its adoption. Finally, the service provider's reputation seemed to play a high role in UAM trust. These components match the underlying factors affecting trust, presented in Figure 7 of Chapter 2.

Perceived ease of use (PEU) in terms of effort expectancy is only related to booking and boarding processes in the case of UAM. As these were not influential in the models, and were noted as rather less important by the respondents, PEU would be considered less relevant for UAM. **Perceived usefulness (PU)** was however considered important, since UAM usefulness was noted as significant and retained in the factor analysis as part of affinity to automation. In terms of performance expectancy, reliability of automation was also noted among the top five factors in UAM adoption. Still, no strong indication between trust and PEU was proved.

Social influence, including affinity to social media or automation enjoyment (as part of affinity to automation), was strongly related to behavioral intention of UAM use. Moreover **value of time** and **perceived costs** were also significant in the resulting models, positively contributing to adoption, and noted among the top factors in UAM adoption. Value of time included the importance given to time savings and perceived costs included the importance of UAM costs being in the range of taxis'. Finally, data concerns seemed to be highly associated with a late UAM adoption.

All of the discussed factors contribute to behavioral intention, and eventually to actual use, but can't be observed as UAM is not yet implemented. The findings lead to adjustments in the proposed UAM, including the following:

- Technological awareness is replaced by affinity to automation, including the enjoyment and trust of automation.
- Trust/Safety are key parameters that are first considered in the UAM TAM.
- Service provider's reputation is added as an underlying factor affecting trust.
- Trust is considered first, after which other factors are assessed, such as social behavior, value of time, perceived costs, and data concerns.
- Perceived Ease of Use is disregarded, since it was irrelevant for UAM adoption; Perceived Usefulness is kept.
- Ethicality is replaced by data concerns, including the fear of cyber-security (which itself impacts trust) and fear of data being shared to third parties.

The adjustments are illustrated in the modified UAM TAM and corresponding trust factors, given in Figures 23 and 24 below.

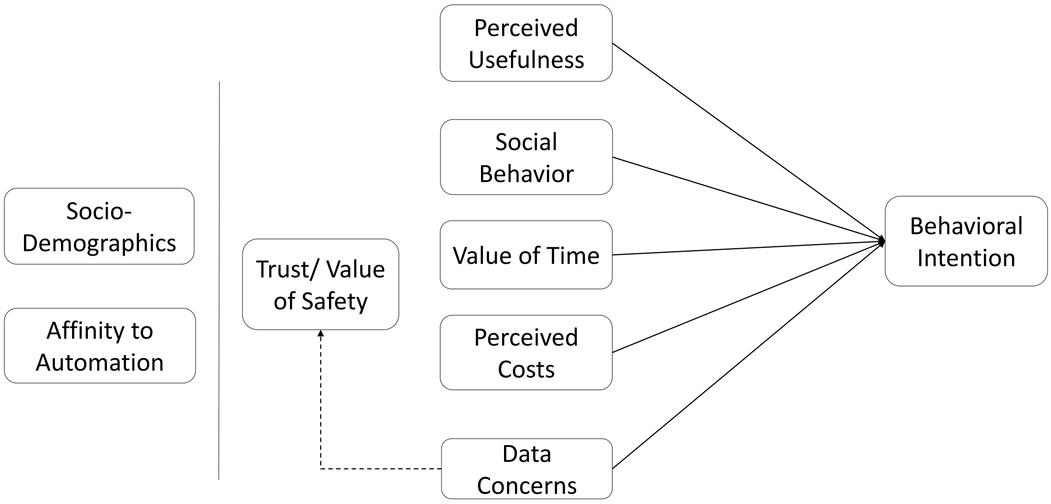

Figure 23: Adjusted Technology Acceptance Model for UAM *(own illustration)*

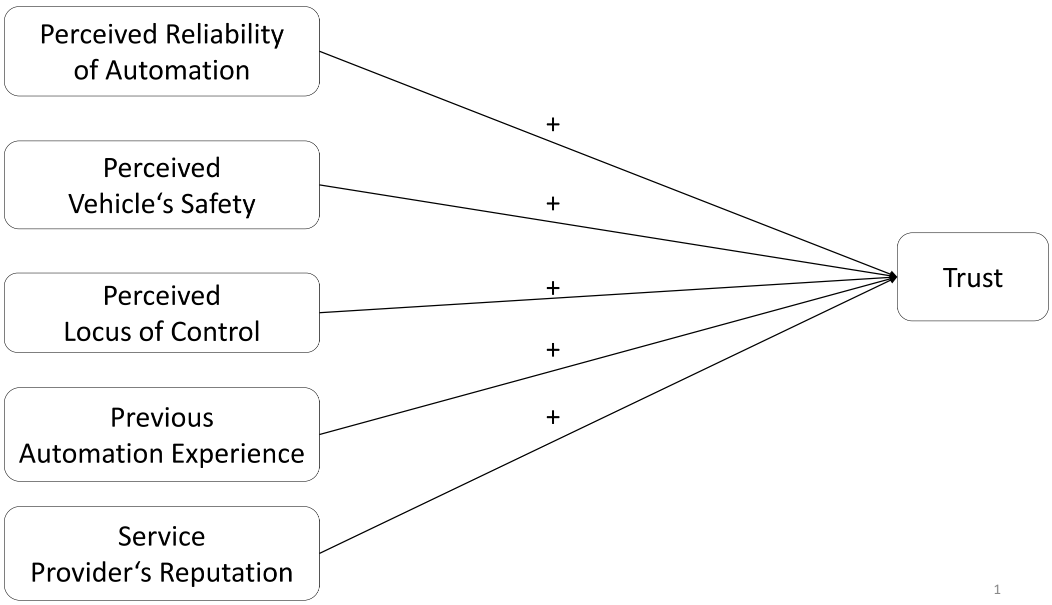

Figure 24: Adjusted factors affecting trust in UAM (*own illustration*)

Notes:

1. *Many of the factors in the TAM discuss perception, whereas the model findings are rather associated with the importance of these factors. Still, the findings at least go in the direction of the proposed model.*

2. *The affinity of automation as a factor can appear as a redundant factor; it is an overarching parameter in UAM adoption, affects trust, but also social behavior of users.*

3. *The technology adoption model serves to model adoption, but doesn't give information about the intended time-frame use.*

6.3 Policy implications

Based on the findings above, recommendations are given and their implications on a policy level are discussed. These are necessary to ensure a higher and smoother adoption process, and improve thereby community acceptance. The implications concern all the relevant stakeholders, and will be divided in three components: automation awareness, safety considerations, and service attributes.

1. **Automation awareness**

    - A higher awareness on UAM and automation in general is necessary to ensure more transparency from the different stakeholders involved. This should include accurate schemes of important attributes of the service, such as trip duration, and costs. The business models of UAM must be openly disclosed, including pricing schemes for vehicle-sharing.
    - A higher sensitization to UAM is necessary to emphasize on the benefits it can bring. These must highlight the environmental and economic impacts induced from congestion reductions and time savings for instance. Also, the different trip purposes fulfilled by UAM must be highlighted. Accordingly, to encourage the use by different demographics, including lower income and/or education levels, discounts could be given for first-time users, or premium accounts and benefits for senior citizens or students for example. Lack of experience with automation should be compensated with a higher awareness on automation for different target groups (in schools and universities for the younger for instance).
    - As UAM has to be inclusive, market segmentation is expected, including genders and age groups, for instance. Different groups are to be therefore addressed according to their specific needs. Marketing and ads should particularly focus on including the less enthusiastic segments (for instance females), for them to overcome their fears or judgments on automation. Considering the cultural aspect might also be of relevance, especially in more conservative societies.
    - Awareness should be spread via different means (offline and online) to focus on enthusiastic adopters with a high affinity to social media, but also on more skeptical groups.

2. **Safety considerations:**

    - Automation reliability is to be proved through testing and required certifications, to ensure users' trust in the service's performance and its on-time reliability.
    - Surveillance cameras must be part of the vehicles to contribute to safety feeling, necessary for trust.
    - The importance of the human factor should not be disregarded and an emphasis on operators (both on the ground and in emergency cases) should be shown.
    - UAM must be operated by highly reputable service providers, for people to gain trust to use it.

3. **Service attributes:**
    - Cost considerations should be taken into account by providing similar price ranges as taxis'.
    - Environmental implications of UAM, including noise and visual impacts, have to be carefully examined. For instance, stringent regulations must be developed to regulate the allowed noise levels and flying altitudes of the vehicles. These regulations must be openly shared to the community.
    - Data concerns have to be addressed on a policy level, with transparent regulations on data sharing. Accordingly, service providers have to comply to these rules.
    - Integration with existing transportation systems is crucial to ensure seamless vertiport connectivity.

The above implications are to be closely reviewed by the relevant stakeholders, including manufacturers, service providers, but also respective authorities and policy makers, to ensure a smooth system integration, and an examination of the relevant aspects in UAM implementation. Accordingly, skepticism regarding missing or erroneous information is likely to be reduced with a higher transparency and more stringent rules, acting upon the most relevant factors, like safety, privacy, information sharing, etc.

7 Conclusions and Future Work

In this chapter, the conclusions of this work are presented, followed by a discussion of the limitations, after which recommendations and research directions are given as suggestions for future work.

7.1 Conclusions

The findings of this thesis suggest strong indications about the main objective: identifying the factors affecting the adoption and use of UAM. As there is a lack of research in UAM acceptance, the factors extracted from the literature mostly came from ground autonomous vehicles acceptance studies. Accordingly, the most prominent factors were adapted in a proposed UAM Technology Acceptance Model (TAM), also based on traditional and extended Technology Acceptance Models. This model was also complemented with hypotheses on the influential parameters in UAM adoption and use. After that, a survey was built to test the hypotheses and identify the factors. This study was a stated preference one, used to assess the perception of users about UAM in relation to their intended time-frame use. The survey was held online for two months and gathered 221 relevant responses, with a subsample of 97 Munich residents. The data analysis of the survey gave evidence on the importance of socio-demographic groups and their attitudes in adoption. Moreover, the factor analysis uncovered latent patterns, explaining and clustering some of the variables. These included data and safety concerns, the affinity to automation, the value of time savings, in addition to social attitudes such as environmental awareness, the affinity to social media, online services, and sharing. The development of statistical models aligned with the methodology framework resulted in significant multinomial and ordered logit models for adoption. Nested logit models however could not be estimated. Subsequently, the interpreted results served as a validation process for the hypotheses and the proposed TAM model. As a result, a discussion followed on the main implications of the findings, and gave way to an adjusted UAM TAM model.

The main research problems formulated in Chapter 1 can be answered as follows.

- The survey design was suitable in identifying time adoption of UAM.
- Exploratory Factor Analysis helped understanding latent constructs in UAM attributes.
- The factor scores resulting from the factor analysis were very significant for the new model estimations, such as the affinity to automation, data and safety concerns, the value of time savings, and the affinity to social media.
- UAM time adoption was modeled using discrete choice modeling, particularly multinomial logit and ordered logit models, with time adoption as a dependent variable. However, it could not be modeled with a nested logit model.
- The obtained factors from the models were significant, and mostly validated the proposed UAM TAM model.

More generally, the main findings of this work can be summarized in the below to answer the main research question.

- Socio-demographic parameters are strongly influential in UAM adoption. There was a clear evidence on females being less enthusiastic about early adoption and some indication that younger respondents (< 24 years old) were rather skeptical about UAM. Also, a cultural impact (observed through the survey language) showed a higher skepticism of respondents filling the study in German as compared to those filling it in English. On the other hand, full-time employment was strongly associated with early adoption and higher income levels somewhat related to early adoption.
- Affinity to automation is crucial for early UAM adoption, including enjoyment and trust of automation, and perceived usefulness of UAM.
- Safety and trust are key components in UAM adoption. These include the needs for in-vehicle surveillance cameras, and for an operator on the ground to override the system in emergency situations. Lack of safety and trust may hinder UAM and lead to late adoption. Moreover, the importance of the service provider's reputation was noted.
- Performance expectancy in terms of service reliability and on-time performance is essential for trust in UAM.
- Value of time savings and perceived costs are crucial considerations in UAM adoption. Particularly, it is important that UAM costs are in the same ranges as taxis'.
- Data concerns such as fear of cyber-security and concerns of data being shared to third parties are essential factors that might hinder UAM adoption.
- Social attitude, including a higher affinity to social media positively contributes to early UAM adoption.
- Commute mode influences adoption. PT commuters were more likely to be late adopters. Also, a higher PT satisfaction was somewhat linked to late UAM adoption.

Overall, the findings of this thesis serve to fill the gap in the literature on UAM perception outside the scope of a mode choice. Most importantly, this work studies the time adoption of UAM, using behavioral modeling, but also ordered logit models with stated time adoption as a dependent variable, contributing thereby to the field of research.

7.2 Limitations

This work has however some limitations that can be summarized in the following:

- The experimental design can be improved by having a more homogeneous sample, but also by focusing on offline surveys. Accordingly, a wider and more representative data could be gathered, as it would include people who do not have access to the internet or are not familiar/comfortable using it. Moreover, the given scenarios could be revised to avoid biases about the service, and thereby prior expectations and judgments on UAM.

- The extracted factors are perception variables resulting from the survey, and the provided case scenarios. As UAM still has many uncertainties in terms of service attributes or adopted business models, the identified factors should be reconsidered with changing service properties.
- Usefulness of the factor analysis should be checked by developing a model with all variables and comparing it against the one using factor scores from the factor analysis, to assess the relevance of the clusters.
- The data did not have alternative-specific attributes as the dependent variable was the stated time adoption. Accordingly the developed models all included decision-maker attributes as independent variables.

7.3 Recommendations and Future Work

7.3.1 Recommendations

Findings of this work suggest that a lot of concerns are still to be addressed to ensure a higher community acceptance. These can be translated in terms of policies, in which different stakeholders have to cooperate. Firstly, safety considerations have to be carefully tackled, including the necessity for surveillance cameras, and operators on the ground and for emergency situations. Moreover, a higher awareness on automation should be spread, including more transparency on its benefits, but also on the impacts it may have. Stringent regulations must define for instance the allowed noise levels and flying altitudes of UAM vehicles. Costs should as well be regulated to be in the range of taxi prices. Data protection laws can also address data concerns including the fear of data being shared to third parties. Furthermore, services should target different market segments to better care for users' specific needs. Finally, UAM must also be integrated with existing transport systems, to provide multimodality from and to the vertiports.

Overall, regulatory body governments should have departments targeting UAM regulations, and should work closely with other countries to have some unified standards; for instance, a unified European framework on suggested safety standards and allowed noise levels. Of course, regulations may differ from a country to another; still, some standards that could act as a framework for policy-making could be very useful.

7.3.2 Future work

Future work could focus on overcoming the limitations of this study by optimizing the survey design, and sharing it offline to avoid potential sample biases. Other studies could also focus on defining different business models and testing the preferences among these, to better extract service attributes and gather alternative-specific variables that could help in building nested models for instance, improving thereby the developed behavioral models. A research motivation could be to build a nested ordered logit model, where one or more nests would be ordered. Other studies could test the developed UAM TAM by applying a confirmatory factor analysis (CFA), and developing a hybrid latent class model for adoption, in which both analysis methods of this thesis (factor analysis and choice models) would be combined.

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A Survey (English Version) and Attributes

User Adoption and Use of Urban Air Mobility (UAM)

A survey for my master's thesis at the Technical University of Munich (TUM Chair of Transportation Systems Engineering), in collaboration with Bauhaus Luftfahrt e.V.

Dear respondents,

Thank you for your participation. My name is Christelle Haddad and I am an MSc student in transportation systems at the Technical University of Munich. This survey is an essential part of my master thesis and will help me better understand **future urban air mobility modes.**

The survey is made of four parts and will not take more than 15 minutes.

The data is solely for research purposes and will remain strictly anonymous.

Please remember that there are no right or wrong answers; we are only interested in your opinion.

For any concerns or suggestions, please feel free to contact me via email at Christelle.AlHaddad@bauhaus-luftfahrt.net.

There are 31 questions in this survey.

Part 1 of 4

General Commute Questions

* 1 How much time do you spend commuting **(both ways)** on average per day?

Choose one of the following answers

- Up to 30 min
- 30 to less than 60 min
- 60 to less than 90 min
- 90 min or more
- Other:

* 2 What is your main mode of transport (commute)?

Choose one of the following answers

- Car as a driver
- Car as a passenger
- Public transport
- Biking
- Walking
- Other:

* 3 Do you have a driver's license?

Choose one of the following answers

- Yes
- No

* 4 Do you have access to a car?

Choose one of the following answers

- Yes
- Sometimes
- No

* 5 Please indicate your level of satisfaction with the public transportation system in your region.

	very dissatisfied	dissatisfied	neither dissatisfied nor satisfied	satisfied	very satisfied
I am	○	○	○	○	○

* 6 Please indicate your level of agreement with the following statements.

	I strongly disagree	I somewhat disagree	I neither disagree nor agree	I somewhat agree	I strongly agree
I enjoy interacting with automated systems, such as Siri (Apple) or Alexa (Amazon).	○	○	○	○	○
I trust such automated systems.	○	○	○	○	○
I think driver assistance systems, such as adaptive cruise control, lane keeping assistance, or other advanced systems, are useful.	○	○	○	○	○
I have used (in my own car or someone else's) such advanced driver-assistance systems.	○	○	○	○	○

User Adoption and Use of Urban Air Mobility (UAM)

A survey for my master's thesis at the Technical University of Munich (TUM Chair of Transportation Systems Engineering), in collaboration with Bauhaus Luftfahrt e.V.

Dear respondents,

Thank you for your participation. My name is Christelle Haddad and I am an MSc student in transportation systems at the Technical University of Munich. This survey is an essential part of my master thesis and will help me better understand **future urban air mobility modes.**

The survey is made of four parts and will not take more than 15 minutes.

The data is solely for research purposes and will remain strictly anonymous.

Please remember that there are no right or wrong answers; we are only interested in your opinion.

For any concerns or suggestions, please feel free to contact me via email at Christelle.AlHaddad@bauhaus-luftfahrt.net.

There are 31 questions in this survey.

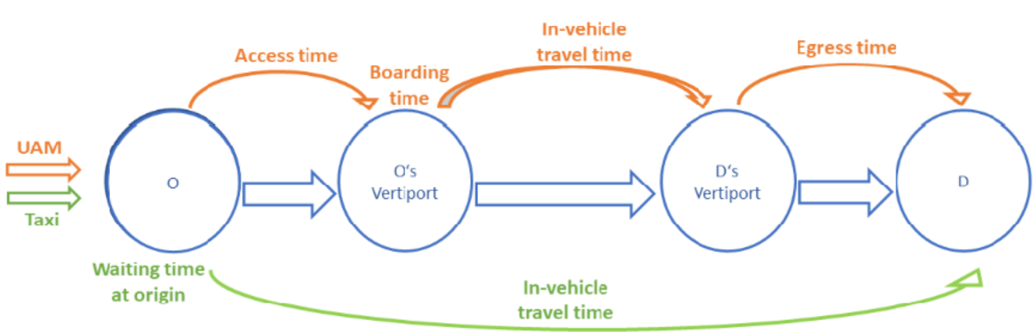
Part 2 of 4

In my study, I am focusing on **Urban Air Mobility (UAM)**, a future mobility service that is taking urban mobility to the third dimension: **the airspace.**

The UAM service is provided with VTOL (Vertical Take-off and Landing) aircraft and has the following properties:

Fully-automated VTOL vehicles: They operate completely on their own; no pilot assistance is needed
Electrically-powered vehicles
On-demand online booking: Book anytime using the service's application or website
4-seat capacity: Book for up to four passengers, including one wheelchair seat
Possibility to **ride-pool:** Save money by sharing the flight with other passengers
Operating speed: Around 150 km/h
Boarding time: Around 5 minutes prior to departure time
Access and egress (exit): Through vertiports: 'Helipad' infrastructures distributed around the city, (i.e. at rooftops) and used for take-off and landing of VTOLs
Vertiport access: Integrated with existing public transportation (PT) systems

The scheme below describes the basic process of a simple UAM trip, from origin (O) to destination (D).



To better illustrate the use of UAM, two scenario **examples** are provided, where UAM could be used (in the region of Munich for example), **hypothetically starting 2030.**

Notes for both examples:

1. *The public transportation option requires more than an hour (in vehicle) from origin to destination, via a necessary transfer in the center of Munich.*
2. *We are only giving travel times and fares for taxis, as a benchmark for the UAM option.*
3. *Taxi ranges (for time and fares) are given depending on road traffic.*

To better illustrate the use of UAM, two scenario **examples** are provided, where UAM could be used (in the region of Munich for example), **hypothetically starting 2030.**

Notes for both examples:

1. *The public transportation option requires more than an hour (in vehicle) from origin to destination, via a necessary transfer in the center of Munich.*
2. *We are only giving travel times and fares for taxis, as a benchmark for the UAM option.*
3. *Taxi ranges (for time and fares) are given depending on road traffic.*

Example 1: A trip from **Munich Airport** to **Dachau:**

	UAM	TAXI
Trip Duration	• 15 min **access time** • 5 min **boarding time** • 13 min **in-vehicle travel time** • 5 min **egress time**	• 5 min **waiting time** • 28-40 min **in-vehicle travel time**
Trip Fare	• 90 €	• 53-69 €

Example 2: A trip from **Planegg** to **Taufkirchen:**

	UAM	TAXI
Trip Duration	• 8 min **access time** • 5 min **boarding time** • 8 min **in-vehicle travel time** • 12 min **egress time**	• 5 min **waiting time** • 30-55 min **in-vehicle travel time**
Trip Fare	• 53 €	• 40-52 €

✱ 7 Which of the following factors are the most important for adopting and using UAM?

Double-click or drag-and-drop items in the left list to move them to the right - your highest ranking item should be on the top right, moving through to your lowest ranking item.

❗ This question is mandatory
❗ Please rank all items.

Your choices	Your ranking
Booking experience	
On-time performance (reliability)	
Operation characteristics (availability/frequency of service)	
Process of boarding	
Safety	
Trip cost	
Trip purpose	
Trip duration	
Vehicle characteristics (comfort and cleanliness)	

✱ 8 Please indicate your opinion on the usefulness of UAM.

❗ This question is mandatory
❗ Please complete all parts.

	not at all useful	Not very useful	neither useless nor useful	somewhat useful	extremely useful
I think UAM is	○	○	○	○	○

✱ 9 Please indicate your level of agreement with the statements below.

❗ This question is mandatory
❗ Please complete all parts.

	I strongly disagree	I somewhat disagree	I neither disagree nor agree	I somewhat agree	I strongly agree
I am worried that my (personal) data goes to a third party.	○	○	○	○	○
My fear of cyber-security could prevent me from using UAM.	○	○	○	○	○
I am concerned about the loss of jobs induced by UAM's automation.	○	○	○	○	○

✱ 10 How much do you agree or disagree with the following statements about UAM's operation characteristics?

❗ This question is mandatory
❗ Please complete all parts.

	I strongly disagree	I somewhat disagree	I neither disagree nor agree	I somewhat agree	I strongly agree
Service reliability (on-time performance) is a very important feature for trusting UAM.	○	○	○	○	○
In order for me to feel safe, I would expect UAM's vehicles to be equipped with surveillance cameras.	○	○	○	○	○
I should be able to talk to an operator on the ground at any time.	○	○	○	○	○
The operator should be able to override the system and remotely control the UAM's vehicles, in case of emergency.	○	○	○	○	○
The service provider's reputation is very important for gaining trust to use UAM.	○	○	○	○	○

✱ 11 Please indicate your level of agreement with the following statements about UAMs' fare.

This question is mandatory
Please complete all parts.

	I strongly disagree	I somewhat disagree	I neither disagree nor agree	I somewhat agree	I strongly agree
I would be willing to use this service as long as its price is in the same range as that of a taxi.	○	○	○	○	○
I would first think about cost when deciding whether or not to use UAM.	○	○	○	○	○
I think UAM's service costs provided in the two scenarios are reasonable.	○	○	○	○	○

✱ 12 Please indicate your level of agreement with the following statements about travel time.

This question is mandatory
Please complete all parts.

	I strongly disagree	I somewhat disagree	I neither disagree nor agree	I somewhat agree	I strongly agree
Travel time saving is a key factor in deciding whether or not to use UAM.	○	○	○	○	○
5-min travel time saving is important.	○	○	○	○	○
10-min travel time saving is important.	○	○	○	○	○
20-min travel time saving is important.	○	○	○	○	○

✱ 13 When are you most likely going to use UAM?

Choose one of the following answers
This question is mandatory

- ○ During the first year of operation (Year 1)
- ○ During the second or third year of operation (Years 2-3)
- ○ During the fourth or fifth year of operation (Years 4-5)
- ○ Starting the sixth year of operation (Years 6 +)
- ○ Never
- ○ Unsure

✱ 14 For which purpose are you most likely going to use UAM?

Choose one of the following answers
This question is mandatory
If you choose 'Other:' please also specify your choice in the accompanying text field.

- ○ Daily commute (e.g. work, education...)
- ○ Business travel
- ○ Leisure
- ○ Other: ______

Part 3 of 4

*** 15 Have you used the following on-demand services?**

	I am not familiar with the service	Never	Once	A couple of times	I use it frequently
Airbnb	○	○	○	○	○
DriveNow/ Car2Go	○	○	○	○	○
Uber	○	○	○	○	○
BlaBlaCar	○	○	○	○	○

*** 16 Do you use the following social media platforms?**

	I don't use it	I use it infrequently	I use it several times a week	I use it once a day	I use it several times a day
Facebook	○	○	○	○	○
WhatsApp	○	○	○	○	○
Instagram	○	○	○	○	○
Twitter	○	○	○	○	○

*** 17 How comfortable are you with the following services?**

	very uncomfortable	somewhat uncomfortable	neither uncomfortable nor comfortable	somewhat comfortable	very comfortable
Online booking (such as hotels, flights, etc.)	○	○	○	○	○
Online banking	○	○	○	○	○
Online shopping	○	○	○	○	○

*** 18 How willing are you to share a ride (such as in a taxi or BlaBlaCar) with strangers?**

	very unwilling	unwilling	neither unwilling nor willing	willing	very willing
I am	○	○	○	○	○

*** 19 How much do you enjoy driving a car?**

	don't enjoy it at all	somewhat don't enjoy it	neither don't enjoy it nor enjoy it	somewhat enjoy it	very much enjoy it
I	○	○	○	○	○

*** 20 How much do you agree or disagree with each of the following statements about the environment?**

	I strongly disagree	I somewhat disagree	I neither disagree nor agree	I somewhat agree	I strongly agree	I don't know
I am concerned about global warming.	○	○	○	○	○	○
I do not change my behavior based on environmental concerns.	○	○	○	○	○	○
I am willing to spend a bit more to buy a product that is more environmentally friendly.	○	○	○	○	○	○

* 21 Have you ever been involved in a car crash?

Choose one of the following answers

- Yes (Major injuries)
- Yes (Minor injuries)
- Yes (No injuries)
- No
- I prefer not to answer

* 22 How comfortable are you with flying?

	very uncomfortable	rather uncomfortable	neither uncomfortable nor comfortable	rather comfortable	very comfortable	Prefer not to answer
I am	○	○	○	○	○	○

* 23 Please indicate your gender

Choose one of the following answers

- Female
- Male
- Other
- I prefer not to answer

* 24 Which age group represents you?

Choose one of the following answers

- 0-17
- 18-24
- 25-34
- 35-44
- 45-54
- 55-64
- 65+

* 25 What is the size of your household (people with whom you share your income, including yourself)?

Choose one of the following answers

- 1
- 2
- 3
- 4
- 5+
- I prefer not to answer

* 26 Is any member of your household, including yourself, physically disabled, and needs assistance in moving around?

Choose one of the following answers

- Yes
- No
- I prefer not to answer

* 27 What is the highest level of education you have completed?

Choose one of the following answers

- Less than high school
- High school diploma (Abitur)
- Apprenticeship
- Bachelor's degree (or Hochschule diploma)
- Master's degree
- Doctoral degree
- Other, please specify
- I prefer not to answer

Please enter your comment here:

* 28 What is your main occupation?

Choose one of the following answers

- Working (Full-time)
- Working (Part-time)
- Self-employed
- Unemployed
- Student
- Homemaker
- Retired
- I prefer not to answer
- Other:

* 29 What is the average **monthly net income** (after deducting all taxes) of your household (people you live with and with whom you share your income)?

Please include all types of income, including income from self-employment, social benefits (or other) for all household members.

Choose one of the following answers

- Up to 500 €
- 500 to less than 1000 €
- 1000 to less than 2000 €
- 2000 to less than 3000 €
- 3000 to less than 4000 €
- 4000 to less than 5000 €
- 5000 to less than 6000 €
- 6000 to less than 7000 €
- 7000 € or more
- I prefer not to answer

30 Where do you currently reside? Please indicate **the country** and **the city.**

Country

City

31 Finally, do you have additional comments, feedback, or recommendations regarding our survey?

Feel free to comment here. Alternatively, you can send me an email on Christelle.AlHaddad@bauhaus-luftfahrt.net.

Table 13: Summary of variables

Variable	Type and levels	Description
ADASUseful	Likert scale: strongly disagree (1) to strongly agree (5)	Perceived usefulness of ADAS
Airbnb	Likert scale: Not familiar (1) to use frequently (5)	Familiarity and use of Airbnb
AutomationAttitude	Weighted scale from the EFA	Affinity to automation
BachelororLower	Binary variable	Highest level of education: bachelor or lower
BehaviorChangeEnv	Likert scale: strongly disagree (1) to strongly agree (5)	I do not change my behavior based on my environmental concerns.
BIKE	Binary variable	Main commute mode: bike
BlabBlaCar	Likert scale: Not familiar (1) to use frequently (5)	Familiarity and use of BlaBlaCar
BoardingProcess	Ranking from 1 to 9; where 1 is the most important	Importance of boarding process for UAM adoption
BookExp	Ranking from 1 to 9; where 1 is the most important	Importance of booking experience for UAM adoption
CAR	Binary variable	Main commute mode: car (as a driver or passenger)
CarAccess	Categorical variable: 2: always; 1: sometimes; 0:No	Access to a car (if DrivLicens=1)
ConcernedGlobalWarming	Likert scale: strongly disagree (1) to strongly agree (5)	I am concerned about global warming.table
CostasTaxi	Likert scale: strongly disagree (1) to strongly agree (5)	I would be willing to use this service as long as its price is in the same range as that of a taxi.

Continuation of Table 13		
Variable	Type and levels	Description
CostFirst	Likert scale: strongly disagree (1) to strongly agree (5)	I would first think about cost when deciding whether or not to use UAM.
CostsReasonable	Likert scale: strongly disagree (1) to strongly agree (5)	I think UAM's service costs provided in the two scenarios are reasonable.
Data concerns	Weighted scale from the EFA	Data-sharing and cyber-security concerns.table
DataGoesThirdParty	Likert scale: strongly disagree (1) to strongly agree (5)	I am worried that my (personal) data goes to a third party.
DEU	Binary variable	German as a starting survey language
Disab	Binary variable	Presence of a physically disabled household member who needs assistance in moving
Doctorate	Binary variable	Highest level of education: doctorate or higher
DriveNow	Likert scale: Not familiar (1) to use frequently (5)	Familiarity and use of DriveNow
DrivingEnjoyment	Likert scale: Don't enjoy it at all (1) very much enjoy it (5)	Enjoyment of driving a car
DrivLicense	Binary variable	Ownership of a driver's license
EnjoyAutomation	Likert scale: strongly disagree (1) to strongly agree (5)	I enjoy inteacting with automated systems, such as Siri (Apple) or Alexa (Amazon).
Environmentalawareness	Weighted scale from the EFA	Attitude concerning several environmental statements
Facebook	Likert scale: I don't use it (1) to use it frequently (5)	Frequency of use of Facebook

Continuation of Table 13		
Variable	Type and levels	Description
FearCyberSecurity	Likert scale: strongly disagree (1) to strongly agree (5)	My fear of cyber-security would prevent me from using UAM.
Female	Binary variable	Gender: female
FlyingComfort	Likert scale: very uncomfortable (1) very comfortable (5)	Comfort with flying
FullTime	Binary variable	Main occupation: full-time employment
Germany	Binary variable	Residence in Germany
HH1	Binary variable	Household size: 1
HH2	Binary variable	Household size: 2
HH3	Binary variable	Household size: 3
HH4	Binary variable	Household size: 4
HH5+	Binary variable	Household size: >5
Inc1	Binary variable	Income: 500 to less than 1000 €
Inc2	Binary variable	Income: 1000 to less than 2000 €
Inc3	Binary variable	Income: 2000 to less than 3000 €
Inc4	Binary variable	Income: 3000 to less than 4000 €
Inc4to7	Binary variable	Income: 3000 to 7000 €
Inc5	Binary variable	Income: 4000 to less than 5000 €
Inc6	Binary variable	Income: 5000 to less than 6000 €
Inc7	Binary variable	Income: 6000 to less than 7000 €
Inc8	Binary variable	Income:7000 € or more
IncPNA	Binary variable	Income: Prefer not to answer
Instagram	Likert scale: I don't use it (1) to use it frequently (5)	Frequency of use of Instagram
InVehCamerasSafety	Likert scale: strongly disagree (1) to strongly agree (5)	In order for me to feel safe, I would expect UAM's vehicles to be equipped with surveillance cameras.
Lessthan24	Binary variable	Age: <24 years old

Continuation of Table 13		
Variable	Type and levels	Description
Lessthan30	Binary variable	Average commute time on average per day (both ways): <30 min
LossJobsConcerns	Likert scale: strongly disagree (1) to strongly agree (5)	I am concerned about the loss of jobs induced by UAM's automation.
Master	Binary variable	Highest level of education: master
MidAdults	Binary variable	Age: 35-44 years old
Morethan90	Binary variable	Average commute time on average per day (both ways): >90 min
Munich	Binary variable	Residence in Munich
Old++	Binary variable	Age: >55 years old
OlderAdults	Binary variable	Age: <45-54 years old
OnlineBanking	Likert scale: very uncomfortable (1) very comfortable (5)	Comfort of use of online banking
OnlineBooking	Likert scale: very uncomfortable (1) very comfortable (5)	Comfort of use of online booking
OnlineServices	Weighted scale from the EFA	Affinity to online services
OnlineShopping	Likert scale: very uncomfortable (1) very comfortable (5)	Comfort of use of online shopping
OnTimePerf	Ranking from 1 to 9; where 1 is the most important	Importance of on-time performance (reliability) for UAM adoption
OpCharact	Ranking from 1 to 9; where 1 is the most important	Importance of operation characteristics (availability or frequency of service) for UAM adoption
OperatorGround	Likert scale: strongly disagree (1) to strongly agree (5)	I should be able to talk to an operator on the ground at any time.

Continuation of Table 13		
Variable	Type and levels	Description
OperatorOverride	Likert scale: strongly disagree (1) to strongly agree (5)	The operator should be able to override the system and remotely control the UAM's vehicles, in case of emergency.
PartTime	Binary variable	Main occupation: part-time employment
PreviousInjuries	Binary variable	Previous car crashes with injuries (major or minor)
PreviousNoInjuries	Binary variable	Previous car crashes without injuries
PT	Binary variable	Main commute mode: walk
PTSatisfaction	Likert scale: very dissatisfied (1) very satisfied (5)	Public transportation satisfaction level
PurpCommute	Binary variable	Stated UAM purpose of use: commute
PurpLeisure	Binary variable	Stated UAM purpose of use: leisure
PurpOther	Binary variable	Stated UAM purpose of use: other
Safety	Ranking from 1 to 9; where 1 is the most important	Importance of safety for UAM adoption
SafetyandControl	Weighted scale from the EFA	Safety and locus of control concerns
ServiceProviderReputation	Likert scale: strongly disagree (1) to strongly agree (5)	The service provider's reputation is very important for gaining trust to use UAM.
ServiceReliabilityTrust	Likert scale: strongly disagree (1) to strongly agree (5)	Service reliability (on-time performance) is a very important feature for trusting UAM.
Sharingperception	Weighted scale from the EFA	Affinity to sharing
Socialmedia	Weighted scale from the EFA	Affinity to social media
SpendEnv	Likert scale: strongly disagree (1) to strongly agree (5)	I am willing to spend a bit more for a product that is more environmentally friendly
Student	Binary variable	Main occupation: student

Continuation of Table 13		
Variable	Type and levels	Description
TripCost	Ranking from 1 to 9; where 1 is the most important	Importance of trip cost for UAM adoption
TripDur	Ranking from 1 to 9; where 1 is the most important	Importance of trip duration for UAM adoption
TripPurp	Ranking from 1 to 9; where 1 is the most important	Importance of trip purpose for UAM adoption
TrustAutomation	Likert scale: strongly disagree (1) to strongly agree (5)	I trust automated systems such as Siri (Apple) or Alexa (Amazon)
TTSavings10min	Likert scale: strongly disagree (1) to strongly agree (5)	10-min travel time saving is important.
TTSavings20min	Likert scale: strongly disagree (1) to strongly agree (5)	20-min travel time saving is important.
TTSavings5min	Likert scale: strongly disagree (1) to strongly agree (5)	5-min travel time saving is important.
TTSavingsImp	Likert scale: strongly disagree (1) to strongly agree (5)	Travel time saving is a key factor in deciding whether or not to use UAM.
Twitter	Likert scale: I don't use it (1) to use it frequently (5)	Frequency of use of Twitter
UAMTimeFrameUse	Dependent variable 0: Unsure 1: Y1 2: Y2-Y3 3: Y4-Y5 4: Y6+ 5: Never	Stated time adoption of UAM

Continuation of Table 13		
Variable	Type and levels	Description
UAMUsefulness	Likert scale: not at all useful (1) extremely useful (5)	Perceived usefulness of UAM
Uber	Likert scale: Not familiar (1) to use frequently (5)	Familiarity and use of Uber
UsedADAS	Likert scale: strongly disagree (1) to strongly agree (5)	I have used ADAS in my own or someone else's car.
VehicChar	Ranking from 1 to 9; where 1 is the most important	Importance of vehicle characteristics for UAM adoption
VOTimeSavings	Weighted scale from the EFA	Value of time savings
WALK	Binary variable	Main commute mode: walk
WhatsApp	Likert scale: I don't use it (1) to use it frequently (5)	Frequency of use of WhatsApp
WillingnesstoShare	Likert scale: very unwilling (1) very willing (5)	Willingness to share a ride with a stranger
30to60	Binary variable	Average commute time on average per day (both ways): 30-60 min
60to90	Binary variable	Average commute time on average per day (both ways): 60-90 min
End of table		

B Additional Plots

B.1 Socio-demographic Distributions of Adoption

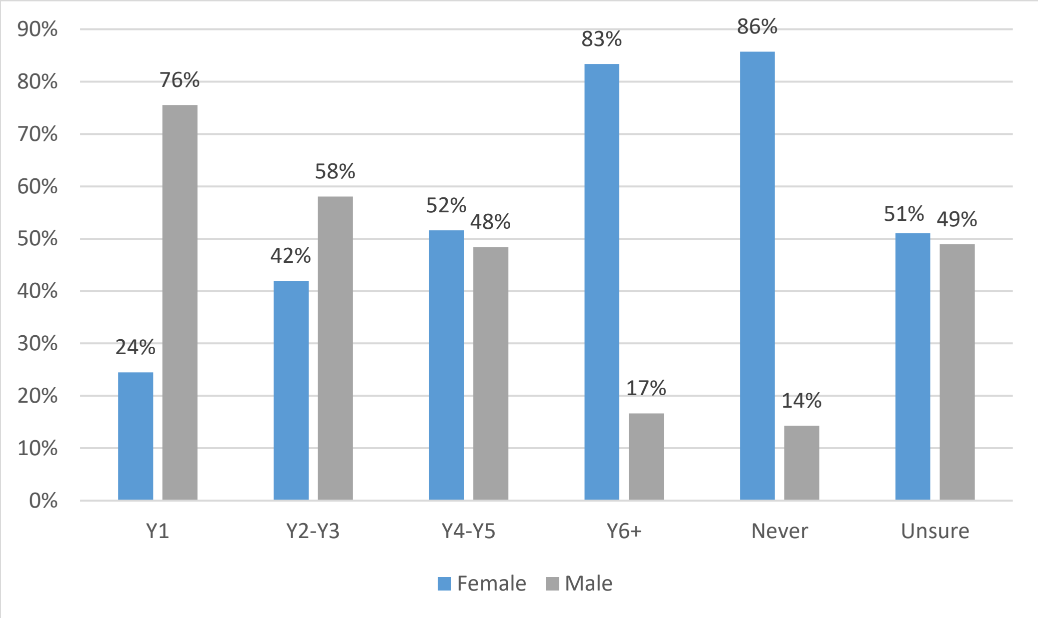


Figure 25: Gender distribution of UAM adoption (N=208)

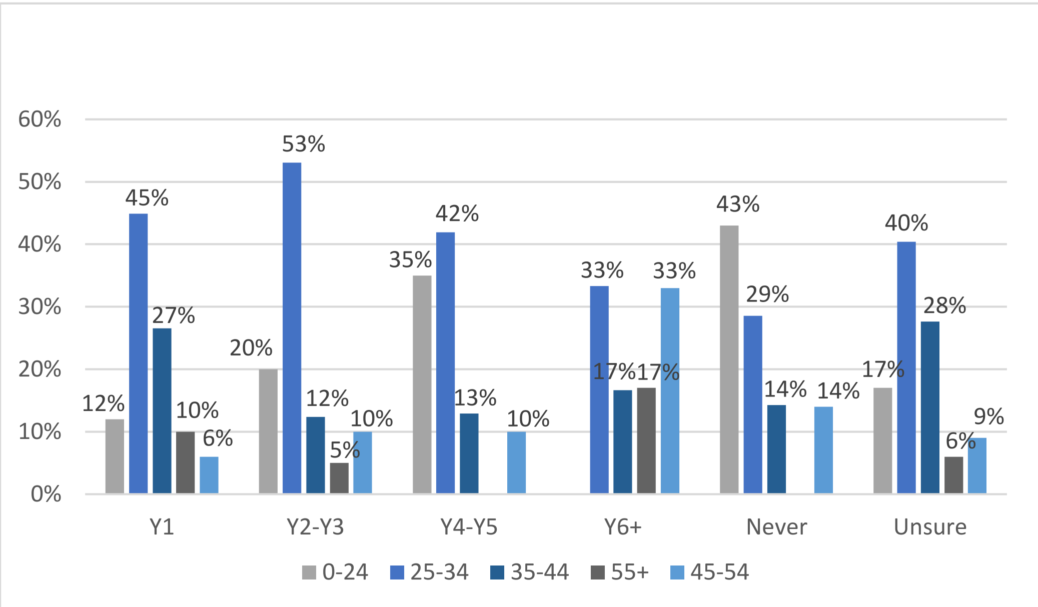


Figure 26: Age distribution of UAM adoption (N=208)

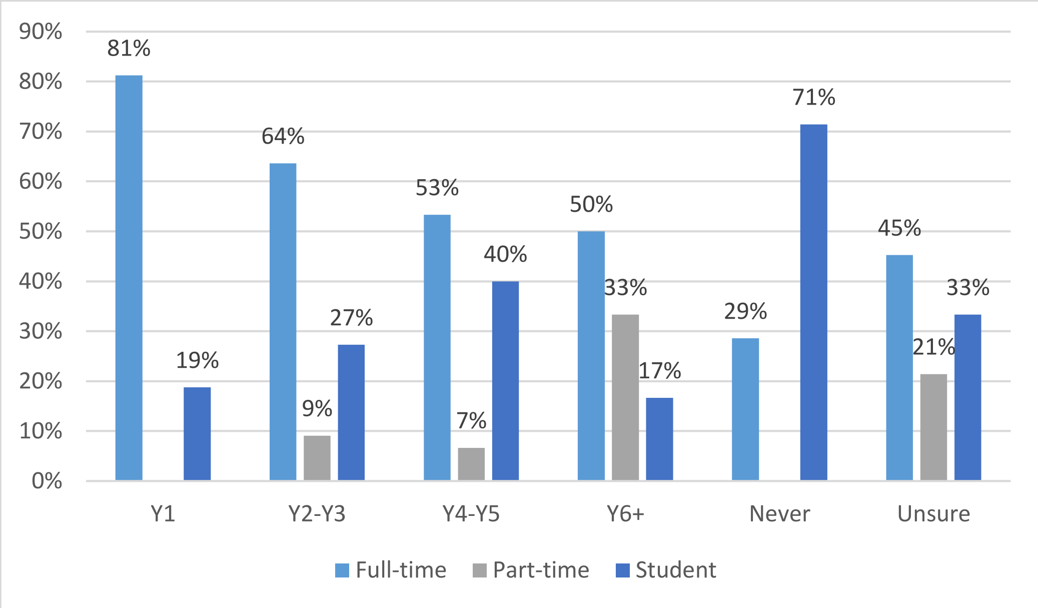


Figure 27: Main occupation distribution of UAM adoption (N=208)

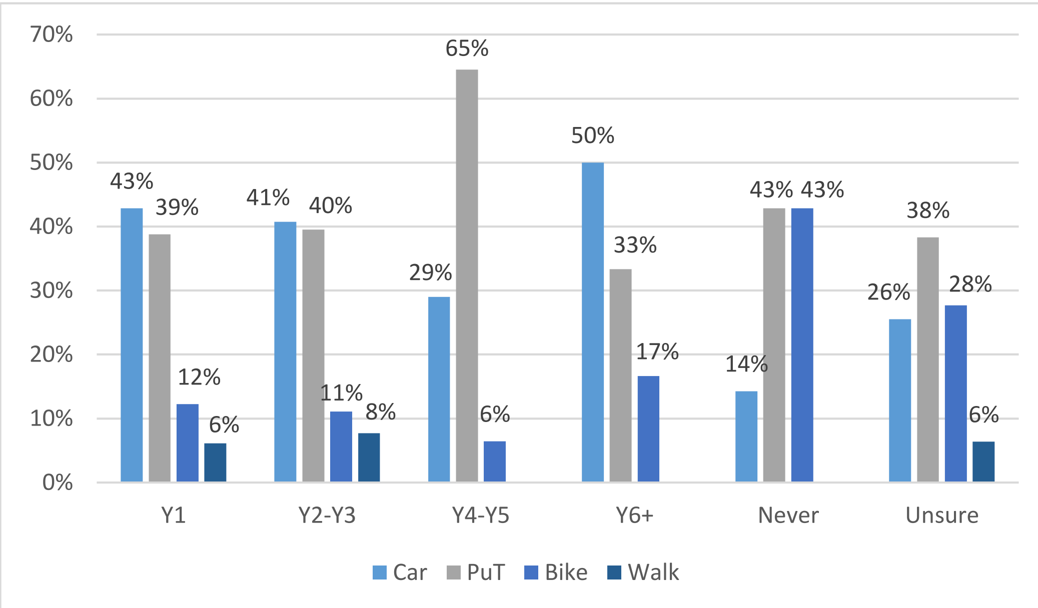


Figure 28: Commute mode distribution of UAM adoption (N=221)

B.2 Adoption by Socio-demographic Groups

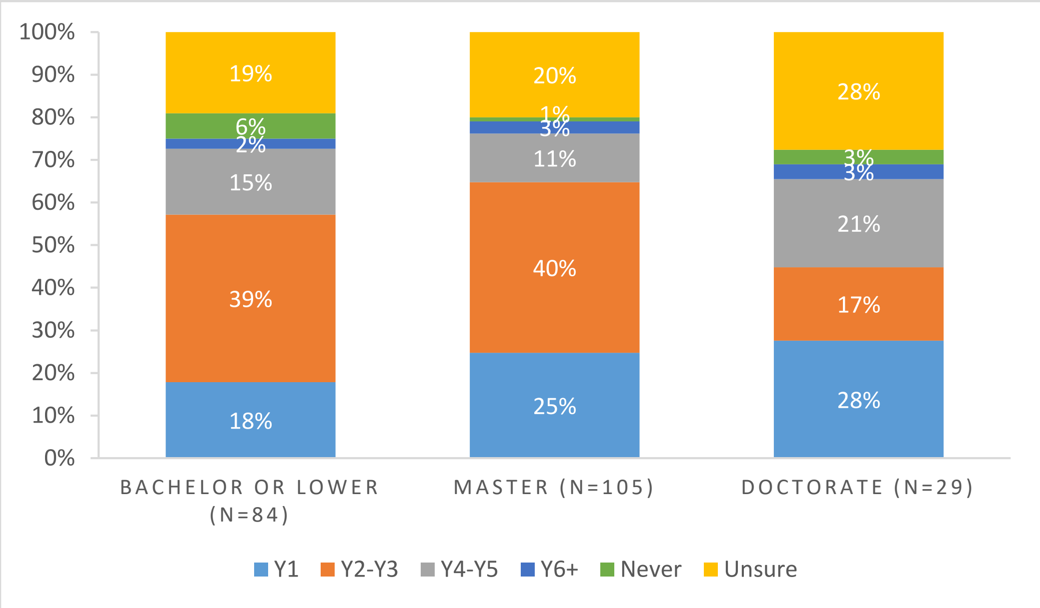


Figure 29: UAM adoption by education (N=218)

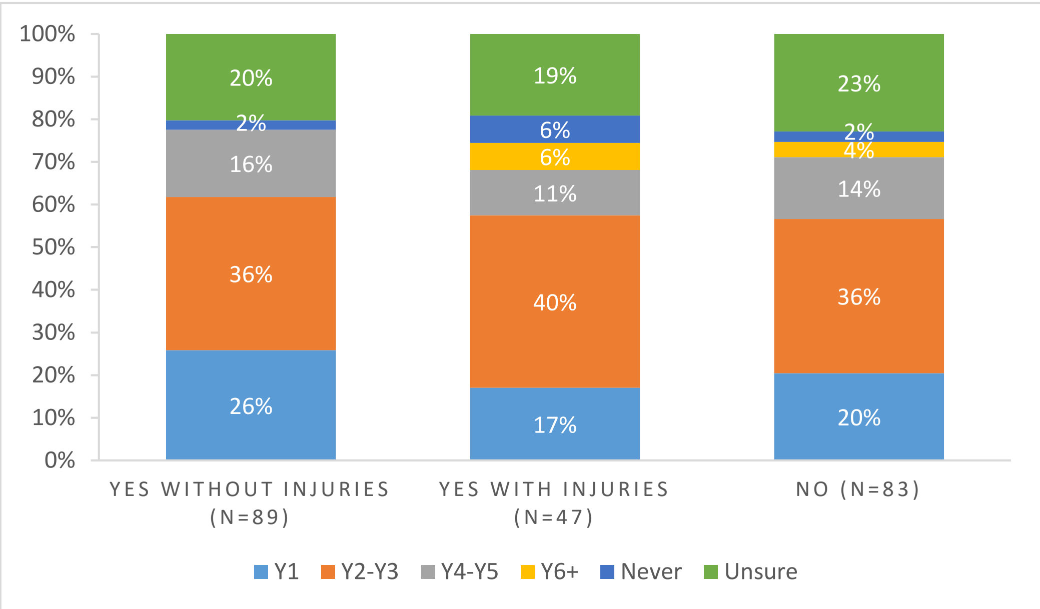


Figure 30: UAM adoption by previous crash experiences (N=219)

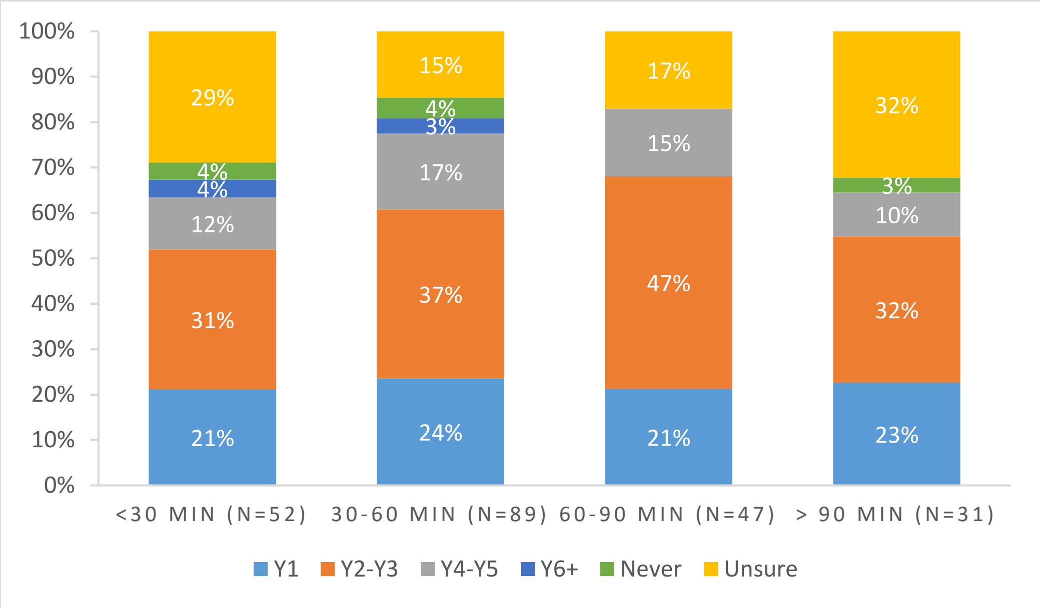


Figure 31: UAM adoption by commute time (N=219)

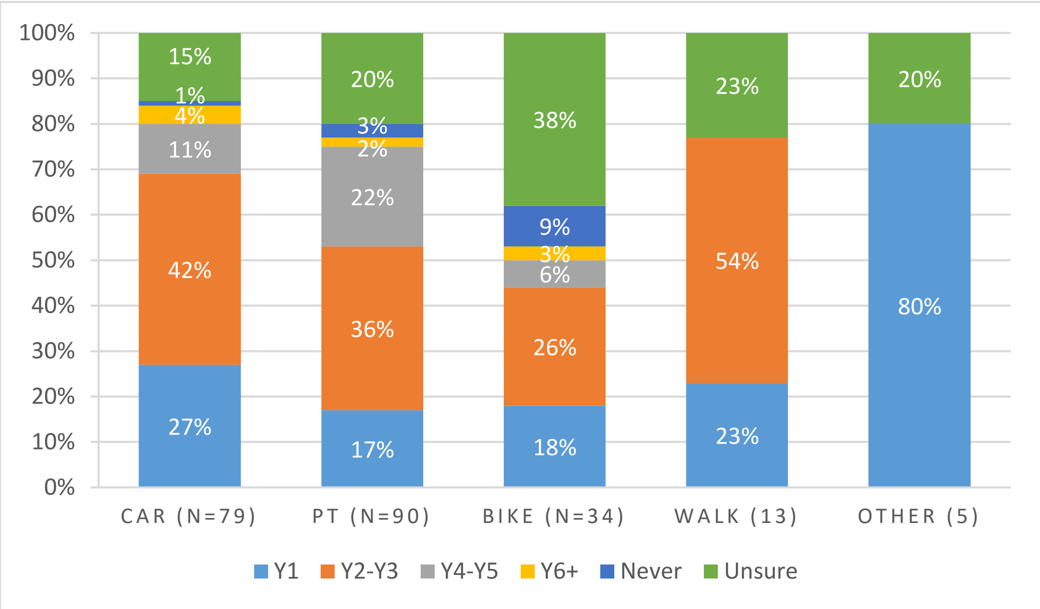


Figure 32: UAM adoption by commute mode (N=221)

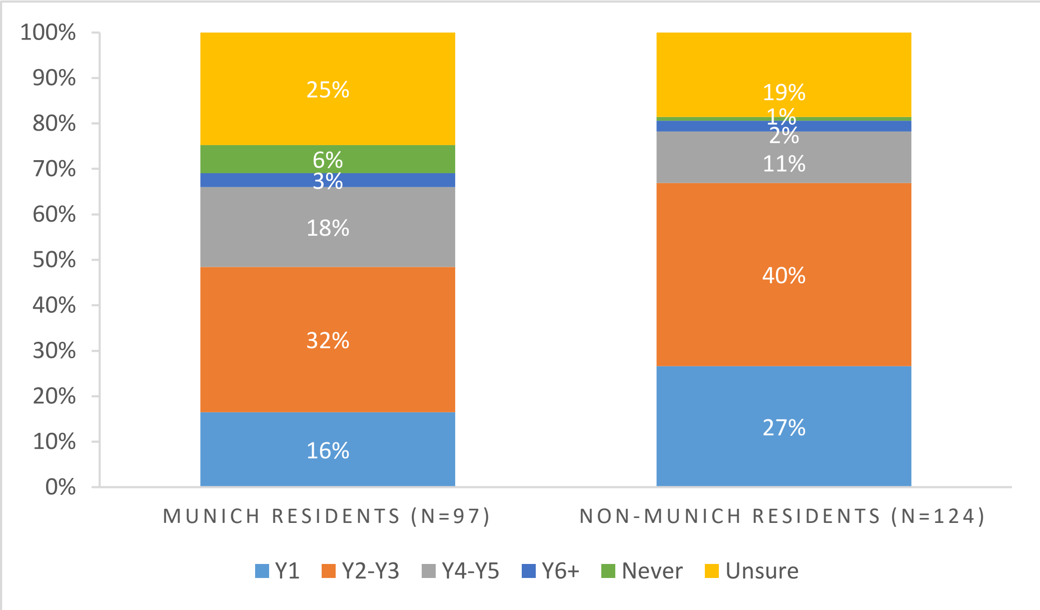


Figure 33: UAM adoption for Munich residents (N=221)

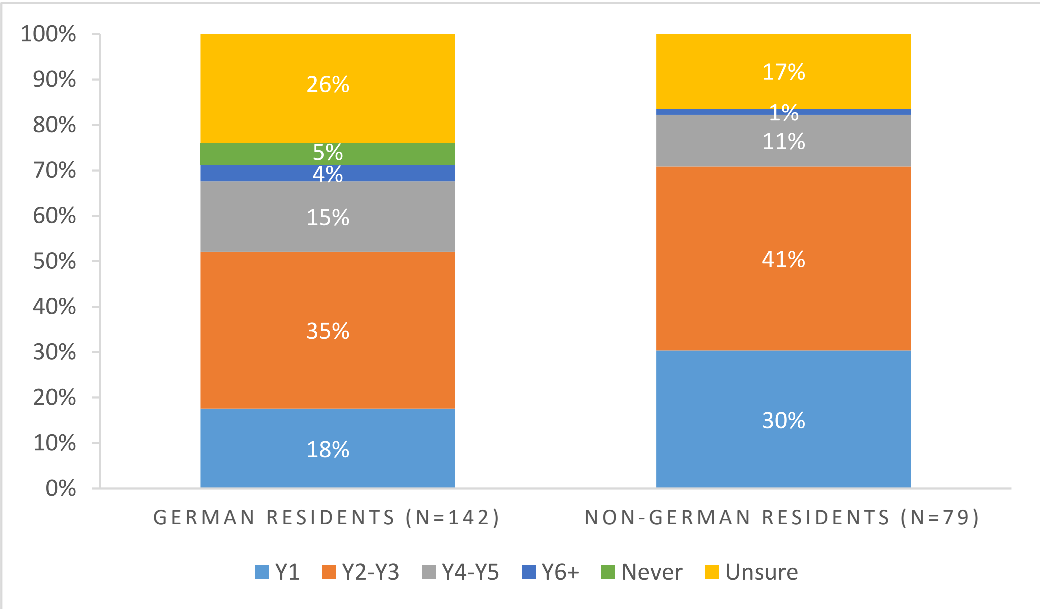


Figure 34: UAM adoption for German residents (N=221)

B.3 Correlation Matrices

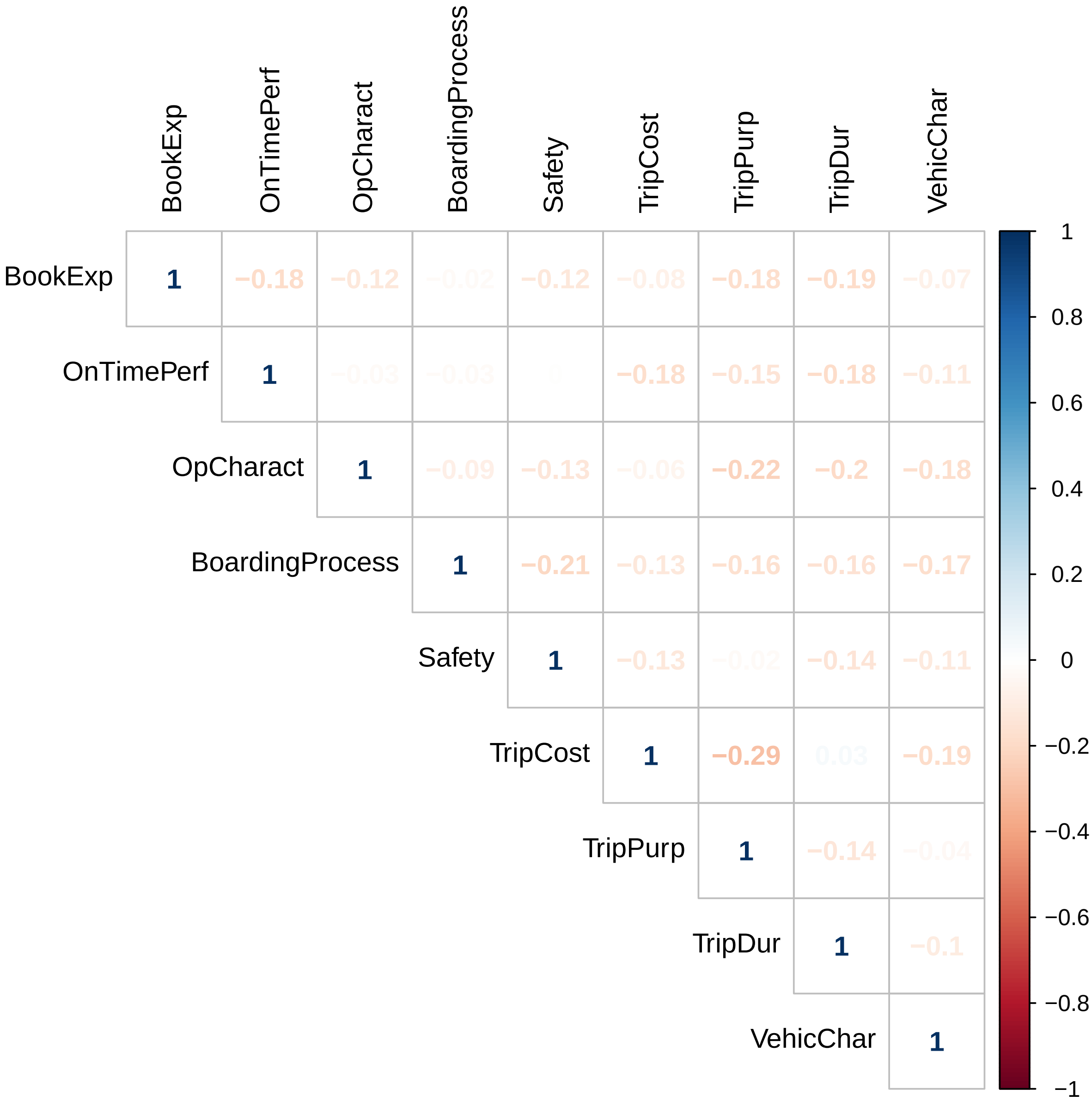


Figure 35: Correlation matrix for factors ranking

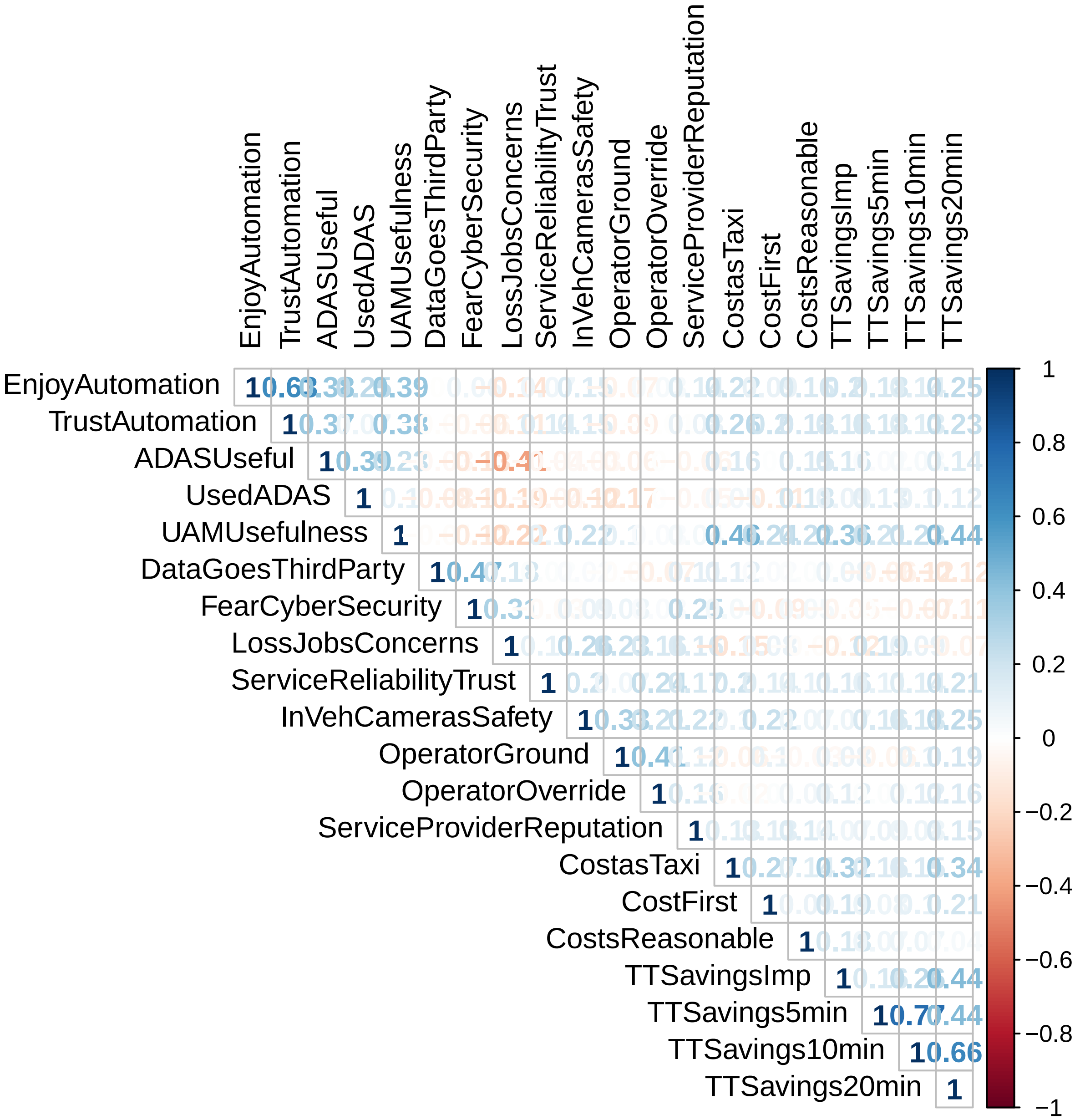


Figure 36: Correlation matrix for the second part of the survey

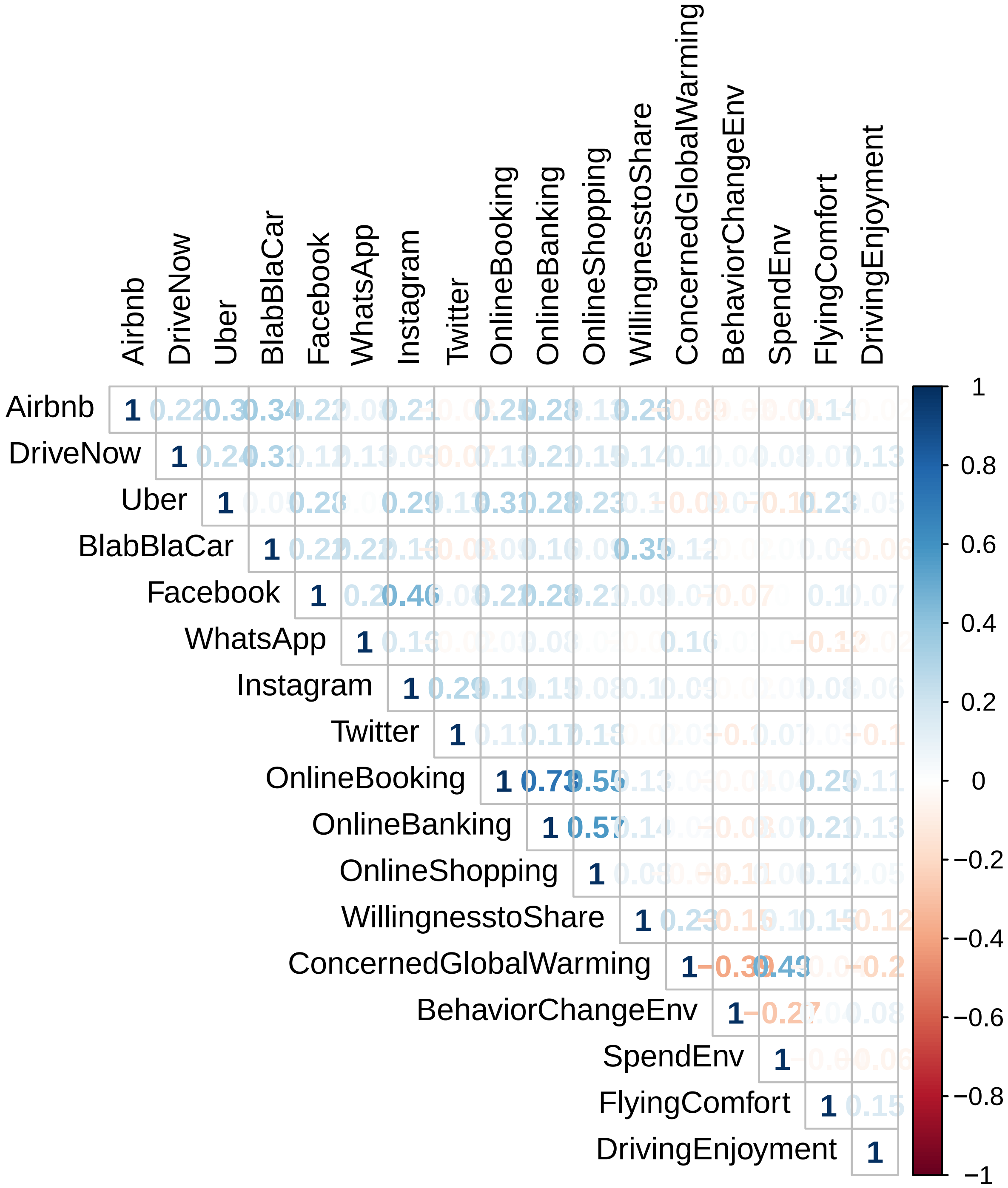


Figure 37: Correlation matrix for the third part of the survey

C Model Specifications

Listing 1: Biogeme MNL Model 1 Specifications

```
V0 =  ASC_Unsure + B_DEU_Unsure * DEU  +  B_PTSat_Unsure * PT_Satisfaction
    + B_Data * DataConcerns + B_FullTime * FullTime
V1 =  ASC_Y1 + B_DEU_Y1 * DEU + B_PTSat_Y1 * PT_Satisfaction +        B_HighInc * Inc4to7
     + B_FullTime * FullTime + B_AUT * AutomationAttitude + B_VOTSavings * VOTimeSavings
V2 =  ASC_Y2Y3 + B_DEU_Y2Y3 * DEU   + B_PTSat_Y2Y3 * PT_Satisfaction
     + B_Safety *  SafetyandControl
V3 = ASC_Y4Y5  + B_DEU_Y4Y5 * DEU + B_PTSat_Y4Y5 * PT_Satisfaction
    + B_VOTSavings * VOTimeSavings  + B_Data * DataConcerns
V4 = ASC_Y6 + B_DEU_Y6 * DEU + B_PTSat_Y6 * PT_Satisfaction
V5 = ASC_Never  + B_DEU_Never * DEU + B_PTSat_Never * PT_Satisfaction

BIOGEME_OBJECT.FORMULAS['Unsure utility'] = V0
BIOGEME_OBJECT.FORMULAS['Y1 utility'] = V1
BIOGEME_OBJECT.FORMULAS['Y2-Y3 utility'] = V2
BIOGEME_OBJECT.FORMULAS['Y4-Y5 utility'] = V3
BIOGEME_OBJECT.FORMULAS['Y6+ utility'] = V4
BIOGEME_OBJECT.FORMULAS['Never utility'] = V5
```

Listing 2: Biogeme MNL Model 2 Specifications

```

# Utility functions

V0 =  ASC_Unsure + B_DEU_Unsure * DEU + B_AUT_Unsure * AutomationAttitude
     + B_Female_Unsure * FEMALE + B_CrashInjuries_Unsure * PreviousInjuries
V1 =  ASC_Y1 + B_DEU_Y1 * DEU +  B_AUT_Y1 * AutomationAttitude +  B_Data_Y1 * DataConcerns
     + B_Safety_Y1 * SafetyandControl + B_FullTime_Y1 * FullTime + B_Female_Y1 * FEMALE
         + B_CrashInjuries_Y1 * PreviousInjuries
V2 =  B_AUT_Y2Y3 * AutomationAttitude  + B_FullTime_Y2Y3 * FullTime + B_Female_Y2Y3 * FEMALE
     + B_Doctorate_Y2Y3 * DOCTORATE + B_CrashInjuries_Y2Y3 * PreviousInjuries
V3 =   B_VOTSavings_Y4Y5 * VOTimeSavings  +  B_AUT_Y4Y5 * AutomationAttitude
      + B_Safety_Y4Y5 * SafetyandControl + B_HighInc_Y4Y5 * Inc4to7 + B_Female_Y4Y5 * FEMALE
          + B_CrashInjuries_Y4Y5 * PreviousInjuries
```

```
V4 = ASC_Y6
V5 = ASC_Never

BIOGEME_OBJECT.FORMULAS['Unsure utility'] = V0
BIOGEME_OBJECT.FORMULAS['Y1 utility'] = V1
BIOGEME_OBJECT.FORMULAS['Y2-Y3 utility'] = V2
BIOGEME_OBJECT.FORMULAS['Y4-Y5 utility'] = V3
BIOGEME_OBJECT.FORMULAS['Y6+ utility'] = V4
BIOGEME_OBJECT.FORMULAS['Never utility'] = V5
```

Listing 3: Biogeme MNL Model 3 Specifications

```
V0 =   B_AUT * AutomationAttitude + B_DEU_Unsure * DEU
         + B_Female_Unsure * FEMALE +  B_CrashInjuries * PreviousInjuries
         + B_SP_Reputation * ServiceProviderReputation + B_Whatsapp * WhatsApp
         + B_SocialMedia * Socialmedia
V1 =  ASC_Y1 + B_DEU_Y1 * DEU + B_AUT_Y1 * AutomationAttitude +  B_Data_Y1 * DataConcerns
      + B_Safety * SafetyandControl + B_FullTime * FullTime + B_Female_Y1 * FEMALE
          + B_CrashInjuries_Y1 * PreviousInjuries + B_SP_Reputation * ServiceProviderReputation
          + B_CostasTaxi_Y1 * CostasTaxi  + B_Whatsapp * WhatsApp + B_SocialMedia * Socialmedia
V2 =   B_AUT * AutomationAttitude + B_FullTime * FullTime + B_Female_Y2Y3 * FEMALE
       + B_CrashInjuries * PreviousInjuries + B_Doctorate_Y2Y3 * DOCTORATE + B_CostFirst * CostFirst
           + B_TT_Imp * TTSavingsImp + B_Whatsapp_Y2Y3 * WhatsApp + B_SocialMedia * Socialmedia

V3 =  B_AUT * AutomationAttitude + B_VOTSavings_Y4Y5 * VOTimeSavings   + B_Safety * SafetyandControl
      + B_HighInc_Y4Y5 * Inc4to7 + B_Female_Y4Y5 * FEMALE + B_CrashInjuries * PreviousInjuries
          + B_CostFirst * CostFirst + B_PT_Y4Y5 * PuT  + B_Whatsapp * WhatsApp
          + B_SocialMedia * Socialmedia
V4 = ASC_Y6_No

BIOGEME_OBJECT.FORMULAS['Unsure utility'] = V0
BIOGEME_OBJECT.FORMULAS['Y1 utility'] = V1
BIOGEME_OBJECT.FORMULAS['Y2-Y3 utility'] = V2
BIOGEME_OBJECT.FORMULAS['Y4-Y5 utility'] = V3
BIOGEME_OBJECT.FORMULAS['Y6+ or Never utility'] = V4
```

Listing 4: Biogeme MNL Model 4 Specifications

```
V0 =   B_AUT * AutomationAttitude + B_DEU_Unsure * DEU
         + B_Female_2 * FEMALE +  B_CrashInjuries * PreviousInjuries
         + B_SP_Reputation * ServiceProviderReputation + B_Whatsapp * WhatsApp
         + B_SocialMedia * Socialmedia
V1 =  ASC_Y1 + B_DEU_Y1 * DEU + B_AUT_Y1 * AutomationAttitude +  B_Data_Y1 * DataConcerns
      + B_Safety * SafetyandControl + B_FullTime * FullTime + B_Female_1 * FEMALE
          + B_CrashInjuries_Y1 * PreviousInjuries + B_SP_Reputation * ServiceProviderReputation
          + B_CostasTaxi_Y1 * CostasTaxi  + B_Whatsapp * WhatsApp + B_SocialMedia * Socialmedia
V2 =   B_AUT * AutomationAttitude + B_FullTime * FullTime + B_Female_1 * FEMALE
       + B_CrashInjuries * PreviousInjuries + B_Doctorate_Y2Y3 * DOCTORATE + B_CostFirst * CostFirst
           + B_TT_Imp * TTSavingsImp + B_Whatsapp_Y2Y3 * WhatsApp + B_SocialMedia * Socialmedia

V3 =  B_AUT * AutomationAttitude + B_VOTSavings_Y4Y5 * VOTimeSavings   + B_Safety * SafetyandControl
      + B_HighInc_Y4Y5 * Inc4to7 + B_Female_2 * FEMALE + B_CrashInjuries * PreviousInjuries
          + B_CostFirst * CostFirst + B_PT_Y4Y5 * PuT  + B_Whatsapp * WhatsApp
          + B_SocialMedia * Socialmedia
V4 = ASC_Y6_No

BIOGEME_OBJECT.FORMULAS['Unsure utility'] = V0
BIOGEME_OBJECT.FORMULAS['Y1 utility'] = V1
BIOGEME_OBJECT.FORMULAS['Y2-Y3 utility'] = V2
BIOGEME_OBJECT.FORMULAS['Y4-Y5 utility'] = V3
BIOGEME_OBJECT.FORMULAS['Y6+ or Never utility'] = V4
```

Listing 5: Biogeme MNL Model 5 Specifications

```
V0 =   B_AUT * AutomationAttitude + B_DEU_Unsure * DEU
         + B_Female * FEMALE +  B_CrashInjuries * PreviousInjuries
         + B_SP_Reputation * ServiceProviderReputation + B_Whatsapp * WhatsApp
         + B_SocialMedia * Socialmedia
V1 =  ASC_Y1 + B_AUT_Y1 * AutomationAttitude +  B_Data_Y1 * DataConcerns
      + B_Safety * SafetyandControl + B_FullTime * FullTime + B_Female * FEMALE
          + B_CrashInjuries_Y1 * PreviousInjuries + B_SP_Reputation * ServiceProviderReputation
          + B_CostasTaxi_Y1 * CostasTaxi  + B_Whatsapp * WhatsApp + B_SocialMedia * Socialmedia
V2 =   B_AUT * AutomationAttitude + B_FullTime * FullTime + B_Female * FEMALE
```

```
        + B_CrashInjuries * PreviousInjuries + B_Doctorate_Y2Y3 * DOCTORATE + B_CostFirst * CostFirst
            + B_TT_Imp * TTSavingsImp + B_Whatsapp * WhatsApp + B_SocialMedia * Socialmedia

V3 =  B_AUT * AutomationAttitude + B_VOTSavings_Y4Y5 * VOTimeSavings   + B_Safety * SafetyandControl
       + B_HighInc_Y4Y5 * Inc4to7 + B_Female * FEMALE + B_CrashInjuries * PreviousInjuries
           + B_CostFirst * CostFirst + B_PT_Y4Y5 * PuT  + B_Whatsapp * WhatsApp
           + B_SocialMedia * Socialmedia
V4 = ASC_Y6_No

BIOGEME_OBJECT.FORMULAS['Unsure utility'] = V0
BIOGEME_OBJECT.FORMULAS['Y1 utility'] = V1
BIOGEME_OBJECT.FORMULAS['Y2-Y3 utility'] = V2
BIOGEME_OBJECT.FORMULAS['Y4-Y5 utility'] = V3
BIOGEME_OBJECT.FORMULAS['Y6+ or Never utility'] = V4
```

Listing 6: Biogeme OLM Case 1 Model 1 Specifications

```
tau1     = Beta('tau1',-1,-10000,0,0,"$\tau_1$")
delta2   = Beta('delta2',2,0,10000,0,"$\delta_2$")
tau2 = tau1 + delta2
delta3   = Beta('delta3',2,0,10000,0,"$\delta_3$")
tau3 = tau2 + delta3
delta4   = Beta('delta4',2,0,10000,0,"$\delta_4$")
tau4 = tau3 + delta4

U =   B_AUT * AutomationAttitude + B_DEU * DEU + B_Data * DataConcerns
       + B_Safety * SafetyandControl + B_FullTime * FullTime + B_Female * FEMALE
           +  B_CrashInjuries * PreviousInjuries + B_SP_Reputation * ServiceProviderReputation
           + B_Whatsapp * WhatsApp + B_SocialMedia * Socialmedia + B_CostasTaxi * CostasTaxi
           + B_TT_Imp * TTSavingsImp +  B_Doctorate * DOCTORATE + B_CostFirst * CostFirst
           + B_PT * PuT + B_HighInc * Inc4to7 + B_VOTSavings * VOTimeSavings

ChoiceProba = {
     1: 1-logisticcdf(U-tau1),
     2: logisticcdf(U-tau1)- logisticcdf(U-tau2),
         3: logisticcdf(U-tau2)- logisticcdf(U-tau3),
```

```
    4: logisticcdf(U-tau3)- logisticcdf(U-tau4),
        5: logisticcdf(U-tau4)
        }

BIOGEME_OBJECT.FORMULAS['Utility'] = U
```

Listing 7: Biogeme OLM Case 1 Model 2 Specifications

```
tau1      = Beta('tau1',-1,-10000,0,0,"$\tau_1$")
delta2    = Beta('delta2',2,0,10000,0,"$\delta_2$")
tau2 = tau1 + delta2
delta3    = Beta('delta3',2,0,10000,0,"$\delta_3$")
tau3 = tau2 + delta3
delta4    = Beta('delta4',2,0,10000,0,"$\delta_4$")
tau4 = tau3 + delta4


U =   B_AUT * AutomationAttitude + B_DEU * DEU + B_Data * DataConcerns
      + B_FullTime * FullTime  + B_CostasTaxi * CostasTaxi


ChoiceProba = {
    1: 1-logisticcdf(U-tau1),
    2: logisticcdf(U-tau1)- logisticcdf(U-tau2),
        3: logisticcdf(U-tau2)- logisticcdf(U-tau3),
    4: logisticcdf(U-tau3)- logisticcdf(U-tau4),
        5: logisticcdf(U-tau4)
        }

BIOGEME_OBJECT.FORMULAS['Utility'] = U
```

Listing 8: Biogeme OLM Case 2 Specifications

```
tau1      = Beta('tau1',-1,-10000,0,0,"$\tau_1$")
delta2    = Beta('delta2',2,0,10000,0,"$\delta_2$")
tau2 = tau1 + delta2
delta3    = Beta('delta3',2,0,10000,0,"$\delta_3$")
```

```
tau3 = tau2 + delta3

U =   B_AUT * AutomationAttitude + B_DEU * DEU + B_Data * DataConcerns
     + B_FullTime * FullTime + B_CostasTaxi * CostasTaxi

ChoiceProba = {
     1: 1-logisticcdf(U-tau1),
     2: logisticcdf(U-tau1)- logisticcdf(U-tau2),
          3: logisticcdf(U-tau2)- logisticcdf(U-tau3),
     4: logisticcdf(U-tau3)
          }

BIOGEME_OBJECT.FORMULAS['Utility'] = U
```

D Additional Models

Table 14: Adoption MNL for all outcomes except Y6+ and Never

	Model 1		Model 2		Model 3	
			Unsure			
Female	0.493	(0.91)	0.391	(0.69)	0.401	(0.71)
German as a starting language	1.761**	(3.15)	1.968**	(3.21)	1.851**	(3.17)
PT satisfaction	0.349+	(1.69)	0.290	(1.30)	0.239	(1.07)
Value of time savings	-0.242	(-1.60)	-0.214	(-1.39)	-0.258	(-1.64)
Affinity to automation	-0.328*	(-2.20)	-0.313*	(-2.05)	-0.299+	(-1.95)
Data concerns	0.319+	(1.79)	0.346+	(1.87)	0.324+	(1.77)
Safety concerns	0.314+	(1.72)	0.251	(1.36)	0.251	(1.36)
UAM purpose commute	-0.216	(-0.33)	-0.199	(-0.29)		
Previous crases with injuries	0.687	(1.06)	0.749	(1.12)	0.793	(1.21)
Age: < 24 years old	0.802	(1.14)	-0.259	(-0.32)	-0.272	(-0.34)
Age: 35-55 years old	0.227	(0.39)	0.228	(0.37)		
Doctorate (or higher) level of education			-0.387	(-0.53)	-0.218	(-0.31)
Full-time employment			-1.779**	(-2.87)	-1.754**	(-2.79)
Residence in Munich			-0.296	(-0.53)		
Driver's license and car access					0.043	(0.13)
High income: 3000-7000 €					-0.581	(-1.04)
Constant	-1.419	(-0.76)	0.334	(0.17)	0.817	(0.39)
			Y1: Base-Case			
			Y2-Y3:			
Female	0.144	(0.30)	0.229	(0.47)	0.141	(0.29)
German as a survey language	1.062*	(2.12)	1.370*	(2.50)	1.338*	(2.57)
PT satisfaction	0.242	(1.44)	0.287	(1.59)	0.197	(1.07)
Value of time savings	-0.052	(-0.42)	-0.052	(-0.41)	-0.046	(-0.36)
Affinity to automation	-0.234+	(-1.85)	-0.220+	(-1.73)	-0.224+	(-1.76)
Data concerns	0.221	(1.48)	0.247	(1.63)	0.265+	(1.76)
Safety concerns	0.451**	(2.80)	0.437**	(2.64)	0.433**	(2.61)
UAM purpose commute	-0.280	(-0.54)	-0.295	(-0.56)		
Previous crashes with injuries	0.994+	(1.81)	0.980+	(1.76)	0.922+	(1.70)
Age: < 24 years old	0.652	(1.10)	0.077	(0.11)	0.139	(0.20)
Age: 35-44 years old	-0.878+	(-1.68)	-0.699	(-1.27)		
Doctorate (or higher) level of education			-1.273+	(-1.79)	-1.349+	(-1.96)
Full-time employment			-0.759	(-1.37)	-0.686	(-1.23)
Residence in Munich			-0.495	(-1.02)		
Driver's license and car access					-0.239	(-0.85)
High Income: 3000-7000 €					-0.094	(-0.21)
Constant	-2.983+	(-1.73)	-2.367	(-1.28)	-2.176	(-1.15)
			Y4-Y5:			
Female	0.500	(0.87)	0.488	(0.83)	0.528	(0.89)

Continuation of Table 14						
	(1)		(2)		(3)	
	Model 1		Model 2		Model 3	
German as a starting language	1.147+	(1.79)	1.254+	(1.84)	1.068	(1.60)
PT satisfaction	0.487*	(2.15)	0.413+	(1.69)	0.314	(1.29)
Value of time savings	0.445**	(2.59)	0.465**	(2.59)	0.421*	(2.36)
Affinity to automation	-0.368*	(-2.17)	-0.359*	(-2.09)	-0.405*	(-2.27)
Data concerns	0.609**	(3.14)	0.644**	(3.25)	0.581**	(3.01)
Safety concerns	-0.049	(-0.25)	-0.060	(-0.30)	-0.087	(-0.43)
UAM purpose commute	-1.158	(-1.59)	-1.102	(-1.50)		
Previous crashes with injuries	0.640	(0.89)	0.706	(0.97)	0.576	(0.79)
Age: <24 years old	1.594*	(2.32)	1.283	(1.59)	1.058	(1.30)
Age: 35-44 years old	-0.387	(-0.55)	-0.517	(-0.69)		
Doctorate (or higher) level of education			0.300	(0.39)	0.713	(0.93)
Full-time employment			-0.538	(-0.77)	-0.442	(-0.62)
Residence in Munich			0.223	(0.36)		
Driver's license and car access					-0.553	(-1.49)
High income: 3000-7000€					-1.865*	(-2.12)
Constant	-5.158*	(-2.34)	-4.955*	(-2.12)	-2.656	(-1.16)
Observations	208		208		208	
Pseudo R^2	0.178		0.209		0.215	

t statistics in parentheses

+ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

End of Table

Table 15: Adoption OLM for certain adopters (excluding Y6+ and Never) including Munich subsample

	(1)		(2)		(3)		(4)		(5)	
	Model 1		Model 2		Model 3		Model 4		Munich subsample	
UAM time-frame use										
Female	0.583^{+}	(1.80)	0.295	(0.82)	0.413	(1.22)	0.286	(0.84)	1.138*	(2.10)
German starting language	0.619^{+}	(1.88)	0.708^{+}	(1.75)	0.673^{+}	(1.73)	0.631	(1.62)	0.959	(1.63)
Commute mode: car	-0.122	(-0.37)	-0.024	(-0.06)						
Doctorate level of education	-0.074	(-0.14)								
Full-time employment	-0.688*	(-1.99)	-0.664^{+}	(-1.81)	-0.381	(-0.97)				
Commute time: >90 min	-0.270	(-0.57)								
Commute mode: bike			-0.768	(-1.37)	-0.846	(-1.57)				
PT satisfaction			0.286^{+}	(1.85)	0.329*	(2.38)	0.181	(1.19)	0.164	(0.63)
Value of time savings			0.180^{+}	(1.93)	0.179*	(1.99)	0.242*	(2.44)	0.326^{+}	(1.87)
Affinity to automation			-0.243*	(-2.22)	-0.215*	(-2.07)	-0.248*	(-2.32)	-0.214	(-1.27)
Data concerns			0.296*	(2.57)	0.316**	(2.89)	0.338**	(3.05)	0.478*	(2.52)
Previous crashes with injuries			0.187	(0.47)						
Affinity to online services			-0.089	(-0.80)						
Environmental awareness			0.092	(0.59)						
Affinity to sharing			0.126	(1.26)						
Affinity to social media			-0.002	(-0.02)						
Age: < 24 years old					0.758^{+}	(1.65)				
Driver's license and car access							-0.524*	(-2.47)	-0.927**	(-2.65)
UAM purpose commute							-0.432	(-1.03)	0.109	(0.14)
Income level: 3000-7000€							-0.955*	(-1.97)	-1.254	(-1.38)
Residence in Munich							0.010	(0.03)	0.000	(.)
Y1 | Y2-Y3	-0.985**	(-2.88)	0.679	(0.37)	1.028	(0.87)	0.188	(0.15)	1.682	(0.91)
Y2-Y3 | Y4-Y5	1.465**	(4.14)	3.410^{+}	(1.83)	3.757**	(3.09)	2.957*	(2.31)	4.562*	(2.35)
Observations	161		161		161		161		64	
Pseudo R^2	0.048		0.119		0.120		0.131		0.188	

t statistics in parentheses

$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

Table 16: Adoption binary logit model for uncertain respondents

	(1) Model 1	
Unsure		
German as a starting language	0.885^{*}	(2.30)
Residence in Munich	-0.250	(-0.66)
Full-time employment	-0.772^{*}	(-2.09)
Value of time savings	-0.293^{**}	(-3.34)
High income levels: 3000-7000 €	-1.993^{+}	(-1.86)
Commute time: > 90 min	0.936^{+}	(1.93)
Constant	1.121	(1.36)
Observations	221	
Pseudo R^2	0.165	

t statistics in parentheses

$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

Table 20: Adoption NL Case 1

Parameter number	Description	Coeff. estimate	Robust Asympt. std. error	t-stat	p-value
1	ASC Y6+/Never	3.84	1.22	3.16	0.00
2	Affinity to automation	0.853	0.225	3.79	0.00
3	Data concerns Y1	-0.0695	0.0487	-1.43	0.15
4	Not first five years	1.00	1.80e+308	0.00	1.00

Summary statistics

Number of observations = 221

Number of excluded observations = 0

Number of estimated parameters = 4

$$\mathcal{L}(\beta_0) = -355.686$$
$$\mathcal{L}(\hat{\beta}) = -323.635$$
$$-2[\mathcal{L}(\beta_0) - \mathcal{L}(\hat{\beta})] = 64.102$$
$$\rho^2 = 0.090$$
$$\bar{\rho}^2 = 0.079$$

Table 17: Adoption MNL Model 1

Parameter number	Description	Coeff. estimate	Robust Asympt. std. error	t-stat	p-value
1	ASC Never	-0.0598	1.79	-0.03	0.97
2	ASC Unsure	1.58	1.30	1.22	0.22
3	ASC Y2-Y3	0.0207	1.49	0.01	0.99
4	ASC Y4-Y5	-0.826	1.20	-0.69	0.49
5	ASC Y6+	0.255	1.76	0.15	0.88
6	Affinity to automation	0.187	0.0952	1.97	0.05
7	Starting language German Never	1.03	2.61e+005	0.00	1.00
8	Starting language German Unsure	0.846	2.77e+005	0.00	1.00
9	Starting language German Y1	-0.866	2.09e+005	-0.00	1.00
10	Starting language Y2-Y3	-0.113	2.69e+005	-0.00	1.00
11	Starting language Y4-Y5	-0.120	2.82e+005	-0.00	1.00
12	Starting language Y6+	0.112	2.50e+005	0.00	1.00
13	Data concerns Y4-Y5, Unsure	0.203	0.0993	2.05	0.04
14	Full-time employment Y1, Unsure	-0.0366	0.298	-0.12	0.90
15	High income 3000-7000 €Y1	0.779	0.399	1.95	0.05
16	PT satisfaction Never	0.0930	1.80e+308	0.00	1.00
17	PT satisfaction Unsure	0.0205	1.80e+308	0.00	1.00
18	PT satisfaction Y1	-0.281	1.80e+308	-0.00	1.00
19	PT satisfaction Y2-Y3	-0.0787	1.80e+308	-0.00	1.00
20	PT satisfaction Y4-Y5	0.155	1.80e+308	0.00	1.00
21	PT satisfaction Y6	0.120	1.80e+308	0.00	1.00
22	Safety concerns Y2-Y3	0.393	0.124	3.17	0.00
23	Value of time savings Y1, Y4-Y5	0.244	0.0697	3.51	0.00

Summary statistics

Number of observations = 221

Number of excluded observations = 0

Number of estimated parameters = 23

$$\begin{aligned}
\mathcal{L}(\beta_0) &= -395.979 \\
\mathcal{L}(\hat{\beta}) &= -299.727 \\
-2[\mathcal{L}(\beta_0) - \mathcal{L}(\hat{\beta})] &= 192.503 \\
\rho^2 &= 0.243 \\
\bar{\rho}^2 &= 0.185
\end{aligned}$$

Table 18: Adoption MNL Model 2

Parameter number	Description	Coeff. estimate	Robust Asympt. std. error	t-stat	p-value
1	ASC Never	2.95	1.96	1.51	0.13
2	ASC Unsure	0.835	1.07	0.78	0.43
3	ASC Y6+	2.79	1.87	1.49	0.14
4	Affinity to automation unsure	1.01	0.410	2.47	0.01
5	Affinity to automation Y1	1.51	0.413	3.66	0.00
6	Affinity to automation Y2-Y3	1.24	0.399	3.10	0.00
7	Affinity to automation Y4-Y5	1.16	0.421	2.75	0.01
8	Previous crashes with injuries unsure	-1.85	0.855	-2.16	0.03
9	Previous crashes with injuries Y1	-2.55	0.992	-2.57	0.01
10	Previous crashes with injuries Y2-Y3	-1.82	0.846	-2.15	0.03
11	Previous crashes with injuries Y4-Y5	-2.06	0.954	-2.16	0.03
12	Starting language German unsure	0.701	0.428	1.64	0.10
13	Starting language German Y1	-1.08	0.520	-2.08	0.04
14	Data concerns Y1	-0.313	0.132	-2.37	0.02
15	Doctorate level or higher Y2-Y3	-1.38	0.531	-2.61	0.01
16	Female respondents Unsure	-2.19	0.864	-2.53	0.01
17	Female respondents Y1	-2.48	0.929	-2.67	0.01
18	Female respondents Y2-Y3	-2.22	0.844	-2.63	0.01
19	Female respondents Y4-Y5	-2.19	0.917	-2.39	0.02
20	Full-time employment Y1	1.57	0.506	3.11	0.00
21	Full-time employment Y2-Y3	0.607	0.340	1.79	0.07
22	High income levels 3000-7000 €Y4-Y5	-1.54	0.664	-2.32	0.02
23	Safety concerns Y1	-0.242	0.108	-2.24	0.03
24	Safety concerns Y4-Y5	-0.364	0.125	-2.90	0.00
25	Value of time savings Y4-Y5	0.385	0.117	3.28	0.00

Summary statistics

Number of observations = 221

Number of excluded observations = 0

Number of estimated parameters = 25

$$\begin{aligned}
\mathcal{L}(\beta_0) &= -395.979 \\
\mathcal{L}(\hat{\beta}) &= -267.377 \\
-2[\mathcal{L}(\beta_0) - \mathcal{L}(\hat{\beta})] &= 257.203 \\
\rho^2 &= 0.325 \\
\bar{\rho}^2 &= 0.262
\end{aligned}$$

Table 19: Adoption OLM Case 1 Model 1

Parameter number	Description	Coeff. estimate	Robust Asympt. std. error	t-stat	p-value
1	Affinity to automation	-0.247	0.0885	-2.79	0.01
2	Cost first	0.101	0.125	0.80	0.42
3	Cost as Taxi	-0.353	0.145	-2.44	0.01
4	Previous crashes with injuries	0.639	0.356	1.79	0.07
5	Starting language German	0.532	0.344	1.55	0.12
6	Data concerns	0.224	0.0847	2.64	0.01
7	Doctorate (or higher) level of education	0.412	0.442	0.93	0.35
8	Female respondents	0.456	0.314	1.45	0.15
9	Full-time employment	-0.784	0.322	-2.44	0.01
10	High income: 3000-7000 €	-0.422	0.335	-1.26	0.21
11	PT commute mode	0.124	0.297	0.42	0.68
12	Service provider reputation	-0.101	0.180	-0.56	0.57
13	Safety concerns	0.0603	0.107	0.56	0.57
14	Affinity to social media	-0.0989	0.0949	-1.04	0.30
15	TT important for UAM	-0.249	0.172	-1.45	0.15
16	Value of time savings	-0.0100	0.0749	-0.13	0.89
17	Affinity to WhatsApp	-0.121	0.126	-0.96	0.34
18	Y1 | Y2-Y3	-6.14	1.54	-3.97	0.00
19	Y2-Y3 | Y4-Y5	-4.02	0.216	9.81	0.00
20	Y4-Y5 | Unsure	-3.176	0.145	5.82	0.00
21	Unsure | Y6+/Never	-0.826	0.309	7.61	0.00

Summary statistics

Number of observations = 221

Number of excluded observations = 0

Number of estimated parameters = 21

$$\mathcal{L}(\beta_0) = -389.123$$
$$\mathcal{L}(\hat{\beta}) = -277.657$$
$$-2[\mathcal{L}(\beta_0) - \mathcal{L}(\hat{\beta})] = 222.932$$
$$\rho^2 = 0.286$$
$$\bar{\rho}^2 = 0.232$$

Table 21: Adoption NL Case 2

Parameter number	Description	Coeff. estimate	Robust Asympt. std. error	t-stat	p-value
1	ASC Y6+/No	9.27	2.16	4.29	0.00
2	Affinity to automation Y2-Y5 and Unsure	0.638	0.423	1.51	0.13
3	Affinity to automation Y1	1.01	0.431	2.34	0.02
4	Cost first Y2-Y5	0.399	0.129	3.09	0.00
5	Cost as taxi Y1	0.374	0.203	1.85	0.06
6	Previous crashes with injuries Y2-Y5 and Unsure	-1.97	1.03	-1.91	0.06
7	Previous crashes with injuries Y1	-2.54	1.17	-2.16	0.03
8	Starting language unsure	1.39	0.334	4.17	0.00
9	Data concerns Y1	-0.395	0.129	-3.06	0.00
10	Doctorate Y2-Y3	-1.40	0.563	-2.49	0.01
11	Female respondents	-3.05	1.13	-2.71	0.01
12	Full-time employment Y1-Y3	0.829	0.304	2.73	0.01
13	High income Y4-Y5	-1.19	0.661	-1.81	0.07
14	PT Y4-Y5	0.958	0.424	2.26	0.02
15	Service provider reputation Y1, Unsure	0.730	0.148	4.95	0.00
16	Safety concerns Y1, Y4-Y5	-0.319	0.0872	-3.66	0.00
17	Social media use	0.534	0.251	2.13	0.03
18	TT important for UAM	0.622	0.145	4.30	0.00
19	VOT Savings Y4-Y5	0.514	0.0874	5.88	0.00
20	Whatsapp Y1-Y5, Unsure	0.504	0.276	1.83	0.07
21	Not first three years	1.00	1.80e+308	0.00	1.00

Summary statistics

Number of observations = 221

Number of excluded observations = 0

Number of estimated parameters = 21

$$\mathcal{L}(\beta_0) = -355.686$$
$$\mathcal{L}(\hat{\beta}) = -242.593$$
$$-2[\mathcal{L}(\beta_0) - \mathcal{L}(\hat{\beta})] = 226.186$$
$$\rho^2 = 0.318$$
$$\bar{\rho}^2 = 0.259$$

Table 22: Adoption NL Case 3

Parameter number	Description	Coeff. estimate	Robust Asympt. std. error	t-stat	p-value
1	ASC Y6+/Never	9.26	2.16	4.29	0.00
2	Affinity to automation Y2-Y5 and Unsure	0.626	0.429	1.46	0.14
3	Affinity to automation Y1	1.02	0.437	2.33	0.02
4	Affinity to automation Y2-Y3	0.677	0.434	1.56	0.12
5	Cost first Y2-Y5	0.390	0.129	3.02	0.00
6	Cost as taxi Y1	0.354	0.203	1.75	0.08
7	Previous crashes with injuries except Y1	-1.96	1.03	-1.91	0.06
8	Previous crashes with injuries Y1	-2.53	1.18	-2.15	0.03
9	Starting language German unsure	1.35	0.343	3.95	0.00
10	Data concerns Y1	-0.396	0.130	-3.05	0.00
11	Doctorate Y2-Y3	-1.39	0.557	-2.50	0.01
12	Female respondents Y1-Y3	-3.15	1.14	-2.75	0.01
13	Female respondents Y4-Y5 and Unsure	-3.01	1.14	-2.64	0.01
14	Full-time employment Y1-Y3	0.788	0.316	2.49	0.01
15	High income Y4-Y5	-1.17	0.672	-1.74	0.08
16	PT Y4-Y5	0.972	0.427	2.28	0.02
17	Service provider reputation Y1, Unsure	0.749	0.151	4.97	0.00
18	Safety concerns Y1	-0.322	0.0884	-3.65	0.00
19	Affinity to social media: Y4-Y5, unsure	0.530	0.251	2.11	0.03
20	TT important for UAM	0.578	0.178	3.24	0.00
21	Value of time savings Y4-Y5	0.528	0.0957	5.52	0.00
22	Whatsapp Y1-Y5, Unsure	0.512	0.274	1.87	0.06
23	Not first year	1.00	1.80e+308	0.00	1.00

Summary statistics

Number of observations = 221

Number of excluded observations = 0

Number of estimated parameters = 23

$$\mathcal{L}(\beta_0) = -355.686$$

$$\mathcal{L}(\hat{\beta}) = -242.334$$

$$-2[\mathcal{L}(\beta_0) - \mathcal{L}(\hat{\beta})] = 226.704$$

$$\rho^2 = 0.319$$

$$\bar{\rho}^2 = 0.254$$

Declaration Concerning the Master's Thesis

I hereby confirm that this Master's thesis is my own work and I have documented all sources and materials used. This thesis has not been previously submitted elsewhere for purposes of assessment.

Munich, November 9th, 2018

Christelle Al Haddad