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How Do Car Sharers and Non-Car Sharers View the Trends in Self-Driving/Autonomous Transport?

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Contents

Abstract

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Car Sharing (CS) and Autonomous Vehicles (AVs) have the potential to solve existing traffic problems and alleviate environmental pressure. Hence, to stimulate the use of CS and AVs, past literature has researched the acceptance of both technologies and the drivers behind it. However, few studies have investigated the acceptance of both technologies combined and the interdependence between them, which is a large research gap that this study aims to address. This research uses Structural Equation Modelling (SEM) and a sample size of $N = 202$ to measure the impact of multiple socio-demographic and behavioral variables on the *Behavioral Intention* (BI) of CS and AVs, a variable indicating a person's intention to use a technology. Moreover, Student's t-tests are performed comparing mean response values of the survey responses, together with ranking respondents' preferred transportation modes to come to additional findings. For the research, a distinction between the whole data set and students-only data set is made since 125 of 202 respondents were students. The results indicated no significant relationship between the BI of CS and the BI of AVs for the complete data set, though this relationship was found significant for the students-only data set. Furthermore, *Attitude* (AT) seemed to have a large impact on the BI in general, as indicated by the data. *Perceived Usefulness* (PU) and *Perceived Ease Of Use* (PEOU) were also key variables that influenced *Attitude* directly and the BI either directly or indirectly through *Attitude*. Other variables such as *Subjective Norm* (SN), *Trust* (TRU), and *Perceived Behavioral Control* (PBC) had significant effects on the BI, although they were less important than the previously mentioned variables. The contribution of this research is that policy makers and companies can stimulate CS and future AV usage by influencing different behavioral variables, leading to a higher BI for both technologies. Despite the results and their implications being interesting, future research has to further investigate the relationship between CS and AV acceptance.

Keywords: Car Sharing (CS); Autonomous Vehicles (AVs); Technology Acceptance; Structural Equation Modelling (SEM); Behavioral Intention (BI); Students

Introduction

Ever since cars became commercialized in the 20th century, the amount of passenger cars on our roads has grown each year. For example, in 2022 there were almost six million passenger cars on Belgian roads, an increase of 0.3% compared to 2021 ("Voertuigenpark — Statbel", 2022). As more cars drive on the road, more problems caused by cars occur. Pollution, accidents, traffic jams, making cities less suitable for weak road users... are some of the disadvantages that come with excessive car use. For instance, the yearly average amount of traffic congestion in Flanders was 759 kilometer-hours (a measure for traffic congestion) from February 2022 until February 2023. This means that, for working days during this time period, an average of 759 kilometers of traffic jams occurred during one hour of the day ("Filezwaarte", 2023). Traffic jams usually plague big cities, causing longer commuting hours and more pollution, among other things.

Many solutions to these problems can co-exist. The possible solutions that we discuss in this paper, in collaboration with Autodelen.net, are Car Sharing (CS), Autonomous Vehicles (AVs), and the synergy between them. Both look promising with regards to solving the issues that auto mobility currently suffers from. In the following sections of the introduction, we discuss how CS and AVs can help alleviate some of the problems and highlight their benefits. Moreover, the extra benefits achieved when combining CS with AVs are touched upon. Subsequently, we shortly go over the research that has been done considering the acceptance of CS and AVs, and address the research gap in the literature. A more in-depth review of the literature is provided in Chapter 2, the Literature Review.

1.1 Benefits of Car Sharing

Throughout recent years, Car Sharing (CS) has grown more and more popular. In Belgium, the amount of car sharers was 194 thousand in 2021, which is an increase of 30% compared to 2020 (Matthijs et al., 2022). This amount is about 2.5% of people in Belgium who hold a driver's license. Moreover, around 4.6 thousand shared cars were in use, giving an average of 22 users per shared car (Matthijs et al., 2022).

Car Sharing exists in many forms. A more detailed explanation of the different types of Car Sharing is given in Section 2.2. Nonetheless, these different types of CS all share the same fundamental principles. All CS organisations work with the following three principles: Having a local impact (1) by providing a membership-based service (2), and guided by environmental and social principles (3) (Carsharing Association, n.d.). By applying these principles, CS aims to bring some benefits to the table.

The literature on CS has highlighted several benefits of CS. A study by Rabbitt and Ghosh (2013) ran an analysis on CS and did a comparison of costs and CO_2 emissions in Ireland. Hereby, they found that people could significantly reduce their annual travel costs and CO_2 emissions by using CS. On top of that, using CS would indirectly encourage people to use more sustainable modes of transportation, such as walking, bicycles and public transport (Rabbitt & Ghosh, 2013). Another study conducted in Flanders did a simulation on the environmental impact of CS in Flanders. In a best-case scenario, CS can reduce on average 1,064 kilograms of CO_2-equivalent emissions from cars each week, showing how CS can help alleviate environmental pressure (Carmen et al., 2019). To add further to this, Efthymiou et al. (2013) present a scorecard to show how CS can benefit multiple areas. As less cars are needed, CS is beneficial for traffic, time savings due to less traffic, and urban design. A report by Millard-Ball et al. (2006) shows that, on average, one Car Sharing vehicle replaces 14.9 privately owned vehicles, which partly explains the previously mentioned benefits. Additionally, besides the obvious benefits, CS has other advantages that are lesser-known. For example, CS aids to economic development by providing a car at a very low cost to job seekers. This also improves equity for people who do not own or can afford a car, as they have a competitive disadvantage compared to regular car owners (Litman, 2000).

1.2 Benefits of Autonomous Vehicles

The development of Autonomous Vehicles (AVs) as we know of today, started in 1986 when Ernst Dickmanns made a self-driving Mercedes-Benz van based on computer vision technology (Bimbraw, 2015). Though almost 40 years later, the technology is still not up to par. One of the pioneers in the field of autonomous driving is Waymo, a company owned by Alphabet, Google's parent company. Waymo, among other leaders in this industry, aims to provide people a more pleasant and safer driving experience with AVs, though it will take a long time until the technology is fully commercialized. A full description of an AV is specified in Section 2.3.

Many studies have been dedicated to measuring the potential impact of AVs as the technology looks very promising. First of all, AVs can significantly reduce the amount of crashes on the roads, which are caused by human error most of the time (Anderson et al., 2014). Furthermore, depending on the share of AVs in traffic, there is a potential to save fuel consumption and reduce traffic congestion by connecting the AVs to each other. Doing so also frees up capacity on the roads (Tientrakool et al., 2011). Autonomous Vehicles also open the door for people who are unable to use a car such as children, the elderly, and disabled people, to travel by car. This decreases their dependence on other people to travel (Fagnant & Kockelman, 2015). Furthermore, AVs have the opportunity to reduce parking related costs. An analysis by Litman (2016) estimates that every AV saves the government about $250 in parking costs, as AVs are able to park themselves outside of the city at cheaper parking areas, relieving the city centre of parking infrastructure. Autonomous Vehicles (AVs) have to be on the road first before it is possible to reap their potential benefits, though it is likely that market penetration will take a long time. Litman (2017) estimates that by the 2050s, AVs will account for 40-60% of new vehicle sales, 20-40% of the vehicle fleet, and 30-50% of vehicle travel. It is unknown when, but it is sure that Automated Driving Systems (ADSs) in cars will be a requirement in the future. Think of it like seat belts, which were once a purchasable option, but are now mandatory in every car for safety reasons.

1.3 Synergy between Car Sharing and Autonomous Vehicles

Combined together, CS and AVs can be very beneficial. The key idea is that CS and AVs are combined to what is known as a Shared Autonomous Vehicle (SAV), complementing each other's benefits and filling the gaps where either one might fall short.

Pakusch et al. (2018) conducted a survey and found that users still prefer a private car over a shared car, but in a scenario of full automation, this preference decreases. This suggests that "the full automation of Car Sharing can help to increase market potential and expand its share in the modal split" (Pakusch et al., 2018). Some of the downsides of current CS services is that shared cars are not always available or lack flexibility, and that CS users still have to travel towards a shared car using other transportation modes such as buses or bicycles. Since AVs are able to drive themselves to a person, these problems eradicate (Krueger et al., 2016). A study conducted by Martinez and Viegas (2017) ran a simulation where, in the city of Lisbon, current transportation modes would be replaced by self-driving shared taxis and self-driving shared taxi-buses. In the case of full adoption of these technologies, the authors conclude the following: First of all, a reduction in emissions and less congestion, leading to an improvement in traffic flow. Secondly, due to more intense vehicle use, a reduction in the life-cycle of vehicles. The vehicles could then be replaced by newer and more environmentally friendly vehicles. Lastly, the authors report a reduction in transportation costs (Martinez & Viegas, 2017). Similar research by Fagnant and Kockelman (2018) adds further to these findings. The results of their simulation, for the case of Austin, Texas (USA), found that using a fleet of SAVs as part of the city's transportation modes reduces travel costs, while also reducing waiting time and total service time (waiting time + time in-vehicle) (Fagnant & Kockelman, 2018).

1.4 Past Research and Research Gap

The benefits of CS and AVs mentioned are just some of an extensive list of benefits that could be achieved by adopting CS and AVs. In spite of the many advantages, lots of challenges still remain. One of those challenges that is studied in this paper more in depth is the acceptance of CS and AVs. Before we can implement these technologies in daily life, it is important to understand what drives people to accept these technologies. Many factors come in to play, such as how easy it is to use a CS service or AV, or how much someone trusts an AV to drive for them.

Lots of research has been done regarding the acceptance of CS and AVs. Some studies look at behavioral factors that influence acceptance of CS and AVs, such as Haldar and Goel (2019) and Mattia et al. (2019) for CS, and Baccarella et al. (2021) and Lee et al. (2019) for AVs. Besides behavioral factors, socio-demographic factors that might determine the acceptance of the technologies are studied. Burkhardt and Millard-Ball (2006) and Efthymiou et al. (2013) for Car Sharing and König and Neumayr (2017) and Rahimi et al. (2020a) are some of the researchers studying the influence of socio-demographic factors on the acceptance of CS and AVs. An extensive overview of the literature that studies the behavioral and socio-demographic factors that contribute to the acceptance of CS and AVs can be found in Sections 2.2 and 2.3.

While many studies have looked at the acceptance of CS and AVs separately, there is a relatively small body of literature that is concerned with the acceptance of CS and AVs combined. Merfeld et al. (2019) conducted a Delphi-study to investigate drivers, barriers, and future developments that are necessary for CS with Shared Autonomous Vehicles (SAVs) to be implemented in the future. Another paper by Müller (2019) looks at the acceptance of AVs, Electric Vehicles (EVs) and CS. However, this study does not look at interaction between the technologies, only at acceptance of the technologies separately. An interesting paper by Curtale et al. (2022) investigates the acceptance of Electric Car Sharing (ECS) on Autonomous Electric Car-Sharing services (AECS). They found that a user's intention to use an ECS influenced the intention to use an AECS. Thurner et al. (2022) studied the likelihood of adopting AVs, CS, and EVs based on socio-demographic and behavioral factors. They did not assume a relationship between the different technologies, but it is still interesting to see if the different technologies have factors in common that increase the likelihood of adopting those technologies. To investigate the *Unwillingness To Pay* for SAV services, Carteni (2020) conducted research in Naples, Italy. He found that *Age* and *Gender*, among other variables, influenced the *Unwillingness To Pay.* Schlüter and Weyer (2019) investigated the effect of CS to raise acceptance of EVs. Their research model included a variable called *Car Sharing Experience*, which was found to have a significant impact on multiple other variables in their research model. A more detailed overview of all the studies that investigate both CS and AVs is given in Section 2.4.

Unfortunately, due to the limited amount of studies on this topic, it is not yet clear what impact the acceptance of CS has on the acceptance of AVs. Therefore, this study is set out to assess the effect of CS acceptance, and the effect of other variables on AV acceptance. Research into this topic is important because it allows for the development of policies for and stimulation of AV acceptance, despite the technology not being available yet. Hence the research question that is investigated in this study, which is also the title of this paper, is as follows:

Research Question: How Do Car Sharers and Non-Car Sharers View the Trends in Self-Driving/Autonomous Transport?

1.5 Addressing the Gap/Study Outline

To address the gap in the existing literature and to answer the research question, this study is composed of five chapters: First, the introduction (Chapter 1) that has already been concluded, argued for this paper's relevance and described the goal of this paper. This is followed by the literature review (Chapter 2), that discusses the acceptance models needed to understand the literature that studies CS and AV acceptance. The literature review gives us a better understanding of the different drivers (behavioral and socio-demographic factors) that have been proven to be significant for the acceptance of both technologies. After the review of the literature that looks at the acceptance of CS and AVs separately, an analysis of the few studies that look into the acceptance of both technologies combined is conducted. The literature review is followed by Chapter 3, research design and methods, that describes the methods used to answer the hypotheses related to the research question and research model. The importance of each variable in the research model is highlighted, together with the formulation of the hypotheses that, when put together, make up the research model of this paper. This chapter also describes how primary data was collected, which measures were used to collect the data and how the research model was validated. We continue to Chapter 4: results, which concerns reporting the results of the data analysis regarding the research model. Along with a report of the significance of each of the variables in the research model, the results of the extra t-tests and ranking questions are given. Finally, the discussion (Chapter 5) concludes the study by elaborating on the results, and provides suggestions for policy makers. Besides that, Chapter 5 goes over the limitations of this study, together with recommendations for future research that has to be done in the field of CS and AV acceptance.

Literature Review

Having introduced the topic of CS and AVs and having explained the relevance of this study, it is now time to dive deeper into the research that has already been conducted in this field. This chapter aims to shed light on the acceptance theories used by the literature, as well as the literature's findings. In this chapter, an in-depth analysis of the research regarding the acceptance of CS, the acceptance of AVs, and the acceptance of both technologies combined is conducted. After explaining the current state of the literature, an analysis of secondary data provided by Autodelen.net is presented.

2.1 Relevant Underlying Theories

In order to fully comprehend the acceptance of a new technology, papers base their methodological framework on previously introduced behavioral models. These models are meant to describe the human behavior, more specifically their thought process, before taking certain actions. When trying to explain the acceptance of a particular technology, the literature extensively makes use of the Theory of Planned Behavior (TPB) by Ajzen (1991), the Technology Acceptance Model (TAM) by Davis (1985), and the Unified Theory of Acceptance and Use of Technology (UTAUT) introduced by Venkatesh et al. (2003). Most studies do not base their conceptual framework entirely on one of these papers, but they aggregate the different models into one model. Others even extend the models with extra features in order to fully capture the human behaviour behind the adoption of a technology. In what follows, the different models will be illustrated in order to facilitate the understanding of the literature on CS and AVs acceptance.

In the following part and the rest of the study, a lot of acronyms are used. In order to make the paper as understandable as possible, Appendix A.1 contains all of the used acronyms together with their meaning and context. Moreover, the figures illustrated in the following parts visualize each of these conceptual frameworks where latent variables are displayed as circles and directly measurable variables as rectangles.

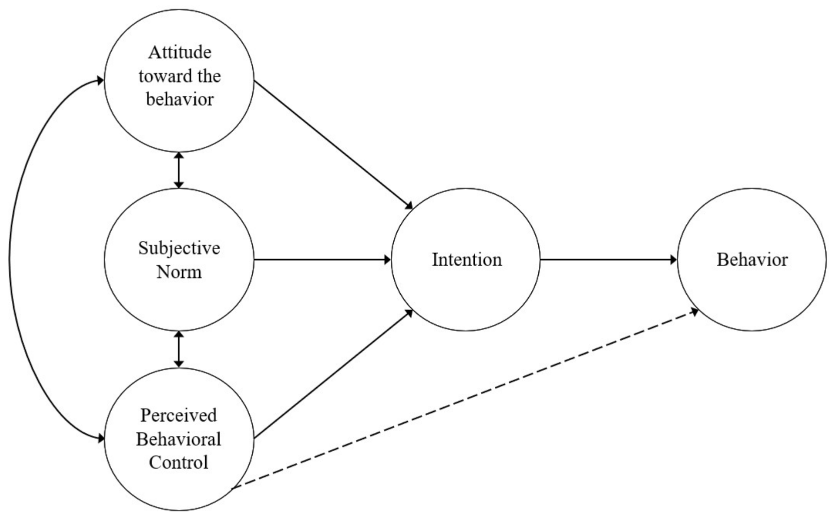
Theory of Planned Behaviour

A frequently used conceptual model is the Theory of Planned Behavior (TPB) by Ajzen (1991) shown shown in Figure 2.1. This model is an extension of an earlier model introduced by the same author called the Theory of Reasoned Action (TRA) (Ajzen, 1980).

Both theories attempt to explain the acceptance of technology from a psychological point of view (Marangunić & Granić, 2015). According to the TPB, a person's *Intention* towards a *Behavior* will eventually determine whether a person will perform said *Behavior* (Ajzen, 1991). The person's *Intention* is in turn influenced by three other factors: the person's *Attitude towards the behavior*, the surrounding *Subjective Norm* (SN) concerning the behavior, and the person's *Perceived Behavioral Control* (PBC). The *Subjective Norm* represents the influence of others on the user's decision regarding the usage of the technology, and the *Perceived Behavioral Control* covers the person's perception of the degree to which the person is capable of engaging in this behavior (Marangunić & Granić, 2015). As shown in Figure 2.1, the TPB (Ajzen, 1991) additionally assumes that the three factors mentioned previously influence each other and, moreover, a direct influence of *Perceived Behavioral Control* on the person's performance of the behavior is indicated.

Figure 2.1

Theory of Planned Behavior



Source: Ajzen, 1991, p.182

Technology Acceptance Model

Based on the previously mentioned TRA (of which TPB is an extension), Davis (1985) introduced the Technology Acceptance Model (Figure 2.2) at the end of 1985 in order to better predict and explain the acceptance of a technology. The model consists of three variables which, when put together, should be able to explain a user's motivation to use a particular technology. Those variables are: *Perceived Usefulness* (PU), *Perceived Ease Of Use* (PEOU) and *Attitude toward using* (AT). In this case, a person's *Attitude toward using* the technology is the main factor which determines whether this person will make use of the technology or not (Davis, 1985). The person's *Attitude toward using* is influenced by the two other variables, *Perceived Usefulness* and *Perceived Ease Of Use*, where *Perceived Usefulness* and *Perceived Ease Of Use* were respectively defined by Davis as:

> The degree to which an individual believes that using a particular system would enhance his or her job performance[1] and the degree to which an individual believes that using a particular system would be free of physical and mental effort. (Davis, 1985, p.26)

Furthermore, Davis' TAM suggests the existence of an indirect effect of *Perceived Ease Of Use* on a person's *Attitude toward using* via the variable *Perceived Usefulness*. Lastly, the different characteristics of a technology (such as price, specifications...), denoted in Figure 2.2 as *X1*, *X2*, and *X3*, will directly influence the *Perceived Usefulness* and *Perceived Ease Of Use* of the user (Davis, 1985).

In 1989, Davis et al. (1989) modified the TAM, as seen in Figure 2.3. The authors added the *Behavioral Intention to Use* (BI), a variable based on the TRA that describes a person's intention to perform a specific type of behavior (Ajzen, 1980). According to the new model, the *Behavioral Intention* is influenced by both the *Attitude toward using* and the *Perceived Usefulness*. The *Behavioral Intention* influences the actual system usage, instead of the *Attitude toward using* as suggested by the model from 1985 (Davis et al., 1989).

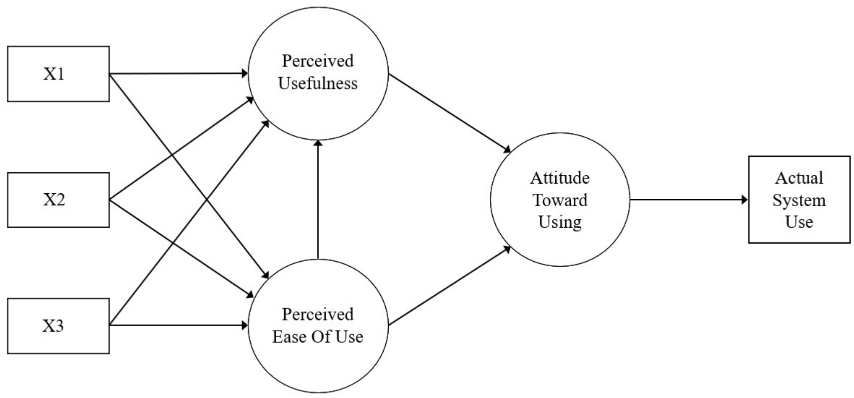
Figure 2.4 shows the final version of the TAM by Venkatesh and Davis (1996). The final model gets rid of the *Attitude toward using*, so only the external variables (also called exogenous variables), *Perceived Usefulness*, *Perceived Ease Of Use*, *Behavioral Intention*, and actual system use remain. Here, the *Behavioral Intention* is influenced by both the *Perceived Usefulness* and *Perceived Ease Of Use*, which was not the case in the previous version of the model from 1989. The *Behavioral Intention* then influences the actual system use, congruent with the previous model (Venkatesh & Davis, 1996).

This paper includes the different versions of the model, as the models used in the literature are based on the different variations of the TAM.

[1]This is the exact definition given by Davis (1985). In the context of this study, the *job performance* refers to the driving process of a car and reaching the desired destination.

Figure 2.2

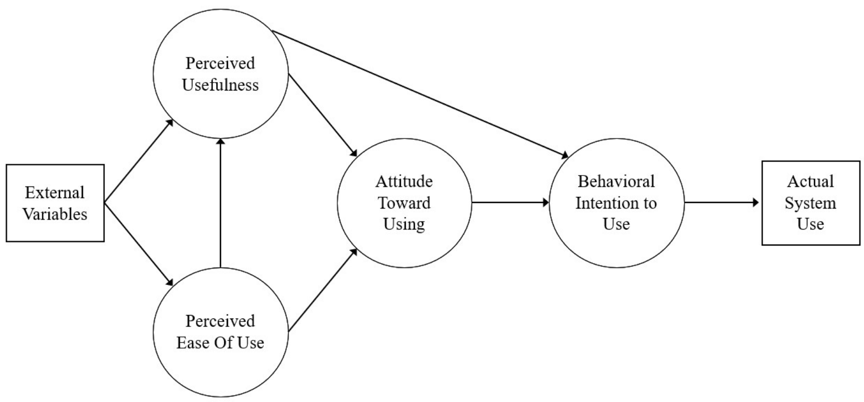
Technology Acceptance Model (1985)



Source: Davis, 1985, p.24

Figure 2.3

Technology Acceptance Model (1989)



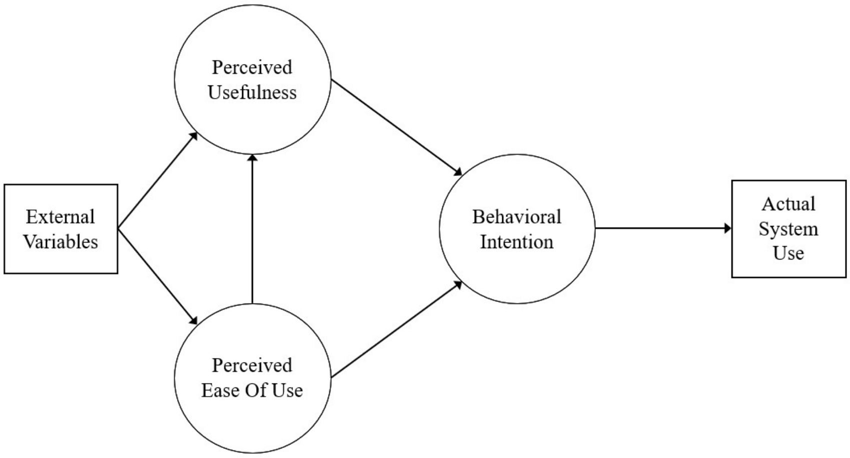
Source: Davis et al., 1989, p.985

Unified Theory of Acceptance and Use of Technology

In 2003, Venkatesh et al. (2003) formulated a new behavioral model, based on the previously introduced models, called the Unified Theory of Acceptance and Use of Technology

Figure 2.4

Technology Acceptance Model (1996)



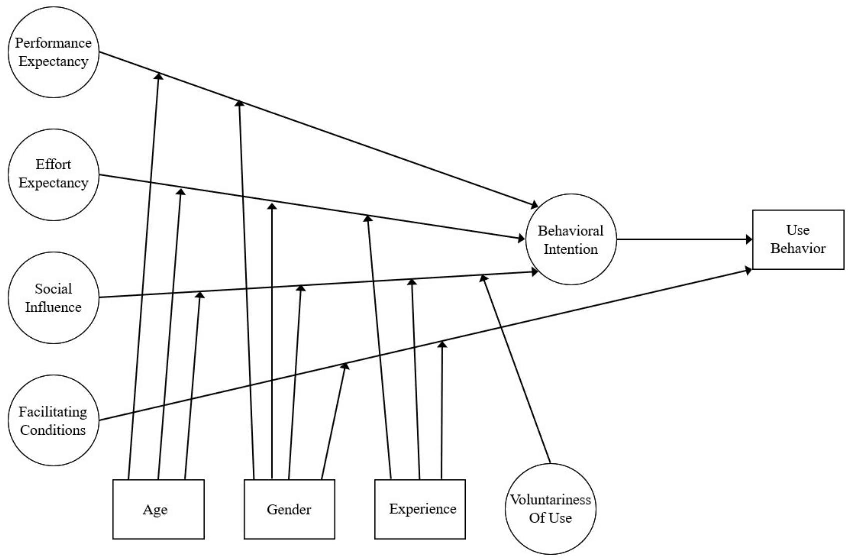
Source: Venkatesh and Davis, 1996, p.453

(UTAUT), which serves the same purpose. When looking at the UTAUT (Figure 2.5), five behavioral variables can be identified: the *Behavioral Intention* (BI), the *Performance Expectancy* (PEX), the *Effort Expectancy* (EE), the *Social Influence* (SI), and the *Facilitating Conditions* (FC). At first sight the model seems to differ from the previously discussed models, but when going more in depth, a lot of similarities between the models' variables can be found. For instance, the definitions of the *Performance Expectancy* and *Effort Expectancy* variables are closely related to the definitions of the previously seen *Perceived Usefulness* and *Perceived Ease Of Use* variables from Davis's TAM, respectively. Appendix A.2 compares the variables coming from the different conceptual frameworks and provides a clear overview of the equivalent variables across the models. In addition, the UTAUT can even be linked to the TPB, since the variables *Social Influence* and *Facilitating Conditions* are based on Ajzen's *Social Norm* and *Perceived Behavioral Control* variables, respectively. According to the UTAUT, a person's final *Use Behavior* is determined by two other indicators which are the *Behavioral Intention* (BI) and *Facilitating Conditions* (FC). The user's *Behavioral Intention* is then, in turn, influenced by three other factors: the *Performance Expectancy*, *Effort Expectancy* and *Social Influence* (Venkatesh et al., 2003).

Lastly, as illustrated in Figure 2.5, the UTAUT adds the moderating effects of certain socio-demographic indicators, which were not included in any of the other previously discussed models (Venkatesh et al., 2003). The inclusion of these factors is also widely adopted in the literature to study the effects coming from socio-demographic characteristics.

Figure 2.5

Unified Theory of Acceptance and Use of Technology



Source: Venkatesh et al., 2003, p.447

2.2 Acceptance of Car Sharing Services

The following part discusses research that has been done to better understand the human behavior regarding the adoption of Car Sharing (CS) modalities. More specifically, the literature tries to answer the question: "What factors drive a person to adopt Car Sharing (CS) facilities?".

Car Sharing (CS) organisations can have four different operational characteristics under which they provide Car Sharing (CS) services. The four operational characteristics, as defined by Rodenbach et al. (2018), are as follows: roundtrip station-based (1), roundtrip home zone-based (2), free-floating with operational area (3), and free-floating with pool-stations (4). Roundtrip and free-floating CS make up for two of the three main categories of CS modalities. The exact definition for these different operational characteristics, as defined by Rodenbach et al. (2018), are:

> (1) Roundtrip station-based or "back to base": a shared car has to be picked up and returned to the same (dedicated) parking spot.
> (2) Roundtrip home zone-based: a shared car has to be picked up and returned to the same area/(home)zone of the city. (No dedicated parking spots are in play).
> (3) Free-floating with operational area: a shared car can be picked up and returned in a large operational area. In most cases it is a whole city or even a different city. (No dedicated parking spots are in play).
> (4) Free-floating with pool-stations: a shared car can be picked up and returned in a large operational area but always in dedicated pool stations. In most cases it is a whole city or even a different city. This kind of service is also known in the literature as one-way station-based CS. (Rodenbach et al., 2018)

Roundtrip and free-floating are two of three major categories for CS. Rodenbach et al. (2018) defines peer-to-peer as a third category for CS. In peer-to-peer CS, people put their own private car open to CS, as opposed to a company owning a fleet of cars as with the first two categories. It is important to mention that since this study is done in collaboration with Autodelen.net, the network for CS and shared mobility in Belgium, the CS trend in its whole is considered instead of focusing on one particular type of CS.

Lots of research has been done regarding the adoption of CS and the determinants thereof. Some studies focus on socio-demographic factors of (potential) users/non-users to gain more insight, while others are based on previously discussed theories and models which try to identify the underlying behavioral factors that determine the acceptance of CS. In the following parts, findings from both types of research are discussed more in depth, starting with the behavioral factors, followed by the socio-demographic characteristics.

2.2.1 Influence of Behavioral Factors (CS)

Most of the papers studying the acceptance of CS technologies base their research models on the TAM and extend it with factors from the TPB, TRA, UTAUT, or even other models in order to understand what behavioral factors influence the acceptance of CS services.

Using this approach, Müller (2019) and Mattia et al. (2019) both confirmed the positive impact of the *Attitude*(AT) of a user towards CS services on the user's *Behavioral Intention* (BI) to make use of CS. This is quite straightforward since a person with a bad attitude towards a technology would be more resistant and less likely to make use of it. Moreover, Davis (1985) stated that a person's *Attitude* towards a technology is, in turn, influenced by two other variables: *Perceived Usefulness* (PU) and *Perceived Ease Of Use* (PEOU). The *Perceived Usefulness* was found to be a positive predictor for the user's *Attitude* (Haldar & Goel, 2019; Müller, 2019), which leads to the conclusion that a person perceiving a high usefulness from CS would have a more positive attitude towards this innovation. On top of that, Müller (2019) also confirmed the positive influence of *Perceived Ease Of Use* on *Attitude*, unlike Haldar and Goel (2019), who concluded that there is no significant relationship between the two variables. In addition, the TAM suggests that *Perceived Ease Of Use* is supposed to influence the *Perceived Usefulness*. This effect is again confirmed by Haldar and Goel (2019), Y. Liu and Yang (2018), and Müller (2019), who studied the acceptance of the sharing economy in general through an extension of the TAM. This implies that the more a user considers CS to be straightforward to use, the more this user would perceive the technology to be useful. Even though Y. Liu and Yang (2018) look into the acceptance of the sharing economy in general instead of CS services specifically, this paper is still included in the literature review since CS services are part of the sharing economy.

Y. Liu and Yang (2018) extend their model with different factors from the TPB, as well as factors from other theories. It is important to note that their model does not include an *Attitude* variable, but instead it only includes the *Behavioral Intention* (BI) of a person. The authors also notice a positive influence of *Perceived Usefulness* and *Perceived Ease Of Use* on the person's *Behavioral Intention*. Given the earlier findings regarding the relationship between a person's *Attitude* towards CS and their *Behavioral Intention* (Mattia et al., 2019; Müller, 2019), one could argue that *Attitude* is an intermediate variable explaining these effects.

Regarding influences from other variables, the literature is very scattered. Different papers explore different factors, models, and relationships, which makes it difficult to summarize the acceptance of CS services in one single model. This shows how the field is far from being explored and how research in the field is still needed.

For instance, Y. Liu and Yang (2018) extend their model with the variable *Subjective Norm* (SN) that was discussed earlier as part of the TPB. They conclude that the subjective norms regarding the engagement in a certain behavior influence both the *Perceived Usefulness*, as well as *Perceived Ease Of Use* of a person. Hence, they state that a user is influenced by opinions of others regarding the use of a technology. The *Subjective Norm* (SN) is also found to have a positive influence on the *Behavioral Intention* (Mattia et al., 2019). This could be due to the impact that the variable has on the *Perceived Usefulness* and *Perceived Ease Of Use* that influence a person's *Attitude*, and subsequently, their *Behavioral Intention*. However, this indirect impact is not considered in the paper of Mattia et al. (2019), and only the direct effect of *Subjective Norm* on *Behavioral Intention* is included. Furthermore, Y. Liu and Yang (2018) introduce a new variable called *Trust* (TRU) to the model which represents the user's trust in the technology, but is found to have no impact on any of the previously mentioned variables. Curtale et al. (2021) formulate similar conclusions regarding the relationship between a person's *Trust* and *Behavioral Intention*. The insignificance of this *Trust*-variable could be due to the familiarity of the public with cars. In essence, CS is just an alternative implementation of the regular cars that are used today.

According to Mattia et al. (2019), the variable *Perceived Behavioral Control* (PBC) from the TPB, discussed in Section 2.1, has a positive influence on a person's *Behavioral Intention*. This means that, the more a person perceives that they are in control of performing a particular behavior (in this case the usage of the CS services), the more likely it is that they will perform that behavior. This variable is also included in the model proposed by Haldar and Goel (2019), who combine parts of the TAM together with parts of the TPB to study the *Willingness To Use* (WTU) CS apps. This can be considered as an equivalent of the variable *Behavioral Intention*. Hereby, a person's *Attitude* towards using a CS app and the *Subjective Norm* concerning the use of these apps impacts the person's *Willingness To Use* in a positive manner, a conclusion that is in line with what has previously been discussed in this section. However, the authors did not find a significant relationship between a person's *Perceived Behavioral Control* and the *Willingness To Use* (Haldar & Goel, 2019).

As previously discussed, another frequently used theoretical model is the Unified Theory of Acceptance and Use of Technology (UTAUT) by Venkatesh et al. (2003). Curtale et al. (2021) and Tran et al. (2019) further extend this model applying it to the case of Electric CS services (ECS). The authors of both articles identify a positive influence of a person's *Performance Expectancy* (PEX) of the technology on the *Behavioral Intention*. This would lead to the same conclusion as with the seen relationship between *Perceived Usefulness* and *Behavioral Intention* due to the similarity between *Performance Expectancy* and *Perceived Usefulness*. Both papers also include the variable *Effort Expectancy* (EE), which has the same definition as *Perceived Ease Of Use* introduced in the TAM (Curtale et al., 2021; Tran et al., 2019). Conclusions regarding the relationship between a person's *Effort Expectancy* and *Behavioral Intention* are conflicting since Curtale et al. (2021) find no proof of a significant relationship. This is against the previous findings of Y. Liu and Yang (2018) and Tran et al. (2019) who observe a significant positive impact.

Müller (2019) and Tran et al. (2019) also study the impact of an additional variable called *Perceived Enjoyment*. This variable is found to have positive effect on both *Perceived Usefulness* and *Perceived Ease Of Use* by Müller (2019). Tran et al. (2019) only concludes that this variable also influences the *Behavioral Intention* positively.

2.2.2 Influence of Socio-Demographic Factors (CS)

Besides studying the influence that behavioral factors have on the adoption of CS services, the literature also tries to find relations between the adoption of CS and a person's socio-demographic characteristics. Multiple papers conclude that current users of CS facilities share a common set of characteristics. For instance, according to Burkhardt and Millard-Ball (2006), Efthymiou et al. (2013), and Le Vine et al. (2014), current users of CS are young, well-educated and usually do not own a car. Efthymiou et al. (2013) even specify that the (young) users are mainly students, and Namazu et al. (2018) further add that current users have more family members who are employed as compared to the followers group[2]. Furthermore, current users have a low household income, are environmentally aware (Burkhardt & Millard-Ball, 2006; Efthymiou et al., 2013), and live in urban neighbourhoods (Le Vine et al., 2014). However, there are some disagreements between the findings of different papers. For instance, Le Vine et al. (2014) identify the current users to be from the middle/upper income class as opposed to the findings by Efthymiou et al. (2013) and Burkhardt and Millard-Ball (2006). In addition, Le Vine et al. (2014) state that the group of users consists of more men than women, which is opposed to the findings of Burkhardt and Millard-Ball (2006).

Previously discussed characteristics of current users are interesting to look at, but are not necessarily influential for the adoption of CS services, hence research has been done to identify the factors that are influential. For instance, the *Age* of a person is found to have a negative impact on a person's intention to use a CS service by multiple papers (Curtale et al., 2021; Prieto et al., 2017; Rahimi et al., 2020a; Thurner et al., 2022). This means that younger people tend to be more open to the idea of CS services, which is in line with the previously mentioned characteristics of current users. Even though this impact has been proven by the previous articles, Efthymiou et al. (2013) concluded that *Age* does not play a significant role for the adoption of CS. Moreover, disagreements also exist with regards to the *Gender* of a person. Papers such as Acheampong and Siiba (2020), Burkhardt and Millard-Ball (2006), Prieto et al. (2017), and Rahimi et al. (2020a) state that men are more favourable towards this technology, while others find no significant relation between the *Gender* of a person and their intention to use CS (Curtale et al., 2021; Thurner et al., 2022). As mentioned before, according to Le Vine et al. (2014), current users of CS services live mainly in urban neighbourhoods. The

[2]Namazu et al. (2018) defines the followers group as the group of respondents who do not own a CS subscription, but who mentioned that they might get persuaded if a certain approach (such as more flexibility, lower costs, etc.) would be implemented.

influence of this factor is found to be significant by Thurner et al. (2022) and Prieto et al. (2017). This means that this technology is more appealing to people who live in cities or urban areas. Nonetheless, Rahimi et al. (2020a) state the *Place of Residence* of a person to be irrelevant.

Research regarding the influence of a person's *Income* seems to be very conflicting as different papers all come to different conclusions. For instance, Thurner et al. (2022) find that this factor has no impact, while Efthymiou et al. (2013) conclude that people with a lower income are more likely to join a CS platform. In contrast to the findings from Efthymiou et al. (2013), Curtale et al. (2021) confirm the opposite relationship and state that a higher income is supposed to have a positive impact on the intention to use CS services. The story is similar for a person's *Education*. Some studies conclude that a higher education would lead to a higher acceptance (Prieto et al., 2017; Rahimi et al., 2020a), whereas Acheampong and Siiba (2020) state the opposite. Others even find no significant impact and conclude that the user's education would have no impact on his or her attitude towards the technology (Curtale et al., 2022; Efthymiou et al., 2013; Thurner et al., 2022).

Furthermore, according to Efthymiou et al. (2013), the *Environmental Attitude* of a person plays a significant role as well. This would mean that a person who is more environmentally aware is expected to be more open towards the technology. However, Acheampong and Siiba (2020) did not find this influence to be of importance. Other factors, such as a person's *Household Size*, *Car Ownership* and *Distance Traveled Daily* have been studied to a limited extent. The size of a person's household was found to have a positive effect and car ownership appeared to have no influence at all (Thurner et al., 2022). Lastly, the distance a person has to travel on a daily basis has a positive impact on the person's intention to adopt CS services. Hence, the longer a person's daily travel distance, the more accepting the person would be of CS. Nonetheless, it is also mentioned that a person who travels larger distances on the daily would be more attached to their private car. This second effect could offset the factor's positive impact on the intention to use CS services (Rahimi et al., 2020a).

2.3 Acceptance of Autonomous Vehicles

The following section discusses the acceptance of Autonomous Vehicles (AVs) and the determinants thereof. Before diving deeper into the factors that drive people to accept AVs, the definition of an AV is explained, together with a short review of the general sentiment of the public regarding AVs. Thereafter, as with the previous section, the influence of behavioural factors is discussed first, followed by the influence of socio-demographic factors. Again, the connection between the influential factors and the acceptance models discussed in Section 2.1 is made to grasp an understanding of what drives people to accept AVs.

Definition of an AV

The On-Road Automated Driving (ORAD) Committee, part of the Society of Automotive Engineers (SAE) institute, defines six levels of Automated Driving Systems (ADSs) ranging from level 0 (no driving automation) to level 5 (full driving automation). In between level 0 and level 5, different components that contribute to driving automation are added subsequently until level 5 is reached (On-Road Automated Driving (ORAD) Committee, 2021). The scope of this thesis is limited to level 5 of ADSs, as agreed with Autodelen.net.

Before the definition of level 5 (full driving automation) can be explained, three concepts regarding ADSs need to be introduced to fully comprehend what is meant by the definition. These concepts are: Operational Design Domain (ODD), Dynamic Driving Task (DDT), and DDT fallback.

First of all, the Operational Design Domain (ODD) considers the conditions under which automatic functions of the AV will work, allowing certain functions to work in certain scenarios. In essence, the ODD is the environment around the car. Elements that describe the environment/conditions are speed, traffic, type of road, location, weather... to name a few. For example, at automation level 3 an AV can drive on a highway at 120 kph but only when sunny, whereas at automation level 4 said vehicle could drive at 120 kph when it is either sunny or raining. It is important to note that the ODD is specified by the manufacturer, so different manufacturers can have different ODDs at the same level of automation. With each increase of the automation level, the conditions under which the automatic functions operate will be less restrictive. At the full driving automation level the ODD is unlimited, i.e., the AV can drive under any condition, in any environment (On-Road Automated Driving (ORAD) Committee, 2021).

Second of all, to understand the Dynamic Driving Task (DDT), three levels of driving effort as described by Michon (1985) need to be explained: strategic, tactical and operational. Strategic driving relates to the overall route planning, namely the destination and route. For tactical driving, decisions such as overtaking, changing lanes etc. are made during the trip. At the lowest level, the operational level, micro-decisions such as the input on the steering wheels and pedals are made, controlling the motion of the vehicle (lateral and longitudinal). The driving efforts are intertwined, such that a driver (in this case an ADS) scans its surroundings to make a decision (tactical) and gives inputs to the car (operational). The tactical and operational driving efforts make up the DDT. A level 5 ADS fully controls the DDT, while the human is responsible for choosing the route and destination (strategic level) that the AV will drive on/to (On-Road Automated Driving (ORAD) Committee, 2021).

Lastly, the DDT fallback is an important component of the ADS in case the system fails or when the vehicle exits the ODD. Often, the human in an AV can get inattentive because the vehicle operates itself, which poses a risk when the system fails and the human is not responsive enough to take control over the vehicle. Hence, a fallback strategy has to be defined to ensure road safety (Emzivat et al., 2017). Different strategies are possible, but at level 5 of driving automation, the ADS takes care of the fallback strategy to achieve the minimal risk condition, e.g., stopping the car on the road, or avoiding a crash (On-Road Automated Driving (ORAD) Committee, 2021)

Now that the different concepts regarding ADSs have been explained, we can clarify the definition of full driving automation. The definition of level 5 - Full Driving Automation, according to On-Road Automated Driving (ORAD) Committee (2021) is: "The *sustained* and unconditional (i.e., not *ODD*-specific) performance by an *ADS* of the entire *DDT* and *DDT fallback*". In other words, an ADS at level 5 is responsible for automating the vehicle's movement at any place, at any time, and in case of failure, the ADS is also responsible for ensuring that risk is kept at a minimum.

An AV is then any type of vehicle where an ADS is implemented to automate the vehicle's movement, with many possible implementations in many transportation modes. Think of any type of transport that requires a human driver, such as a regular car, a bus, a taxi... to name a few. Despite the many possible implementations of ADSs in road vehicles, this study will focus on AVs in general instead of one specific type of AV.

General Sentiment Regarding AVs

According to research, the general sentiment of people regarding AVs is positive, though people are still wary of the technology. Kyriakidis et al. (2015) conducted a survey on automated driving and found that most people would still prefer manual driving over automated driving, even though 33% of their respondents would find driving an AV highly enjoyable. Despite one third liking the thought of driving an AV, 22% is not willing to pay more than 0$, i.e., pay nothing for full self-driving functions. Moreover, their participants believe that the technology looks promising with 69% believing that between 2014, when the study was conducted, and 2050, AVs would make up half of the vehicles driving on the road. People are still concerned however, mainly about issues regarding software security (hacking), legality, and safety of the system (Kyriakidis et al., 2015). Another study conducted by König and Neumayr (2017) confirms the concerns from the previously mentioned study, as respondents indicate issues with trust in the technology (relating to safety), hackers, and legal issues being their main concerns. Abraham et al. (2017) say that trust in AVs is something that has to develop over time, but that said trust could also go away in case something bad happens such as a fatal accident. Moreover, if people want to reap the benefits that AVs could offer them, they should accept the fact that they will have less control over the vehicle. Acheampong and Cugurullo (2019) indicate the same as the previously mentioned articles, and observe that most of their participants also expect positive benefits paired with AVs. Despite the expected benefits there are still concerns, mostly about the possible failure of the technology and about how the AV reacts when it encounters road users that are not other cars. The authors relate both the benefits and concerns to a more general perception of newer technologies, that states that for any new technology people have an overall positive attitude towards the technology, while also being anxious about the technology (Acheampong & Cugurullo, 2019).

Having defined what is meant by level 5 of driving automation and having explained the public sentiment regarding AVs, we will now move on to discuss the different factors that influence the acceptance of AVs. As with Section 2.2, both behavioral factors and socio-demographic factors that contribute to the acceptance of AVs are touched upon, in the order mentioned.

2.3.1 Influence of Behavioral Factors (AV)

The following part of this paper describes the behavioral factors that influence people to use Autonomous Vehicles (AVs) in greater detail. Analogous to Section 2.2.1 that reviewed the literature regarding different behavioral factors of CS acceptance, this section discusses the literature on the behavioral factors that possibly influence users to accept AVs. An overview of the literature that studies the link between AVs and different acceptance models is given, including extensions of the different models.

Many of the studies looking into the acceptance of AVs base their research model on the TAM (Davis, 1985; Davis et al., 1989; Venkatesh & Davis, 1996). They investigate the effects of the different factors in the TAM, and extend the model with extra factors that relate to AVs. Regarding the effect of the *Perceived Usefulness* (PEOU) on the *Behavioral Intention* (BI), lots of papers find a significant effect. As talked through in the general findings, many people indicate that they expect positive benefits from AVs, which reflects itself in the positive effect of *Perceived Usefulness* on BI (Baccarella et al., 2021; Lee et al., 2019; Leicht et al., 2018; Panagiotopoulos & Dimitrakopoulos, 2018; Xu et al., 2018; Zhu et al., 2020). Another important factor that influences the BI is the *Perceived Ease Of Use*, which estimates how much effort people think they have to put into a technology, either physically or mentally. While some of the papers found a significant effect of the *Perceived Ease Of Use* on the BI (Panagiotopoulos & Dimitrakopoulos, 2018; Xu et al., 2018), others did not (Baccarella et al., 2021; Lee et al., 2019). Furthermore, the literature suggests that the *Perceived Usefulness* has a larger effect than the *Perceived Ease Of Use* when it comes to the BI, especially in the context of AVs (Panagiotopoulos & Dimitrakopoulos, 2018). To raise people's *Perceived Ease Of Use*, Abraham et al. (2017) suggest giving people training to become more familiar with the technology. Müller (2019), who based their research model on Davis' TAM from 1989 (Davis et al., 1989), found a significant positive effect of *Perceived Usefulness* and *Perceived Ease of Use* on the *Attitude toward using*. This *Attitude toward using* is then, in turn, found to have a positive impact on the BI. For AVs, the *Attitude toward using* is measured by posing questions that relate to people's mental construct of AVs, such as "I like the idea of using Autonomous Vehicles" (Müller, 2019).

Research also extends the TAM with other factors that could determine the acceptance of car sharing. Two of those factors commonly found in the literature are *Perceived Risk* (PR) and *Perceived Safety* (PS). While these are not exact opposites, it is assumed that a higher *Perceived Risk* has a negative impact on the *Behavioral Intention* (BI), whereas a higher *Perceived Safety* has a positive impact on the *Behavioral Intention* (BI). For *Perceived Risk*, researchers asked questions about possible concerns that people have about AVs, such as system failure and legal issues. P. Liu et al. (2019) found that *Perceived Risk* was significant for general acceptance of AVs, but not for the *Behavioral Intention* to use AVs. Others stated a significant relationship between *Perceived Risk* and *Behavioral Intention*, where *Perceived Risk* was found to have a negative impact on the BI (Lee et al., 2019; Zhu et al., 2020). To measure *Perceived Safety*, Xu et al. (2018) let their participants drive in an AV, and afterwards, asked questions such as: "I felt safe during riding in the AV". In their experiment, they found a significant relationship between *Perceived Safety* and *Behavioral Intention.* In general, it is important to consider risk and safety, as they are crucial for the adoption of AVs (Fagnant & Kockelman, 2015; Kyriakidis et al., 2015). Moreover, Hulse et al. (2018) did research on the perceptions of risk and safety regarding AVs from different points of view. They found that AVs were rated more risky than Human Operated Vehicles (HOVs) from a passenger point of view, but from the perspective of a pedestrian AVs were rated less risky than HOVs (Hulse et al., 2018). Besides that, people that already have automated features in their cars tend to see more safety benefits from AVs than people that do not (König & Neumayr, 2017).

Another important factor related to risk and safety is *Trust* (TRU), i.e., how much a person trusts an AV to drive for them. P. Liu et al. (2019), Xu et al. (2018), and Panagiotopoulos and Dimitrakopoulos (2018) found that *Trust* has a significant positive impact on the *Behavioral Intention.* This is again confirmed by Du et al. (2021), yet their acceptance model is based on the Social Cognitive Theory (SCT) by Bandura (1986). Also, when considering *Perceived Usefulness* and *Perceived Ease Of Use*, *Trust* is found to have a significant positive impact on both variables. The more a person trusts an AV, the more he or she thinks it is useful, while also perceiving AVs as easy to use (Xu et al., 2018). Moreover, *Trust* is found to have an impact on *Perceived Risk* and *Perceived Benefits* (PB), with a lower *Perceived Risk* for higher levels of *Trust* and higher *Perceived Benefits* for higher levels of *Trust* (P. Liu et al., 2019).

Technology *Anxiety* also plays a role in the acceptance of AVs and is implemented in some of the acceptance models in the literature. In general, *Anxiety* is hypothesized to have a significant negative impact on the other factors that make up the acceptance models. A study conducted by Baccarella et al. (2021) found that *Anxiety* did not have a significant direct impact on the *Perceived Usefulness* However, a negative indirect effect from *Anxiety* on the *Behavioral Intention* through *Perceived Usefulness* was found. The same study also found a negative effect of *Anxiety* on the *Perceived Ease Of Use*, together with an indirect negative effect of *Anxiety* on *Behavioral Intention* through the

Perceived Ease Of Use (Baccarella et al., 2021). However, for this variable, a direct negative impact on the *Behavioral Intention* is confirmed by Hohenberger et al. (2016), though they do not base their research model on the TAM.

Self-efficacy (SE), or a person's belief that they are capable of achieving their goals, is another commonly used factor in research to determine the acceptance of AVs, and stems from the Social Cognitive Theory (SCT) (Bandura, 1986). In the context of AVs, a person's *Self-efficacy* relates to their belief in their capability to travel with an AV (Zhu et al., 2020). *Self-efficacy* is found to have a positive impact on multiple factors in the acceptance models. Firstly, *Self-efficacy* has a positive impact on the *Behavioral Intention* (Du et al., 2021; Lee et al., 2019; Zhu et al., 2020). Secondly, Lee et al. (2019) also discovered a significant positive impact of *Self-efficacy* on the *Perceived Ease Of Use*. Lastly, *Self-efficacy* is found to have a positive effect on *Perceived Usefulness* (Zhu et al., 2020). Overall, one could say that if a person believes that they can successfully travel using an AV, the more likely they are to accept AVs in general.

The influence of other people's perceptions of AVs can not be underestimated with respect to the acceptance of AVs. Research looks at both the *Subjective Norm* (SN) from the TPB and *Social Influence* (SI) from the UTAUT as factors that determine the acceptance of AVs. Du et al. (2021) looked at the effect of *Subjective Norm* on the *Behavioral Intention*, and found a significant positive effect, which is also confirmed by another study from Zhu et al. (2020). The same study by Zhu et al. (2020) found a positive effect of the *Subjective Norm* on both the *Perceived Usefulness* and *Perceived Ease Of Use*, with the effect of *Subjective Norm* on *Perceived Ease Of Use* also found by Acheampong and Cugurullo (2019). Moreover, other research found a positive relationship between *Subjective Norm* and both the *Perceived Benefits* and *Perceived Behavioral Control* (Acheampong & Cugurullo, 2019). Lastly, the *Social Influence*, which is heavily related to *Subjective Norm*, is also confirmed to have a positive impact on the *Behavioral Intention* (Leicht et al., 2018; Panagiotopoulos & Dimitrakopoulos, 2018). All in all, what other people think of AVs is important for the individual's acceptance of AVs.

Besides the "regular" factors that could make up the acceptance of AVs, the literature also looks at factors about the enjoyment of driving an AV. Factors such as *Perceived Enjoyment* (PE), *Pleasure*, and *Novelty Seeking* (NOV) are studied. Müller (2019) discovered that the *Perceived Enjoyment* of driving an AV positively influences both the *Perceived Usefulness* and *Perceived Ease Of Use*. Moreover, *Pleasure*, which is heavily related to *Perceived Enjoyment*, is also found to positively influence the *Behavioral Intention* (Hohenberger et al., 2016). *Novelty Seeking* (NOV) also has an effect on *Behavioral Intention*. More specifically, *Novelty Seeking* has an indirect effect on the *Behavioral Intention* through both the *Perceived Usefulness* and *Perceived Ease Of Use* (Baccarella et al., 2021).

Lastly, a feeling of ownership seems to be important when it comes to accepting AVs.

The study from Lee et al. (2019) found that *Psychological Ownership* (PO), i.e., the feeling that an SAV belongs to the person, has a positive impact on the *Behavioral Intention*.

2.3.2 Influence of Socio-Demographic Factors (AV)

Not only behavioral factors that determine the acceptance of AVs are studied in the literature. In the following section, this study dives deeper into the socio-demographic characteristics of a person that could determine if they are more accepting of AVs. In the literature that uses acceptance models including behavioral factors, socio-demographic factors are often used as moderators, though some papers study the direct effect between these factors and the acceptance of AVs. In what follows, an overview of the different characteristics such as *Age*, *Gender*, and *Income* and their relationship with the acceptance of AVs is given.

Age seems to be important for the acceptance of AVs, as multiple studies have found that younger people tend to be more open to use an AV (Khan, 2017; König & Neumayr, 2017; Rahimi et al., 2020b; Rahimi et al., 2020a; Thurner et al., 2022). Acheampong and Cugurullo (2019) discovered that older people do not see the benefits (*Perceived Benefits*) of driving AVs as opposed to younger people, which could explain why people of younger age are more open towards using AVs. Besides *Age*, *Gender* also seems to play a part. More specifically, research has found men to be more willing to use an AV (Khan, 2017; König & Neumayr, 2017; P. Liu et al., 2019; Thurner et al., 2022). Acheampong and Cugurullo (2019) add further to this and state that in general, women are more sceptical about the benefits that AVs bring, and that women are less agreeing on the fact that AVs will become the norm. Researchers also investigated *Education* and its effect on AV acceptance, arguing that people of higher education are more accepting of AVs, as they possess more knowledge that people of lower education levels do not have (Prieto et al., 2017; Rahimi et al., 2020a). Thurner et al. (2022) did not find a relationship between *Education* and the acceptance of AVs. A study by Acheampong and Cugurullo (2019) found that a higher education level has a positive influence on both the *Perceived Benefits* and *Perceived Ease Of Use*, leading to a higher likelihood of accepting AVs. Living in a city, according to the literature, also makes a person more likely to use an AV (Thurner et al., 2022). With regards to *Income*, Rahimi et al. (2020a) have found that people of low and high income are more open to drive AVs. In other words, people of a middle class income are less open to drive AVs as compared to people that are low or high earners. On the contrary, a study from the same main author found that people with a low income are less likely to accept AVs (Rahimi et al., 2020b). For the variable *Household Size*, Rahimi et al. (2020b) found a positive relationship between *Household Size* and AV acceptance (also confirmed by Thurner et al. (2022)), but another study by Rahimi found a negative impact of *Household Size* regarding the acceptance of AVs (Rahimi et al., 2020a).

Characteristics of people and their car use (even if they do not own a car) is also studied in the literature. Owning a car (not to be confused with *Psychological Ownership*, which refers to the feeling of owning something, even if you do not possess that item) was also studied to measure its effect on the acceptance of AVs, but was not found significant (Thurner et al., 2022). Also, people that use a car (even if they do not have one) more frequently are less willing to accept AVs (König & Neumayr, 2017; Rahimi et al., 2020b). Lastly, the current automation level of people's cars could determine whether or not they are more accepting of AVs. The reasoning here is that people who already have some level of automation in their car, would be more accepting of AVs. König and Neumayr (2017) confirm this, saying that people with some level of automation in their car already enjoy some benefits of (partial) automation and thus are more likely to accept full self-driving vehicles. A study from Kyriakidis et al. (2015) even argues that this factor is the best predictor for future adoption of AVs.

Other studies found interesting relationships between the socio-demographic factors and other behavioral factors. One study by Leicht et al. (2018) found that a *Consumer's Innovativeness*, which also captures information about a person's age, gender etc., influences a consumer's intention to purchase. They state that the effects of the *Performance Expectancy* (PEX), *Effort Expectancy* (EE), and *Social Influence* (SI) (factors from UTAUT) on the intention to purchase are moderated by the *Consumer's Innovativeness*, such that the intention to purchase differs for different levels of the *Consumer's Innovativeness*. Another study conducted by Hohenberger et al. (2016) found that *Gender* plays a role in the *Pleasure* and *Anxiety* a person gets from driving an AV. According to their research, men get more pleasure out of driving an AV while also having less anxiety. The opposite is true for women, who experience less pleasure and get more anxiety when driving an AV. They also found an indirect negative relationship of being a woman on the *Willingness To Use* (WTU) an AV through *Anxiety*, and that this relationship depends on *Age*. In other words, a younger woman experiences less anxiety from AVs than an older woman, and thus has a higher WTU an AV than an older woman.

The driving factors behind AV acceptance (both behavioral and socio-demographic) have been discussed, though there are still some final remarks before moving on to discuss the acceptance of CS and AVs taken together. Acceptance is different for different types of people, but for the implementation of AVs we need acceptance from everyone. To tackle the problem of general acceptance, research has to better understand the human behavior (and also the effect of *Age*, *Gender*, etc.) behind the acceptance of AVs. One study by Kuderer et al. (2015) suggests that the Automated Driving Systems (ADSs) can be tweaked according to the user's characteristics, such that for different users different speeds, distance to other cars... are implemented.

Appendices A.3 and A.4 give an overview of all the studied relationships between behavioral variables for both CS and AVs. Furthermore, a summary of the discussed socio-demographic variables for CS and AVs can be found in Appendix A.5.

2.4 Acceptance of CS and AVs Combined

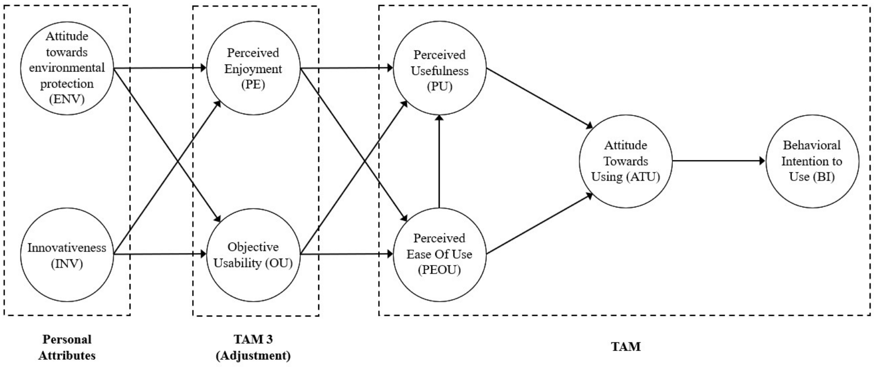
So far, this chapter has only discussed the acceptance of CS and AV separately, using research models that focus on the acceptance of either one of them. The following section will review the literature that has investigated both CS and AV adoption in one paper to better understand if the acceptance of one helps in accepting the other. There are only a few articles that have studied this relationship. Hence, each study is discussed separately and more in depth, making it easier for the reader to comprehend each study. This part is arguably the most important part of the literature review, since this study tries to address the gaps in the literature that are discussed in the following section.

The first paper that is discussed is a study conducted by Merfeld et al. (2019). Their research investigates CS with Shared Autonomous Vehicles (SAVs) by means of a Delphi-study with 40 experts who provide different drivers, barriers, and future developments needed for CS with SAVs to be implemented in the next decade. Firstly, the three main drivers were: convenience of the service, advancements in autonomous driving technology, and consumer demand (Merfeld et al., 2019). These drivers mainly consider both technological and economical aspects of SAV services. The convenience of the service can be linked to the *Perceived Usefulness* and *Perceived Ease Of Use* used in the TAM: the more convenient the service is, the higher people will perceive it as useful to perform their job (traveling from point A to point B), and the easier it will be to use such a service. The advancement of ADSs is, logically speaking, another important driver, as the technology has to be there in order to make SAV services work. As of today, there are still many advancements in the field that have to be made before a wide-range adoption of AVs is possible. Linking this back again to the TAM, one could argue that this driver can be considered as an external (also called exogenous) variable. Consumer demand is, according to the study, the third most important driver, and considers the economics of SAVs. Without consumer demand it would not be economically attractive to develop SAVs. Looking back again at the TAM, the consumer demand can be linked to the *Behavioral Intention*, i.e., the consumers' intention to use SAVs. The authors mention the costs of transportation as the fourth most important driver, as this mode of transportation will (in)directly compete with other modes of transportation, such as taxis, public transport, bicycles... (Merfeld et al., 2019). Secondly, the three most critical barriers are: technological availability of AVs, perceived security of SAVs, and legislation, with the technological availability of AVs being the most critical one. As long as AVs are not available, SAV service providers will not be able to offer the service, as the availability of AVs is a key requirement to make such a service work. Some experts that participated in the study argued that overcoming this barrier is just a matter of time, as AVs will become available in the future (Merfeld et al., 2019). The perceived security of SAVs is also key. In this context, security relates to the safety aspects that can pose a problem. The experts stress the importance of safety issues such as crashes, hacking, and software issues (Merfeld et al., 2019). Previous literature discussed in Section 2.3 also mentions that these are the key concerns of people when considering driving AVs (König & Neumayr, 2017; Kyriakidis et al., 2015). The safety barrier relates to the *Perceived Risk* and *Perceived Safety* used in acceptance models from different studies that were previously mentioned (Lee et al., 2019; P. Liu et al., 2019; Xu et al., 2018; Zhu et al., 2020). A third important barrier to overcome is legislation, such as liability or insurance issues (Merfeld et al., 2019). This barrier is also highlighted by König and Neumayr (2017) and Kyriakidis et al. (2015), who looked into people's main concerns when it comes to SAVs. Lastly, the authors provide an overview of expected future developments. The experts in the study place a high emphasis on the safety of SAVs, followed by general consumer acceptance of SAVs. The three highest ranked future developments are: technological progress for SAVs to function fully, a (successful) test phase for SAVs, and public acceptance of SAVs. Before SAV services can be rolled out, it is important to test SAVs in a closed-off environment to ensure safety, which is considered to be one of the main requirements for the public to accept SAVs (Merfeld et al., 2019).

Müller (2019) studied the acceptance of AVs, Electric Vehicles (EVs), and CS using an extended version of the TAM. However, the author tested the same research model for the three technologies separately, without any interaction between the technologies. Despite not looking into the interaction between the different technologies, the findings for some of the technologies are interesting to look at. The study includes the TAM by Davis et al. (1989) and extends the research model with TAM 3 by Venkatesh and Bala (2008) that also includes *Perceived Enjoyment* (PE), and *Objective Usability* (OU); *Perceived Enjoyment* describes how a user thinks they will enjoy the technology, and *Objective Usability* describes the actual level of effort someone has to put in (not perception) to achieve a goal. Figure 2.6 shows the research model used by Müller (2019). Both *Perceived Enjoyment* and *Objective Usability* are supposed to have an effect on *Perceived Usefulness* and *Perceived Ease Of Use*. The author then further extends the model with *Attitude towards environmental protection* (ENV) and *Innovativeness* (INV), both personal attributes that influence both *Perceived Enjoyment* and *Objective Usability* (Müller, 2019). Interestingly, all effects from the original TAM and TAM 3 were significant. The effect of *Attitude towards environmental protection* on *Objective Usability* was not significant for any of the three technologies, but *Attitude towards environmental protection* did have an effect on the *Perceived Enjoyment* for EVs and CS. Hence, in the context of CS, one could promote the environmental benefits of CS to stimulate the *Perceived Enjoyment* of CS services. Moreover, *Innovativeness* had a significant effect on *Objective Usability* for all three technologies, and also had a significant effect on *Perceived Enjoyment* for AVs and EVs (Müller, 2019). *Consumer Innovativeness* is also important for the actual effort someone has to put into using those technologies, highlighting the possible importance of *Consumer Innovativeness* (also mentioned in Leicht et al. (2018)). Thus, the more innovative a consumer is, the more enjoyment they will get out of using an AV. This is not the case for *Innovativeness* and *Perceived Enjoyment* when considering CS, since CS is not really a technology but rather a different way of how a person uses a car.

Figure 2.6

Müller Research Model

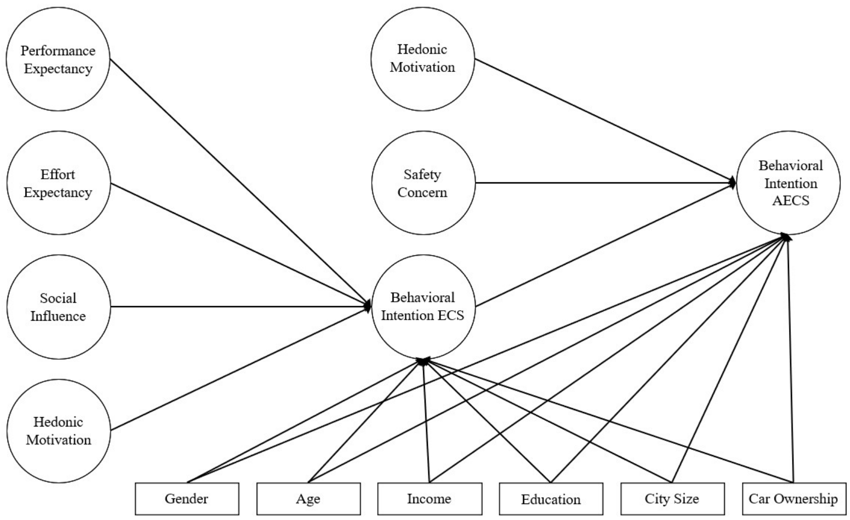


Source: Müller, 2019, p.3

Another study by Curtale et al. (2022) investigates the acceptance of Autonomous Electric Car-Sharing services (AECS). Their research model is based on UTAUT2, an extension of the original UTAUT (Venkatesh et al., 2012). The model looks into the *Behavioral Intention* to use AECS and how it is influenced by the direct effects of *Hedonic Motivation*, *Safety Concerns*, and the *Behavioral Intention* to use Electric Car-Sharing services (ECS). To determine the *Behavioral Intention* to use ECS, the model uses factors from UTAUT2 (*Performance Expectancy*, *Effort Expectancy*, *Social Influence*, and *Hedonic Motivation*). Besides behavioral variables, the model also includes socio-demographic factors that were previously mentioned in this paper such as *Gender*, *Age*, *Income* etc. Figure 2.7 shows the full conceptual model used by Curtale et al. (2022). First of all, all behavioral factors that have an effect on the *Behavioral Intention* of ECS were found to be significant. Of the socio-demographic factors that can influence the *Behavioral Intention* of ECS, only *City Size* (population smaller than 20k and population over 500k), *Car Ownership*, and *Age* were significant. Second of all, for the *Behavioral Intention* of AECS too, all behavioral factors were significant. Important to mention here is that the *Behavioral Intention* for ECS had a significant effect on the *Behavioral Intention* of AECS. The socio-demographic factors *Age*, *Gender*, and *Income* had a significant effect on the *Behavioral Intention* of AECS. More specifically, *Age* and being a woman affects the BI of AECS negatively, and having a high income has a positive effect on the BI of AECS. Interestingly, the *Behavioral Intention* of ECS and *Behavioral Intention* of AECS only share one common socio-demographic factor, namely *Age*, that affects both BIs negatively (higher *Age* leads to lower *Behavioral Intention*). The results for the socio-demographic factors in this study are somewhat in line with the research done on the influence of socio-demographic factors on either CS or AVs, though it might be interesting to include other socio-demographic factors such as *Education*, which was found to have a positive influence on both CS and AVs by some studies (Acheampong & Cugurullo, 2019; Prieto et al., 2017; Rahimi et al., 2020a).

Figure 2.7

Curtale et al. Conceptual Model



Source: Curtale et al., 2022, p.4

To further add to the common factors that are related to the acceptance of CS and AVs, this paper looks deeper into a study by Thurner et al. (2022). Their research looks at the likelihood of adopting different transport technologies (AVs, CS, and EVs) based on socio-demographic and a few behavioral factors. Note that, once again, no relation between the different technologies is assumed, and thus the effect of each variable on the acceptance of the technologies is viewed separately. For this study, the factors that estimate the likelihood of adopting EVs are disregarded and only common factors for adopting AVs and CS are looked at. For the socio-demographic factors that have an effect on the adoption of AVs and CS, only *Age* (-), *City* (urban or rural area, with urban having a positive effect), and *Household Size* (+) had a significant effect on both technologies (Thurner et al., 2022). This result confirms the same as Curtale et al. (2022) regarding *Age*. Furthermore, living in an urban area positively affects the likelihood of using AVs and CS (Thurner et al., 2022), contrary to Curtale et al. (2022) who only found a significant effect for living in a big city on ECS. For factors related to people's attitude, being a believer in technology (*Attitude to science and technology*) and being an early adopter (*Attitude to novelties*) increases the likelihood of someone to adopt AVs or CS (Thurner et al., 2022).

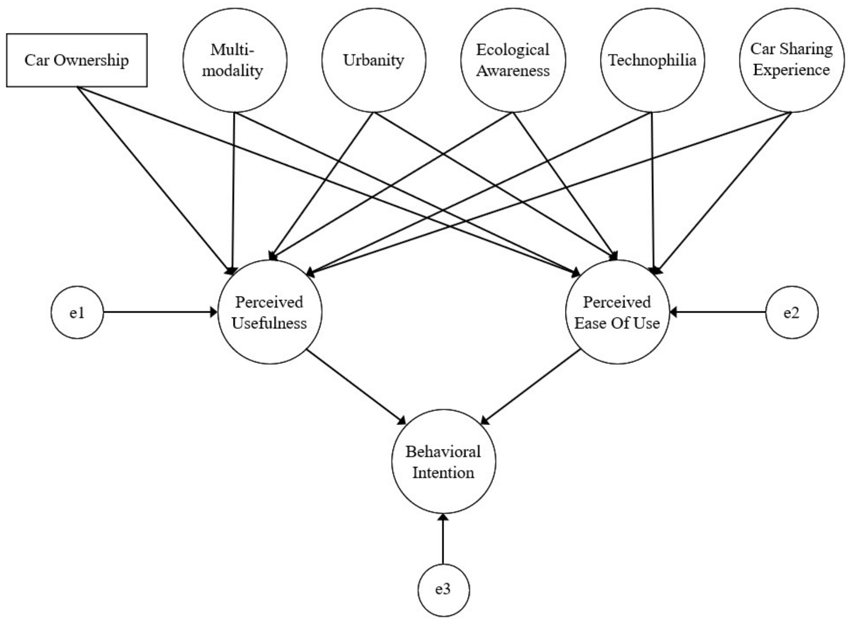
Carteni (2020) investigated the acceptability value of SAV services in Naples, Italy. He looks at the *Unwillingness To Pay* for self-driving transportation modes, as past research has proven that people are reluctant to using (S)AVs due to a lack of trust, mainly because of issues regarding safety and security (see König and Neumayr (2017) and Kyriakidis et al. (2015)). Using a discrete choice experiment and a mixed logit model, the author tries to uncover the monetary value behind the *Unwillingness To Pay*. In his findings, Carteni (2020) reports a mean monetary value of -2.31 euros per trip (*Unwillingness To Pay*), meaning that a person is willing to pay 2.31 euros more to use other modes of transport, such as a bus or a taxi, instead of an SAV (for the same trip) (Carteni, 2020). Besides looking at the general *Unwillingness To Pay*, the study also looks at the effects of *Age*, *Gender* and whether a person already has automation features in his or her car. For *Age*, younger people were found to be less reluctant and had a lower *Unwillingness To Pay*. This result is comparable with past research that looks at the acceptance of CS and AV and the effect of *Age* (Curtale et al., 2022; Thurner et al., 2022). *Gender* was also found to have a significant impact. More specifically, men should be less reluctant to the technology than women, having a lower *Unwillingness To Pay*, which is a similar result to that of Curtale et al. (2022) who state that women have a lower *Behavioral Intention* to use AECS. Interestingly, people that already use (partial) automation features in vehicles have a positive willingness to pay, meaning they would pay more to use (S)AVs than other transportation modes. This result from Carteni (2020) is in line with that of König and Neumayr (2017), who found that people using automation systems see the benefits of their use.

Lastly, a paper by Schlüter and Weyer (2019) that looks at CS as a mean to raise the acceptance of EVs is reviewed. Though it is not relevant to look at the acceptance of EVs for this paper, their study is still interesting to look at because the methods used could be helpful for this paper. The authors of the study use a basic version of the TAM that includes *Perceived Usefulness*, *Perceived Ease Of Use*, *Behavioral Intention*, and extend it with external variables such as *Car Ownership*, *Multimodality*, *Urbanity* etc. (Schlüter & Weyer, 2019). One of the external variables that was proven to be important in their research was *Car Sharing Experience*, a variable that can possibly be of interest for this research. Figure 2.8 shows the research model used in the study by Schlüter and Weyer (2019). The results found that *Car Sharing Experience* had a positive significant impact on the *Perceived Usefulness*. Furthermore, positive relationships between *Car Sharing Experience* and *Urbanity* (living in dense areas), and *Car Sharing Experience* and *Multimodality* (variety of transportation options) were discovered. Lastly, there is a negative relationship between *Car Sharing Experience* and *Car Ownership* (Schlüter & Weyer, 2019). The relationships between *Car Sharing Experience* and the other variables imply that people with CS experience usually live in dense areas, use a variety of transportation modes, and own less cars. Besides testing the hypotheses included in their research model, the authors also investigated the relationship between *Car Sharing Experience* and the *intentions to buy an EV*, and the relationship between *Car Sharing*

Experience and the *intentions to use EV car sharing* (if available), which both relate to the *Behavioral Intention* to use EVs (Schlüter & Weyer, 2019). Both hypotheses were supported, meaning that prior *Car Sharing Experience* had a direct impact on the *Behavioral Intention* to use EVs, according to the study.

Figure 2.8

Schlüter and Weyer Research Model



Source: Schlüter and Weyer, 2019, p.7

The next section of this chapter goes over the analysis of secondary data received from Autodelen.net. The goal of this analysis is to see if the findings from the previously discussed research and the findings that come forth from the secondary data analysis are consistent with one another.

2.5 Analysis iVOX Data Set

Before analyzing the primary data for this research, Autodelen.net provided secondary data that they have collected from a survey in collaboration with iVOX, a market research and polling agency based in Leuven, Belgium. The analysis of this data and possible results are considered part of the literature review, since the survey constructed and data collected are not in line with this paper's particular research question. Still, it is interesting to see if there are any findings that come forth. The aim of this data analysis is to see whether (possible) relations found in the data are similar to those found in the literature reviewed in Sections 2.2, 2.3, and 2.4. In the following subsections, we go over how data was collected, together with a descriptive and statistical analysis of the data.

Data Collection

The data was obtained through the use of an online questionnaire, held between the 26th of September 2019 and the 7th of October 2019. One limitation that has to be kept in mind is that this data is old, and that people's preferences could have changed in this four-year period. Appendix B contains the questions of the survey conducted by iVOX. The survey, conducted among 1,000 Flemings (N = 1,000), is representative on age, gender, province, and educational degree. Of the 1,000 respondents, 506 (50.6%) were male and 494 (49.4%) were female. The age of the respondents ranged from 18 until 79, with a mean age of 49.7. Hereby, only 15 out of the 1,000 respondents (1.5%) were members of a CS service. The small amount of CS members meant that, to compare the difference in means between CS and non-CS members, Welch's t-tests were used (Delacre et al., 2017). A full overview of the the socio-demographic characteristics of the respondents is shown in Table 2.1.

Descriptive Analysis

General Remarks

First, a descriptive analysis of the data was done to identify potential trends and relationships in the data. For car sharers, the question "How often did you use Car Sharing the past month?" was asked. Of the 15 car sharers, 9 people (60%) indicated that they did not use CS in the past month, 4 people (26.67%) said they used car sharing less than weekly in the past month, and only 2 (13.33%) indicated that they used car sharing 1 to 3 times per week in the past month. Non-car sharers were asked the question "How likely are you to become a member of a Car Sharing service?". From the 985 who were not yet members of a CS service, 768 (77.97%) answered "Certainly not" or "Likely not", 89 (9.04%) answered "Certainly yes" or "Likely yes", while 128 respondents (13%) had no opinion. This result implies that there is still a lot of work to do regarding the adoption of CS.

Cross Table Results

The survey agency iVOX provided a cross table for the different variables measured in the survey. From the cross table, several results came forth. Firstly, car sharers tend to live more in urbanized areas, whereas non-car sharers live more in rural areas. Studies by Prieto et al. (2017) and Thurner et al. (2022) have found a similar result, reporting

Table 2.1

Socio-Demographic Characteristics iVOX Data

Characteristic	n	%
Gender		
Male	506	50.6
Female	494	49.4
Age		
<= 34	237	23.7
35-54	387	38.7
55+	376	37.6
Diploma		
Lower Education	616	61.6
Higher Education	384	38.4
Urbanisation		
Urban	452	45.2
Rural	548	54.8
Family Situation		
Single	227	22.7
Living Together	698	69.8
Other	75	7.5
Employment		
Working	601	60.1
Non-Working	399	39.9
Family Income		
<20k	106	10.6
20k-30k	164	16.4
30k-40k	161	16.1
40k-50k	140	14.0
>50k	190	19.0
Prefer Not To Say	239	23.9
Driving License		
Owns	902	90.2
Does Not Own	98	9.8
Member CS Organisation		
Yes	15	1.5
No	985	98.5

Note. N = 1,000

that living in an urban area has a significant effect on the acceptance of CS. Secondly, compared to non-car sharers, car sharers use more sustainable modes of travel, such as bicycles and public transport. Rabbitt and Ghosh (2013) noted the same, saying that using CS indirectly promotes people to use other, more sustainable forms of transport. Moreover, car sharers are less likely to own a car (and when they own one, barely use it) and live in more urbanized areas (where public transport is more easily available) compared to non-car sharers, hence they use other modes of travel instead of a privately owned car. Lastly, car sharers are, in terms of percentage, more often subscribed to an electric scooter sharing platform than non-car sharers.

Scores on Car Sharing Questions

Some questions in the survey were asking car sharers' and non-car sharers' opinions on various aspects of CS. CS_Convenience, CS_Features, and CS_Parking questioned a total of 25 aspects of CS to non-car sharers with the question: "To what extent would the following aspects of Car Sharing convince you to use Car Sharing?". The same 25 aspects were asked to car sharers as well, but now the question was formulated as: "To what extent do you find the following aspects of Car Sharing important as a Car Sharing user?". Because the same aspects were asked to car sharers and non-car sharers, it was easy to compare what aspects both parties agreed the most on. CS_Convenience consisted of 8 aspects regarding the overall ease of use of CS, such as rental options, how easy it is to make a reservation, as well as support when something goes wrong. Things like the features of a shared car, look and feel of the car, the car model, the possibility to take animals with you etc. were asked in CS_Features which included 9 aspects. Lastly, CS_Parking asked about 8 aspects regarding parking availability, unlimited parking, parking spots close to public transport,... among others. The results from the Welch's t-tests, visible in Table 2.2, show that car sharers scored significantly higher on the aspects of CS as compared to non-car sharers, suggesting that car sharers are more motivated to use CS than non-car sharers. Overall, car sharers seemed to score the highest on CS_Convenience, followed by CS_Parking, whereas for non-car sharers the opposite was true. This result could be caused by the fact that car sharers are already familiar with how and where they should park a shared car, and want a more user-friendly experience for making reservations etc. Both parties scored the lowest on CS_Features, meaning that they do no attach great importance to how the car looks, the possibility to transport animals etc. as compared to the other aspects of CS.

For each of the questions, we ranked the top three highest scoring aspects in the question and made a comparison between car sharers and non-car sharers. Firstly, for CS_Convenience, the top three was the same for both groups. Both parties prefer the possibility to get assistance when something goes wrong (damage, breakdowns etc.), the availability of the cars on demand, and the possibility to reserve a car hours or days beforehand. Secondly, for questions concerning CS_Features, the top three was again the same for both groups. Car sharers and non-car sharers favour the ease of using a

Table 2.2

Scores on Questions iVOX Data Set

Question	Average Score (out of 4)		p
	Car Sharers	Non-Car Sharers	
CS_Convenience	3.24	2.31	<.001
CS_Features	2.74	2.12	.001
CS_Parking	3.05	2.37	.003
Question	Average Score (out of 5)		p
	Car Sharers	Non-Car Sharers	
CS_Platform	3.31	2.43	<.001
AV_Q1	2.89	2.85	.98
AV_Q2	2.86	2.86	.90
AV_Q3	2.90	2.67	.36

shared car, the cleanliness of the car, and an increase in the total amount of available cars. Lastly, as opposed to the previous two questions, the results differed across the groups for CS_Parking. Car sharers prefer improvements in parking spaces, such as the location of the parking spaces, the amount of parking spaces, and the connection from those parking spaces to public transport. Non-car sharers however, rather have the availability to park wherever they want or reserve parking spots at guarded parking lots to save them the hassle of finding a parking spot. The difference between car sharers and non-car sharers is likely due to car sharers already being used to parking a shared car at dedicated parking spots, and them wanting to see improvements for those parking spots, whereas non-car sharers view this as a barrier to entry; they rather have the ability to park anywhere, instead of parking at a dedicated spot and having to travel to their final destination using other transportation (Note: Krueger et al. (2016) mentioned that by full automation of shared cars, this barrier to entry could disappear).

Car Sharing Platform Scores

In the survey, participants received a question asking their preferences regarding four different types of mobility platforms (CS_Platform). Of these four options, car sharers showed the most preference for a platform dedicated to reserving and ordering shared mobility, such as shared cars, shared scooters, and shared bicycles. Non-car sharers favoured a platform where they could do the same as mentioned in the previous sentence, while also having the ability to buy tickets for public transport through this platform. In general, car sharers scored higher than non-car sharers on the question about mobility platforms, p <.001 (see CS_Platform in Table 2.2). Furthermore, participants were also asked to rank different aspects of a Car Sharing platform based on their personal preferences. The top three aspects for car sharers were related to a pleasant user experience of the application, the availability to have a shared car in the area, and one administrative procedure (one registration) for all mobility services. The non-car sharers' top three looked slightly different, with the availability of a shared car at number one. Besides that, they prefer a low cost of using the platform and one application for all mobility. Interestingly, 34.4% of non-car sharers indicated none of the aspects in the question for three possible reasons: none of the aspects interest them, they simply do not have an opinion, or they are generally not interested in CS. When it comes to the willingness to pay for such a platform, either via a monthly fee or transaction costs, 53% of car sharers indicated they would be willing to pay to use the platform, as opposed to 31% of non-car sharers.

Scores on Autonomous Vehicle Questions

Finally, respondents received statements about Autonomous Vehicles (AVs) in questions AV_Q1, AV_Q2, and AV_Q3. The first two questions contained a total of 15 statements about AVs in general, while AV_Q3 consisted of three statements regarding Shared Autonomous Vehicles (SAVs). Overall, the differences between the average scores of car sharers and non-car sharers for those three questions were not statistically significant, as shown in Table 2.2. When comparing the highest scoring statements for car sharers and non-car sharers there are a lot of similarities, though non-car sharers were more skeptical about the trustworthiness of AVs.

Statistical Analysis

After making a descriptive analysis of the data, statistical methods are used to measure the impact of some of the variables on others. The goal of this analysis is to see if findings from this data are in line with the findings from the literature. More specifically, we identify different socio-demographic characteristics and their influence on the (average) scores on the questions related to CS and AVs. The questions related to CS and AVs are related to the external variables that influence the *Perceived Usefulness* and *Perceived Ease Of Use* from the TAM (Davis, 1985) discussed in Section 2.1. In the following, the preparation of the data is explained, followed by an elaborate discussion of the regression analysis used to find the relationships in the data.

Preparing the Data for Analysis

The data set provided by iVOX contained many variables, of which some were selected for the analysis. Hereby, the socio-demographic characteristics that were found to be important in the literature are included. *Age*, *Gender*, *Education*, and *Place of Residence* are factors discussed in the literature and are considered to have an influence on the intention to use CS and AVs, hence they are included. Past research has also investigated the effects of *Household Size* (HH_Size) and *Household Car Ownership* (HH_CO), though these were not extensively studied. To measure their impact, both variables are included in the analysis. Other variables that are not discussed in the research but seemed interesting to include are *Employment* (Emp), *Drivers License* (DL), and *Subscriptions* (Subs). These variables are included because there might be differences in the acceptance of CS and AVs based on people's preferred transportation modes and their employment status. For CS, variables *Car Sharing Member* (CS_Member), aspects of CS (CS_Convenience, CS_Features, and CS_Parking), scores on statements regarding a sharing platform (CS_Platform), and the Willingness To Pay for such a platform (Platform_WTP) are included. Moreover, the questions on AVs (AV_Q1, AV_Q2, and AV_Q3) are also incorporated in the analysis data set. Other variables were asked in the survey, but those are not included in the data used for the analysis since they are not discussed in previous research, or are variables that are only useful for descriptive statistics. *Household Income* was a variable that could have been included in the analysis, but since 245 out of the 1,000 (24.5%) indicated they would rather not answer this question, the variable was left out of the analysis.

Because some of the questions in the survey had the option to be answered with "no opinion" and some were measured on a different scale (some on a 1-4 scale, others on a 1-5 scale), the data was treated to ensure all variables had the same scale and thus equal weights in the model. This was accomplished by removing all respondents who answered "no opinion" at least once in either CS_Convenience, CS_Features, CS_Parking, CS_Platform, AV_Q1, AV_Q2, or AV_Q3, and by normalizing the different scales of those questions to a 0-1 interval. Doing so resulted in the remaining data set containing 406 respondents, 7 of which are car sharers, and 399 being non-car sharers.

The second statement of AV_Q2, AV_Q2r2, led to an issue. Out of the remaining 406 respondents, 139 (34.2%) did not have their answer recorded in the data. Instead of deleting their response, we imputed the missing data using the k-nearest neighbors algorithm (Cover & Hart, 1967) with AV_Q2r2 as the target variable, and the scores on the questions regarding AVs (AV_Q1, AV_Q2, and AV_Q3) as the independent variables. Here, the algorithm looks at the scores of the independent variables and the score on AV_Q2r2 for non-missing values, and calculates the score on AV_Q2r2 for missing values based on the 5 nearest-neighbors (people who scored similarly on AV_Q1, AV_Q2, and AV_Q3).

Furthermore, the Cronbach's alphas (Cronbach, 1951) for questions CS_Convenience, CS_Features, CS_Parking, CS_Platform, AV_Q1, AV_Q2, and AV_Q3 were calculated and are shown in Table 2.3. An acceptable cut-off value for the Cronbach's alpha is .7 (Cortina, 1993), resulting in AV_Q2 not being kept as its alpha was lower than .7 (.65).

Table 2.3

Cronbach's Alphas

Variable	Cronbach's Alpha
CS_Convenience	.98
CS_Features	.95
CS_Parking	.95
CS_Platform	.95
AV_Q1	.80
AV_Q2	.65
AV_Q3	.75

For the remaining variables (CS_Convenience, CS_Features, CS_Parking, CS_Platform, AV_Q1, and AV_Q3) the average score on that question for each respondent was calculated and normalized to a 0-1 scale.

Categorical variables (Emp, HH_Size, DL, CS_Member, HH_CO, Subs, Platform_WTP, Gender, Education, and Place of Residence) are dummy encoded. Variables with k categories (e.g., HH_CO) are encoded with k-1 dummies. As mentioned before, some variables are measured on a 1-4 Likert scale (CS_Convenience, CS_Features, CS_Parking), while other are measured on a 1-5 Likert scale (CS_Platform, AV_Q1, AV_Q3). To put them on the same 0-1 scale, they are normalised using the following formula:

$$X_{\text{norm}} = \frac{X - X_{\text{min}}}{X_{\text{max}} - X_{\text{min}}}$$

Age is also normalised to a 0-1 scale, so that all variables used in the analysis have equal weights in the models used. All variables used for the analysis are shown in Table 2.4.

Regression Analysis

Two different multiple linear regression models based on Ordinary Least Squares (OLS) predict the scores of the questions on CS and AV. For Model 1, the average score on the CS questions (CS_Convenience, CS_Features, CS_Parking, and CS_Platform) was calculated and made into one variable "Q_CS", which serves as the dependent variable for Model 1 and can be interpreted as the external variables from the TAM that influence the PU and PEOU (Davis, 1985). The regression equation for Model 1 is shown below.

$$\begin{aligned} \text{Q\_CS} = \beta_0 &+ \beta_1 \text{Emp} \\ &+ \beta_2 \text{HH\_Size\_2} + \beta_3 \text{HH\_Size\_3} + \beta_4 \text{HH\_Size\_4} \end{aligned}$$

Table 2.4

Variables Included in iVOX Analysis

Variable	Measurement	Type	Other Information
Emp	Employment	Categorical	Working = 1, Non-Working = 0
HH_Size	Household Size	Categorical	Dummified: Base Level = 1 person, HH_Size_2 = 2 people, HH_Size_3 = 3 people, HH_Size_4 = 4 people or more
DL	Driving License	Categorical	Owns DL = 1, Does Not Own DL = 0
CS_Member	Car Sharing Member	Categorical	Yes = 1, No = 0
HH_CO	Household Car Ownership	Categorical	Dummified: Base Level = 0 cars, HH_CO_2 = 1 car, HH_CO_3 = 2 cars, HH_CO_4 = 3 cars or more
CS_Convenience, CS_Features, CS_Parking	Car Sharing Aspects	Ordinal	Normalized to a 0-1 scale
Subs	Subscriptions	Categorical	Subsr1 = public transport, Subsr2 = shared bikes, Subsr3 = shared scooter, Subsr4 = shared electric scooter, Subsr5 = none
CS_Platform	Car Sharing Platform	Ordinal	Likert scale normalized to a 0-1 scale
Platform_WTP	Willingness To Pay CS Platform	Categorical	Yes = 1, No = 0
AV_Q1, AV_Q3	Autonomous Vehicle Statements	Ordinal	Likert scale normalized to a 0-1 scale
Geslacht	Gender	Categorical	Male = 1, Female = 0
Geboortejaar	Age	Numerical	Normalized to a 0-1 scale
Diploma2	Education	Categorical	Lower Education = 1, Higher Education = 0
Urban2	Place of Residence	Categorical	Urban = 1, Rural = 0
Q_CS	External Variables CS	Numerical	Average score per respondent of CS_Convenience, CS_Features, CS_Parking, and CS_Platform. Dependent variable for regression Model 1. Also used as independent variable in regression Model 2
Q_AV	External Variables AV	Numerical	Average score of AV_Q1 and AV_Q3. Dependent variable for regression Model 2.

$$
\begin{aligned}
&+ \beta_5 \text{DL} \\
&+ \beta_6 \text{CS\_Member} \\
&+ \beta_7 \text{HH\_CO\_2} + \beta_8 \text{HH\_CO\_3} + \beta_9 \text{HH\_CO\_4} \\
&+ \beta_{10} \text{Subsr1} + \beta_{11} \text{Subsr2} + \beta_{12} \text{Subsr3} + \beta_{13} \text{Subsr4} + \beta_{14} \text{Subsr5} \\
&+ \beta_{15} \text{Platform\_WTP} \\
&+ \beta_{16} \text{Geslacht} \\
&+ \beta_{17} \text{Age\_norm} \\
&+ \beta_{18} \text{Diploma2} \\
&+ \beta_{19} \text{Urban2} + \epsilon
\end{aligned}
$$

Model 2 takes the average of the questions on AVs (AV_Q1, AV_Q3), named "Q_AV", as the dependent variable and represents the external variables of AVs that influence the PU and PEOU of AVs. In Model 2, the same independent variables from Model 1 are used, with "Q_CS" as an extra independent variable in the model to measure the impact the score on "Q_CS" has on the score on "Q_AV". The regression equation used for Model 2 is written below.

$$
\begin{aligned}
\text{Q\_AV} = \beta_0 &+ \beta_1 \text{Emp} \\
&+ \beta_2 \text{HH\_Size\_2} + \beta_3 \text{HH\_Size\_3} + \beta_4 \text{HH\_Size\_4} \\
&+ \beta_5 \text{DL} \\
&+ \beta_6 \text{CS\_Member} \\
&+ \beta_7 \text{HH\_CO\_2} + \beta_8 \text{HH\_CO\_3} + \beta_9 \text{HH\_CO\_4} \\
&+ \beta_{10} \text{Subsr1} + \beta_{11} \text{Subsr2} + \beta_{12} \text{Subsr3} + \beta_{13} \text{Subsr4} + \beta_{14} \text{Subsr5} \\
&+ \beta_{15} \text{Platform\_WTP} \\
&+ \beta_{16} \text{Geslacht} \\
&+ \beta_{17} \text{Age\_norm} \\
&+ \beta_{18} \text{Diploma2} \\
&+ \beta_{19} \text{Urban2} \\
&+ \beta_{20} \text{Q\_CS} + \epsilon
\end{aligned}
$$

The goal of the regression models is to see if different independent variables have an influence on the external variables from CS (Model 1), or on the external variables from AVs (Model 2). If the independent variables can predict the value of the dependent variables, then the findings from past research hold in the iVOX survey. In each iteration of estimating a model, insignificant variables ($p < .1$) were removed until all the variables in the model were found significant. This approach is adopted for both Model 1 and Model 2.

Model 1 was iterated three times before all variables in the model had a significant impact on the data. The independent variables in the model predicted the score on the

Table 2.5

Model 1: Regression Output, Response Variable = Q_CS

Effect	Estimate	*SE*	95% CI		*p*
			LL	*UL*	
Intercept	.601	.064	.476	.727	<.001
Diploma2	-.078	.026	-.128	-.027	.003
Age_norm	-.257	.050	-.356	-.158	<.001
HH_CO_2	-.141	.061	-.261	-.021	.021
HH_CO_3	-.174	.060	-.292	-.055	.004
HH_CO_4	-.236	.072	-.378	-.094	.001
Platform_WTP	.301	.027	.248	.354	<.001

Note. SE = Standard Error, CI = Confidence Interval, *LL* = Lower Limit, *UL* = Upper Limit.

CS variable, R^2 = .316, F(6,399) = 30.78, p < .001. Table 2.5 shows the coefficient, standard error, t-statistic, p value, and 95% confidence interval for each of the independent variables. We can see that being low educated (Diploma2) had a negative impact on Q_CS, t = -3.02, p = .003. This suggests that people who are lowly educated are less likely to notice the benefits of CS and thus have a more negative view towards CS. Also *Age* (Age_norm) seemed to negatively influence the scores, t = -5.09, p < .001. In the literature, *Age* was also found to be a significant factor that negatively influences the *Behavioral Intention* of using CS (Curtale et al., 2022; Prieto et al., 2017; Rahimi et al., 2020a; Thurner et al., 2022). Furthermore, being a household that has cars also lowered the score for Q_CS, with owning more cars having a stronger negative effect (HH_CO_2, HH_CO_3, HH_CO_4). The more cars a household has, the less they have the need to use CS. Lastly, being willing to pay for a sharing platform (Platform_WTP) is a positive indicator for Q_CS, t = 11.20, p < .001.

In Model 2, all independent variables were significant after 4 iterations. In this model, Q_CS was also incorporated as an independent variable to see if it had any effect on Q_AV. The model itself was significant, R^2 = .249, F(5,400) = 26.56, p < .001. Table 2.6 displays the coefficients, standard errors, t-statistics, p values, and confidence intervals for all of the independent variables. First of all, being a man (*Gender*) positively influenced the score on the questions regarding AVs, t = 2.67, p = .008. Just as in Model 1, being of low education (Diploma2) had a negative impact on Q_AV, t = -2.88, p = .004, and a person's *Age* (Age_norm) also had a negative influence on the dependent variable, t = -3.58, p < .001. In research previously done on the acceptance of AVs, several studies have found similar results for *Gender* (Khan, 2017; König & Neumayr, 2017; P. Liu et al., 2019; Thurner et al., 2022), *Age* (Khan, 2017; König & Neumayr,

Table 2.6

Model 2: Regression Output, Response Variable = Q_AV

Effect	Estimate	*SE*	95% CI		*p*
			LL	*UL*	
Intercept	.3700	.035	.302	.438	<.001
Geslacht	.0544	.020	.014	.094	.008
Diploma2	-.0592	.021	-.100	-.019	.004
Age_norm	-.1464	.041	-.227	-.066	<.001
HH_CO_3	.0553	.020	.015	.096	.007
Q_CS	.2805	.035	.213	.348	<.001

Note. SE = Standard Error, CI = Confidence Interval, *LL* = Lower Limit, *UL* = Upper Limit.

2017; Rahimi et al., 2020b; Rahimi et al., 2020a; Thurner et al., 2022), and *Education* (Acheampong & Cugurullo, 2019). Owning two cars in a household (HH_CO_3) also seems to have a positive effect on Q_AV, $t = 2.70$, $p = .007$. A possible explanation for this is that households owning two cars see the benefits of having an AV, and would rather have an AV than a regular car. Interestingly, scoring high on the questions about CS (Q_CS) has a positive effect on the questions about AVs, $t = 8.13$, $p < .001$. Though not the same, Curtale et al. (2022) found that the *Behavioral Intention* of using Electric Car Sharing services (ECS) had a positive significant impact on the *Behavioral Intention* to use Autonomous Electric Car Sharing services (AECS). This last result is of particular interest for this study, since it investigates whether the acceptance of CS leads to a higher acceptance of AVs.

To conclude this section on the analysis of the iVOX data set, some findings came forth, but were limited due to problems with the data. We now know more about the preferences of car sharers and non-car sharers regarding the use of CS and the use of AVs, more specifically that car sharers have a more positive attitude towards CS than non-car sharers, but also that both groups have a similar attitude when it comes to AVs. The regression analysis also reveals that some of the variables that were found to be significant in the literature are also significant in this data. Moreover, scoring high on the questions about CS has a positive impact on the score on the questions regarding AVs, showing us that there is a possible relationship between the acceptance of CS and the acceptance of AVs. Despite the results being a good indication for the primary research conducted in this study, it is important to mention that the results are limited on their own. Firstly, having different scales for questions and the option to answer "no opinion" makes it more difficult to analyze the data. Secondly, the data provided was not fully in line with the research purpose of this study, but rather had a more general purpose, which had an impact on the variables that could be analyzed and the results that came forth. Lastly, the data is old, making the data less reliable and more inaccurate. It is likely that current behaviour has changed and that, if the survey was conducted now, the results would have been different.

Research Design and Methods

The previous chapter has concluded all the relevant background literature to grasp a better understanding of past research that has been done regarding the acceptance of CS, AVs, or both. Despite the wide range of literature that studied the acceptance of these technologies, a big research gap still exists, more specifically with respect to CS as a mean to stimulate the acceptance of AVs. This chapter of the paper goes over the research design and methods used to try and close the gap in the research and to make a meaningful contribution in the research field of CS and AVs. More specifically, the research aims, model development, and measures are discussed. The chapter concludes with the analysis, in which the data collection and pre-processing are explained, together with the different steps taken in the analysis process.

3.1 Research Aims

Up until now, only Curtale et al. (2022) recognized the potential relationship between CS and the acceptance of autonomous driving. They studied the influence of the *Behavioral Intention* (BI) of Electric Car Sharing (ECS) on the BI of Autonomous Electric Car Sharing (AECS), which they found to be significant. However, not only the specific case of shared electric vehicles should be studied since these vehicles could also be bought for private use and do not necessarily need to be shared, just like we drive regular cars today. Hence, this paper aims to study this relationship in a wider sense, looking at the influence of CS in its entirety on the acceptance of AVs as a whole, without considering a particular type of implementation. More specifically, the influence of a person's BI of CS on their BI of AVs will be analyzed. This is important because if this relationship exists, and is found to be significant, then future acceptance of AVs could already be stimulated starting today. This would mean that policy makers and manufacturers of AVs could influence the population's future intention to use AVs in the present by making sure people know about CS, its workings, benefits, etc.

Furthermore, not only the *Behavioral Intention* of both CS and AVs is studied, but other relevant variables are included as well. These variables give us insights into the drivers behind the acceptance of these technologies, which can help design smart approaches and policies to increase the public's acceptance of both CS and AVs. Besides these particular aspects, socio-demographic factors also appear to be of relevance in this field of study. Even though a person's socio-demographic characteristics are (nearly) impossible to influence, recognizing the impact of these characteristics is already a big step in the right direction. For instance, imagine this study concludes that women are significantly less willing to adopt AVs for safety reasons. In that case, special programs or activities could be designed for women in order to ensure them about the vehicles' safety and give them the opportunity to ask questions to experts. By adopting this logic, each socio-demographic characteristic can tell us more about a person's BI, and help policy makers and manufacturers to maximize the general acceptance of both technologies. Hence, the impact of a person's socio-demographic characteristics should most certainly not be neglected.

3.2 Model Development

As discussed in Section 3.1, the *Behavioral Intention* (BI) of CS and AVs are not the only variables included in this study. A lot of other behavioral variables, together with socio-demographic factors, are also included to gain as many insights as possible. In this part, an explanation of the selected variables and factors is given, together with the reason why they have been chosen. This lays the foundation for the hypotheses formulated and tested in this study (summarized in Table 3.1) which then, in turn, make up the research model analyzed in this paper.

3.2.1 Variables and Hypotheses Formulation

Behavioral Variables

Behavioral Intention

The *Behavioral Intention* (BI) of CS and AVs are the most important variables for this study's model since they express the user's intention to perform a certain behavior, more specifically the intention to use CS or AVs. This variable is included in all of the behavioral models mentioned in Section 2.1 as the dependent variable. This particular study is interested in finding out what factors drive the BI of both CS and AVs, and tests whether the BI of CS actually has an impact on the BI of AVs.

Hypothesis 1 (H1): The *Behavioral Intention* of CS has a positive impact on the *Behavioral Intention* of AVs.

Attitude

The user's *Attitude* (AT) towards the technology is, according to the TAM and TPB, a crucial determinant of the user's BI of the technology (Ajzen, 1991; Davis et al., 1989). Even though Venkatesh and Davis (1996) eventually removed this variable from the TAM, it still is proven to be of importance for the acceptance of the technologies that are studied in this paper. For instance, as discussed in Section 2.3.1, Müller (2019) finds AT to be a significant driver of the BI for both CS and AV, and the same conclusion is formed by Mattia et al. (2019) for CS.

Hypothesis 2 (H2): The *Attitude* towards the technology has a positive impact on the *Behavioral Intention* for both CS and AVs.

Perceived Usefulness and Perceived Ease of Use

Perceived Usefulness (PU) and *Perceived Ease of Use* (PEOU), equivalent to *Performance Expectancy* (PEX) and *Effort Expectancy* (EE) respectively (see Appendix A.2), are fundamental elements of the TAM and UTAUT (Davis, 1985; Venkatesh & Davis, 1996; Venkatesh et al., 2003). Both are included in many technology acceptance studies, and have been proven to be of significant importance for both CS and AVs, as can be seen in the overview provided in Appendices A.3 and A.4. All papers that have been discussed in Chapter 2 confirm both the positive relationship between PU and *Attitude* (AT), as well as the relationship between PU and *Behavioral Intention* (BI) for both CS and AVs. As opposed to PU, the literature is a bit more divided about the importance of PEOU. For instance, Baccarella et al. (2021) and Lee et al. (2019) do not identify the positive influence of PEOU on the BI for AVs, while Curtale et al. (2021) form the same conclusion for CS. However, the amount of papers that conclude this insignificance is very low and most papers do find the effect of PEOU on AT and BI to be relevant as shown in Appendices A.3 and A.4. Hence, it is important to make sure the user knows about the technologies' usefulness, benefits, convenience of use, etc. since in theory, this improves the adoption. Due to the importance of PU and PEOU in the literature, they are both included in the research model of this paper. Moreover, not only their direct impact on BI will be analyzed, but their indirect influence on BI through AT will be tested as well.

Hypothesis 3a (H3a): The *Perceived Usefulness* has a positive impact on the *Attitude* for CS and AVs.

Hypothesis 3b (H3b): The *Perceived Usefulness* has a direct positive impact on the *Behavioral Intention* for CS and AVs.

Hypothesis 3c (H3c): The *Perceived Usefulness* has an indirect positive impact on the *Behavioral Intention* through *Attitude* for CS and AVs.

Hypothesis 4a (H4a): The *Perceived Ease of Use* has a positive influence on the *Attitude* for CS and AVs.

Hypothesis 4b (H4b): The *Perceived Ease of Use* has a direct positive influence on the *Behavioral Intention* for CS and AVs.

Hypothesis 4c (H4c): The *Perceived Ease of Use* has an indirect positive impact on the *Behavioral Intention* through *Attitude* for CS and AVs.

Subjective Norm

Subjective Norm (SN), or *Social Influence* (SI), is the variable that takes external influences on the individual into account, and is part of the TPB and UTAUT (Ajzen, 1991; Venkatesh et al., 2003). This variable determines whether people are influenced by their peers, such as colleagues and close-ones, when adopting new technologies. The SN has been proven to have a significant positive effect on the BI by many papers for both CS and AVs (Appendix A.4). The study conducted by Tran et al. (2019) is the only one that does not confirm this influence. However, SN is an important part of the TPB and UTAUT, and has been proven to be significant multiple times. Thus, this paper will explore the effect of this variable on the acceptance of CS, as well as on the acceptance of AVs.

Hypothesis 5 (H5): The *Subjective Norm* has a positive impact on the *Behavioral Intention* for CS and AVs.

Perceived Behavioral Control

Perceived Behavioral Control (PBC), also called *Facilitating Conditions* (FC), is an essential part of the TPB and UTAUT (Ajzen, 1991; Venkatesh et al., 2003). The PBC is the user's perception of the degree to which he or she is in control of the performance of a certain behavior, as explained in Section 2.1 (Marangunić & Granić, 2015). In this paper, the PBC is only included for CS since no papers were found where this variable was studied for AVs. This could be due to the fact that AVs are not on our roads yet, which makes it difficult to asses this factor without having had any type of interaction with the technology. Concerning CS, the only paper that studied the effect of the PBC on the *Behavioral Intention* (BI) for CS is the paper by Mattia et al. (2019), who conclude this variable to be significant.

Hypothesis 6 (H6): The *Perceived Behavioral Control* has a positive impact on the *Behavioral Intention* for CS.

Trust

Trust (TRU) is a crucial part of the adoption of any new technology and invention. Since you have no control over an AV, you place your life in the hands of the AV once you set foot in it. This is why TRU is especially important for the acceptance of AVs, and why many papers have extended their models with this variable. Like expected, the significance of this variable is proven by Du et al. (2021), P. Liu et al. (2019), Panagiotopoulos and Dimitrakopoulos (2018), and Xu et al. (2018) for AVs . As opposed to AVs, TRU does not seem to be significant for the adoption of CS (Y. Liu & Yang, 2018). A possible explanation for this could be that we are already used to conventional cars, and since we already trust them, there is no trust aspect that comes into play. Car Sharing is just a different type of implementation of conventional cars, and not a new radical technology like AVs. Hence, this study only includes TRU for the acceptance of AVs.

Hypothesis 7 (H7): *Trust* has a positive impact on the *Behavioral Intention* for AVs.

Self-Efficacy

Another relevant variable for the acceptance of AVs is *Self-Efficacy* (SE), which stems from the Social Cognitive Theory (SCT) by Bandura (1986), and expresses a person's belief that they are capable of achieving a certain goal (Bandura, 1986). In this case, the goal is making use of an AV, as explained in Section 2.3.1. This is especially relevant for people who do not consider themselves to be good with new technologies, which is why many papers, such as Lee et al. (2019), Du et al. (2021), and Zhu et al. (2020), extend their acceptance models for AVs with this variable. Moreover, SE does not necessarily only relate to the person's capability of making use of new technologies, but also relates to other aspects like the financial resources, physical abilities, etc. The general question is thus whether the person is capable of making use of the technology, which can depend on many different things. This variable can be confused with the previously discussed variable *Perceived Ease of Use* (PEOU). However, a distinction can be made between SE and PEOU. The PEOU refers to the person's belief on how easy it is to use a technology, how user-friendly it is made..., and does not incorporate the person's personal belief in their own capabilities. Unlike PEOU, SE refers to the person's personal belief in their capabilities together with other personal aspects, which could prevent the person from using AVs. As shown in Appendix A.4, SE has a significant positive impact on the *Behavioral Intention* (BI) according to Lee et al. (2019), Du et al. (2021), and Zhu et al. (2020). It has however not been included in any CS acceptance studies, hence this will also not be the case in this paper.

Hypothesis 8 (H8): *Self-Efficacy* has a positive impact on the *Behavioral Intention* for AVs.

Psychological Ownership

Lastly, AVs could be integrated into our society in many ways: they can be privately owned cars, they can be shared, they can be part of the public transport infrastructure, etc. This was shortly discussed in Chapter 1 of this paper. *Psychological Ownership* (PO) is a crucial variable in the case AVs are shared and thus implemented as Shared Autonomous Vehicles (SAVs) (Lee et al., 2019). It refers to the person's feeling of ownership over the car, even if they do not own the car themselves. Hereby, Lee et al. (2019) find that this needs to be taken into account when trying to implement SAVs, where they conclude that a person will be more likely to make use of SAVs when s/he experience a high level of ownership over it. As discussed in Section 2.3.1 and shown in Appendix A.4, only one paper has studied the influence of PO on SAV acceptance. Hence, it is important to further investigate the potential influence of this variable to gain more insights into its effect.

Hypothesis 9 (H9): *Psychological Ownership* has a positive impact on the *Behavioral Intention* for SAVs.

Table 3.1

Hypotheses Formulation

		Variables	Included for CS	Included for AVs
Hypothesis 1		BI (CS) $\rightarrow$ BI (AV) (+)		
Hypothesis 2		AT $\rightarrow$ BI (+)	X	X
Hypothesis 3	**a**	PU $\rightarrow$ AT (+)	X	X
	b	PU $\rightarrow$ BI (+)	X	X
	c	PU $\rightarrow$ AT $\rightarrow$ BI (+)	X	X
Hypothesis 4	**a**	PEOU $\rightarrow$ AT (+)	X	X
	b	PEOU $\rightarrow$ BI (+)	X	X
	c	PEOU $\rightarrow$ AT $\rightarrow$ BI (+)	X	X
Hypothesis 5		SN $\rightarrow$ BI (+)	X	X
Hypothesis 6		PBC $\rightarrow$ BI (+)	X	
Hypothesis 7		TRU $\rightarrow$ BI (+)		X
Hypothesis 8		SE $\rightarrow$ BI (+)		X
Hypothesis 9		PO $\rightarrow$ BI (+)		X

Socio-demographic factors

A different approach was adopted for the analysis of the socio-demographic factors. For these, no hypotheses are formulated because the literature is very scattered regarding the effects of these factors. Some papers find certain factors to have a positive impact, others find this impact to be negative, and sometimes, even no significant relationship is found. Thus, for these variables, no hypotheses are formulated and this paper will assess their impact by looking at the collected data.

Age

The literature suggests for both CS and AVs that younger people tend to be more accepting of these technologies. Appendix A.5 shows that only one paper did not prove the significance of this factor, which was the paper by Efthymiou et al. (2013) that studied the acceptance of CS. The remaining papers do conclude *Age* to have a negative impact on the acceptance of these technologies. Furthermore, it can be very interesting to study the influence of a person's *Age* on his/her BI, which is why this research will analyze this effect more in depth.

Gender

As discussed in Sections 2.2.2 and 2.3.2, some inconsistencies exist around the actual impact of a person's *Gender* on his/her likelihood to make use of these technologies. As shown in Appendix A.5, most research finds that being a woman has a negative influence on the acceptance of CS and AVs. This means that, on average, women tend to be less open to these technologies, especially for AVs. However, Curtale et al. (2021) and Thurner et al. (2022) do not form this conclusion, and state that a person's *Gender* does not matter when considering the acceptance of CS, making it even more interesting to include this factor in this study.

Place of Residence

Furthermore, a person's *Place of Residence* has been proven multiple times to be important for CS and AVs by Prieto et al. (2017), Thurner et al. (2022), König and Neumayr (2017), and Rahimi et al. (2020b). Only one paper (Rahimi et al. (2020a)) states that this variable is insignificant for CS. In general, the main conclusion is that people who live in an urban setting or cities tend to be more accepting of these technologies. This makes it interesting to study the influence of this factor, and test whether this effect in fact does exist.

Education

In the literature, *Education* has been studied in terms of a person's highest achieved degree, and whether this has an influence on his/her acceptance levels. Appendix A.5 however shows the scattered conclusions regarding this socio-demographic factor. Some researchers find a positive impact, some find a negative impact, and others even find no relation at all. The indecisive literature makes this variable even more appealing to include and study in this paper. However, it is important to mention that a different approach will be adopted than the one traditionally used in the literature. In this paper, a person's *Education* is only recorded for people who are currently studying, and refers to their field of study instead of their highest achieved level of education. This way, an analysis could be done around the different fields of study in order to determine whether there is a difference in behavior between students of different educational backgrounds. For example, a student from engineering might be more open towards new technologies than someone with a background in history. Since this variable is examined in a different way than in the literature, it is not included in the research model. The effect of this variable will be added later on, and further Student's t-tests will be performed regarding the scores of students coming from different fields of study.

Driving Frequency

In this paper's literature review (Chapter 2) it was shown that some papers also examine the effect of a person's *Driving Frequency*. These particular studies were conducted by König and Neumayr (2017) and Rahimi et al. (2020b) for AVs, who found that this factor has a significant negative impact. This would mean that, in general, people who use their car more often are less likely to adopt AVs. However, no papers were found where this variable was being analyzed for the acceptance of CS, which is the reason why this study does include the effect of this factor for both technologies.

Usage of Driver Assistance Systems

According to König and Neumayr (2017) and Kyriakidis et al. (2015), the more someone makes use of Driver Assistance Systems (DASs), the more open they tend to be towards AVs. This is evident since these automatic systems can help increase the trust in AVs. The more you use them, the more you realize that they are trustworthy, thus you would be more open towards using a fully automated vehicle. Hence, this factor is included in this paper to test its effect on the acceptance of AVs.

CS User

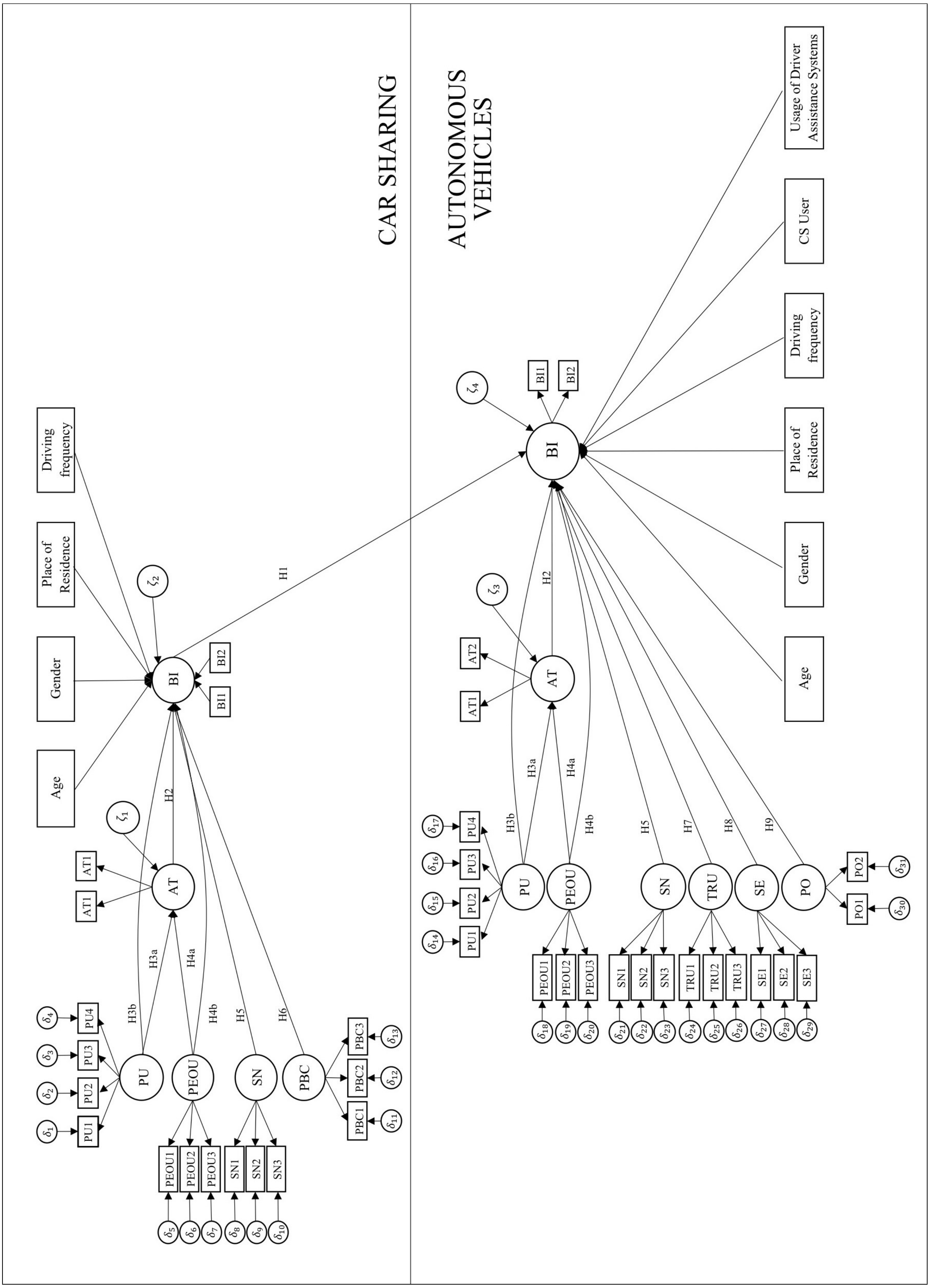
Lastly, besides studying the influence of the *Behavioral Intention* (BI) of CS on the BI of AVs, the impact of CS usage will be assessed via this additional factor as well. The aim is to determine whether a person who has already made use of CS is more accepting of AVs. This has not been done in the literature yet.

3.2.2 Research Model

The previously discussed variables and hypotheses form, when all put together, the research model of this paper, as illustrated in Figure 3.1. This model will be tested by making use of *Structural Equation Modeling* (SEM), which will be explained more in depth later on in the paper (Ullman & Bentler, 2012). This research model incorporates variables from different models and merges them into one big model. *Perceived Usefulness* (PU) and *Perceived Ease of Use* (PEOU) stem from the TAM and UTAUT (Davis, 1985; Venkatesh et al., 2003), while *Attitude* (AT) originates from the TAM and TPB (Ajzen, 1991; Davis, 1985). Next, there are *Subjective Norm* (SN) and *Perceived Behavioral Control* (PBC) that are introduced in the TPB as well as in the UTAUT (Ajzen, 1991; Venkatesh et al., 2003), followed by *Self-Efficacy* (SE) from the Social Cognitive Theory (SCT) (Bandura, 1986). Lastly, the model includes the variables *Trust* (TRU)

Figure 3.1

Research Model



and *Psychological Ownership* (PO), which are general extensions used in the acceptance models concerning AVs in studies like Panagiotopoulos and Dimitrakopoulos (2018) and Lee et al. (2019) respectively. The previously mentioned behavioral variables, together with the socio-demographic variables, are included to test their impact on the *Behavioral Intention* of CS and AVs which are the dependent variables in the research model.

3.3 Measures

In order to test the research model illustrated in Figure 3.1, a survey has been constructed to collect the necessary data. For each variable included in the research model, a set of statements adapted from the existing literature, called items, are displayed to the respondent. Tables 3.2 and 3.3 summarize these items, together with the papers that they are adapted from, for CS and AVs respectively. The respondents are supposed to give their honest opinion about each of these statements concerning either CS or AVs on a five-point Likert scale ranging from 'Strongly disagree' to 'Strongly agree'. The reason why a five-point Likert scale was preferred over a seven-point Likert scale is due to the added complexity of a seven-point Likert scale, which could lead to people leaving the survey unfinished. Moreover, the statements have an odd number of response options since it has been proven that respondents rather have an odd number of response options than even ones (Taherdoost, 2019). To come up with a general score for a certain variable, an average of the scores given on the variable's statements is computed, where 1 and 5 correspond to 'Strongly Disagree' and 'Strongly Agree', respectively. In case a particular question is formulated in a negative sense, the scale for that question will be reversed in order to measure the correct average score for that variable. At the end of the survey, general questions are asked regarding the respondent's socio-demographic characteristics, summarized in Table 3.4. As can be seen in Table 3.4, depending on the answers given on certain questions, different questions can be shown to the respondent. For instance, the exact age is asked to the group of students, while non-students simply have to select their age category, and only students are asked to fill in their field of study. Also, questions regarding a person's driving frequency and usage of Driver Assistance Systems (DASs) are only displayed to people with a driver's license.

3.4 Analysis

3.4.1 Data Collection

The data used to test the research model has been collected through a survey constructed and published with Qualtrics. Since a significant part of potential respondents would be Dutch-speaking, the survey was not only formulated in English, but also translated to Dutch. This translation was revised multiple times by multiple people to make sure that all statements were consistent across both surveys. Before publishing the final version of the survey, a pilot study that included 11 people was conducted to identify and correct potential mistakes. After correcting and perfecting the survey, it was officially

Table 3.2

Car Sharing - Constructs and Items

Car Sharing - Questionnaire Items	**Adapted From**
Perceived Usefulness (PU)	Davis (1989)
PU1. I find Car Sharing useful as means of transport.	Tran et al. (2019)
PU2. I think Car Sharing is better and more convenient than my current main form of travel.	Venkatesch et al. (2003)
PU3. I believe Car Sharing makes travelling more difficult.	
PU4. I think Car Sharing can help me save travel time.	
Extra. I think Car Sharing is better and more convenient than owning a regular car.	
Perceived Ease of Use (PEOU)	Tran et al. (2019)
PEOU1. I think Car Sharing is easy to use.	Venkatesch et al. (2003)
PEOU2. I can learn how to make use of Car Sharing in little time.	
PEOU3. I do not think I am able to make use of Car Sharing.	
Subjective Norm (SN)	Tran et al. (2019)
SN1. If many people would use Car Sharing, I would as well.	
SN2. I think I am more likely to use Car Sharing if my friends and my family use it.	
SN3. I would use Car Sharing if my colleagues would make use of it.	
Perceived Behavioral Control (PBC)	Mattia et al. (2019)
PBC1. I have the resources necessary to use Car Sharing. (E.g., Time, Money, Physical ability, etc.)	Venkatesch et al. (2003)
PBC2. I have the knowledge necessary to make use of Car Sharing.	
PBC3. Cars from Car Sharing services are not always easily available.	
Attitude (AT)	Müller (2019)
AT1. I like the idea of using Car Sharing.	
AT2. I think that Car Sharing is beneficial to me.	
Behavioral Intention (BI)	Müller (2019)
BI1. If I had access to Car Sharing in my area, I think I would make use of it.	Venkatesh and Bala (2008)
BI2. I plan to make use of Car Sharing on a regular basis in the future.	

published in the period between the 22nd of March 2023 and the 12th of April 2022, thus it was active for approximately three weeks. The survey was spread across personal social media channels, such as Facebook, Instagram, and LinkedIn. Also, KULeuven Engage, the promotor of this thesis Martina Vandebroek, and Autodelen.net spread the survey through their respective channels to reach as many people as possible. Moreover, to incentivize filling in the survey, a lottery for five Kinepolis duo-tickets was organized among the respondents who chose to fill in their e-mail. It is important to note that the contact information of a respondent participating in the contest was collected by redirecting them to a new survey. This way, their private information could not be linked to the answers that they had previously given, and thus their responses to the survey were still recorded completely anonymous. After taking the survey offline on the 12th of April, 238 respondents' answers were recorded, of which 202 were fully complete. Of the 202 respondents, 125 indicated that they are currently studying. Unfortunately, out of these 202 respondents, five were able to finish the survey without answering every single question even though the software should have prevented this from happening. It is remarkable that these unanswered questions were the same across all five respondents. Luckily, this was only the case for the extra statements and the ranking question

Table 3.3

Autonomous Vehicles - Constructs and Items

Autonomous Vehicles - Questionnaire Items	Adapted From
Perceived Usefulness (PU)	Davis (1989)
PU1. I find Autonomous Vehicles useful as means of transport.	Tran et al. (2019)
PU2. I think Autonomous Vehicles will be better and more convenient than my current main form of travel.	Venkatesch et al. (2003)
PU3. I believe Autonomous Vehicles will make travelling more difficult.	
PU4. I think Autonomous Vehicles will help me save travel time.	
Extra. I think Autonomous Vehicles will be better and more convenient than regular cars.	
Perceived Ease of Use (PEOU)	Tran et al. (2019)
PEOU1. I think Autonomous Vehicles will be easy to use.	Venkatesch et al. (2003)
PEOU2. I can learn how to make use of Autonomous Vehicles in little time.	
PEOU3. I do not think I will be able to make use of Autonomous Vehicles.	
Subjective Norm (SN)	Tran et al. (2019)
SN1. If many people would use Autonomous Vehicles, I would as well.	
SN2. I think I am more likely to use Autonomous Vehicles if my friends and my family use it.	
SN3. I would use Autonomous Vehicles if my colleagues would make use of it.	
Trust (TRU)	Xu et al. (2018)
TRU1. I think Autonomous Vehicles will be safe to use.	
TRU2. I will be scared of seeing Autonomous Vehicles on the roads.	
TRU3. Overall, I think I can trust Autonomous Vehicles in the future.	
Self-Efficacy (SE)	Lee et al. (2019)
SE1. I will be able to make use of an Autonomous Vehicle if there is a manual for it.	
SE2. I will be able to make use of an Autonomous Vehicle if someone shows me how to do it first.	
SE3. I think I will be able to make use of an Autonomous Vehicle without any help or manual.	
Psychological Ownership (PO)	Lee et al. (2019)
PO1. A Shared Autonomous Vehicle would feel like my personal space.	
PO2. I would think that the Autonomous Vehicle is mine.	
Extra1. I prefer Shared Autonomous Vehicles providers over buying my own Autonomous Vehicle.	
Extra2. I would prefer Shared Autonomous Vehicles providers over buying my own Autonomous Vehicle if the car settings could automatically be customized to my preferences without having to give that information each time. (E.g., the car temperature is set to your preferred temperature, the seats are adjusted, etc.)	
Attitude (AT)	Müller (2019)
AT1. I like the idea of using Autonomous Vehicles.	
AT2. I think that Autonomous Vehicles are beneficial to me.	
Behavioral Intention (BI)	Müller (2019)
BI1. If I had access to Autonomous Vehicles, I think I would make use of it.	Venkatesh and Bala (2008)
BI2. I plan to make use of Autonomous Vehicles on a regular basis in the future.	

included in the survey which were meant to give additional insights next to the research model. Hence, it was still possible to include these respondents in the estimation of the research model.

Furthermore, as already mentioned, almost 62% of the data set consists of students (125 out of the 202 respondents), which means that there is an over-representation of this group in the sample. This makes it interesting to isolate the group of students and subsequently test the same research model for this subset of the data.

Table 3.4

Socio-Demographic Measures

Are you currently a student?
- Yes - No

If student:

What do you study?
Open question

Please specify your age.
Open question

What is your age? (Students did not receive this version of the question)
- 17 or younger - 18 to 25 - 26 to 35 - 36 to 45 - 46 to 55 - 56 to 65 - 66 or older

What is your gender?
- Male - Female - X - Prefer not to say

How would you describe the location where your place of residence is situated?
- Rural / Countryside - Suburban - Urban / City

Do you have a driver's license?
- Yes - No

If yes:

How often do you drive?
- (Nearly) never - Once every month - Once a week - (Nearly) every day

Do you make use of Driver Assistance Systems? (For example parking sensors, cruise control, lane assist, etc.)
- Yes - No

Have you ever made use of a Car Sharing service?
- Yes - No - I do not know

3.4.2 Data Processing

After the data had been collected, it was pre-processed using Python and its extra packages "Pandas" and "NumPy" to get it ready for analysis. First of all, data that were collected through Qualtrics that were not needed for the analysis, such as the start date and end date of the survey, duration of the survey etc. were removed. Secondly, as mentioned in Section 3.4.1, incomplete recorded responses from the survey were removed from the data set, which resulted in 202 out of the 238 recorded responses being kept and used for the analysis. Lastly, some of the column names were flawed, hence the column names were modified to the correct name.

Since the raw data contained columns for both responses in English and responses in Dutch, the responses from both languages were merged to make the analysis easier. Column names from the raw data file were also modified to have a clearer understanding of the different items that were questioned in the survey. For example, in the raw data, the first item for *Perceived Usefulness* (PU) of AVs was called "NL - AV - PU_1", but was renamed to "AV_PU1". Students, besides having their age as a numerical value in the data, also have their age put into the same categories as the non-students in the variable "Age_numerical".

Each of the latent variables, shown by the circles in Figure 3.1, consists of multiple items. By taking the average score of the items for a certain variable, we get a representative value for that variable for each of the respondents. As mentioned before in Section 3.3, some questions were asked in a negative sense and needed to have their scores inverted in order to calculate the correct scores for the latent variables. By inverting the scores, "Strongly Disagree" becomes "Strongly Agree" (and vice versa), "Somewhat Disagree" becomes "Somewhat Agree" (and vice versa), and lastly, "Neither agree nor disagree" stays the same. The questions which have their scores reversed are: CS_PU3, CS_PEOU3, CS_PBC3, AV_PU3, AV_PEOU3, and AV_TRU2. The exact statements can be found in Tables 3.2 and 3.3.

Other variables, eight in total, had their values re-coded for the analysis, as shown in Table 3.5. STU_dummy indicates whether a participant is currently a student or not. Age_numerical is measured on an numerical scale and regards the age category a person belongs to, with 17 or younger (1) being the lowest category, and 66 or older (7) being the highest. The third re-coded variable is Gender, for which 3 dummy variables have been created, each representing a certain option indicating a person's gender, as can be seen in Table 3.5. Participants had the option to indicate that they are male (reference level), female (Gender_cat1 = 1), any other gender marked by X (Gender_cat2 = 1), or the option to not reveal their gender (Gender_cat3 = 1). This third category of *Gender* was not included in the estimation of the Structural Equation Model since it does not represent a particular category. Resid_cat1 and Resid_cat2 tell more about the urbanisation of the area a participant lives in, including the categories rural (reference level), suburban (Resid_cat1 = 1), and urban (Resid_cat2 = 1). License_dummy indicates whether or not a person is in possession of a driving license. If the person possesses a driving license, two other variables are applicable. The first variable is DrFreq_numerical which is measured on a numerical scale and explains how often a person drives a car, going from (nearly) never (1) to (nearly) every day (4). The second variable that comes from License_dummy is DAS_dummy, that indicates if a participant has already used Driver Assistance Systems (DASs) such as lane assist, cruise control etc. Finally, the last variable that was re-coded is CS_dummy and shows whether a respondent has already made use of a CS service, with answer options Yes (1) and No (0). Here, an extra option was provided to the respondent, namely the option "I do not know", which has not been included in the estimation of the model due to its irrelevance.

Lastly, students were also asked to fill in their field of study in a text box. As many fields of study would make analyzing the data more difficult, the different fields of study were put in a higher category manually. For example, studies such as "Business Engineering" and "Applied Economics" were put under the category "Business". Seventy of the 125 students (56%) were business students whereas other categories contained much less students, hence the variable ”Business_dummy” was created to measure the difference in CS or AV acceptance between business students and other students.

Table 3.5

Re-Coded Values of Variables

Variable	Type	Re-coded Values
Student		
STU_dummy	Categorical	Student = 1, NOT student = 0
Age		
Age_numerical	Numerical	17 or younger = 1, 18-25 = 2, 26-35 = 3, 36-45 = 4, 46-55 = 5, 56-65 = 6, 66 or older = 7
Gender		
Gender_cat1	Categorical	Female = 1, Other = 0
Gender_cat2	Categorical	X = 1, Other = 0
Gender_cat3	Categorical	Prefer not to say = 1, Other = 0
		→ Reference Level = Male
Place of Residence		
Resid_cat1	Categorical	Suburban = 1, Other = 0
Resid_cat2	Categorical	Urban = 1, Other = 0
		→ Reference Level = Rural
Driving License		
License_dummy	Categorical	Has Driving License = 1, Does NOT have Driving License = 0
Driving Frequency		
DrFreq_numerical	Numerical	(Nearly) never = 1, Once a month = 2, Once a week = 3, (Nearly) every day = 4
Driver Assistance System		
DAS_dummy	Categorical	Yes = 1, No = 0
CS User		
CS_dummy	Categorical	Yes = 1, No = 0

3.4.3 Cronbach's Alphas

Before analyzing the data more in depth and testing the research model, Cronbach's alphas were computed to assess the reliability of each of the variables (Cronbach, 1951), which can be found in Table 3.6. According to Cortina (1993), a Cronbach's alpha of .7 or higher is an acceptable value for a variable's reliability. When applying this logic for the values in Table 3.6, a few variables with a Cronbach's alpha lower than .7 are identified. This is the case for the variable *Perceived Ease of Use* (PEOU), which does reach the desirable value for both CS and AVs. Furthermore, *Perceived Behavioral Control* (PBC) and *Self-Efficacy* (SE) score very poorly for CS and AVs, respectively. Potential explanations for the low Cronbach's alphas of the previously mentioned variables can be formulated. Firstly, as can be seen in Table 3.2 and Table 3.3 these particular variables, except for SE, include a question which is formulated in a negative sense. Hence, there is a possibility that certain respondents did not pay enough attention to these particular statements and simply filled in a similar answer as before. Also, it is important to note that the statements found in the literature were adapted and tweaked to this paper's specific context, which might have reduced certain variables' reliability. These adjustments to the statements were made since many of the statements were perceived as confusing or unclear during the pilot study. Moreover, the impact of the small size of this data set should not be neglected since this could have also led to lower Cronbach's alphas (Bujang et al., 2018). Despite the limitations, the decision was made to still include these variables in the analysis of the data and research model.

Table 3.6

Cronbach's Alphas

Variable	Complete dataset		Student dataset	
	Car Sharing	Autonomous Vehicles	Car Sharing	Autonomous Vehicles
Perceived Usefulness	.72	.80	.72	.81
Perceived Ease of Use	**.62**	**.56**	**.52**	**.58**
Subjective Norm	.83	.90	.77	.89
Perceived Behavioral Control	**.33**	-	**.31**	-
Trust	-	.87	-	.84
Self-Efficacy	-	**.47**	-	**.49**
Psychological Ownership	-	.70	-	.74
Attitude	.85	.87	.79	.82
Behavioral Intention	.84	.86	.81	.82

Note. Cronbach's Alphas $<$ .70 are displayed in bold text.

3.4.4 Structural Equation Model

This paper's research model, illustrated in Figure 3.1 has been tested by making use of Structural Equation Modeling (SEM), a multivariate statistical analysis technique that allows to test multiple regressions (Ullman & Bentler, 2012). Structural Equation Models contain two types of variables, namely measured and latent variables, where the former stands for directly measurable variables (displayed by rectangles), whereas the latter implies variables which are not directly observable (displayed by circles). This is also the reason why the statistical formulation of these models usually consists of two separate models. First, a measurement model, which explicitly formulates how the latent variables are measured/estimated, is defined. More specifically, it is going to identify the measured variables that are used to estimate a value for that specific latent variable (Ullman & Bentler, 2012). In the case of this paper's research model, no measurement model was defined since each of these latent variables is simply assigned a score which corresponds to the mean value of the scores on their items. This decision was made since the same procedure is adopted in the literature, and no paper estimates a measurement model. Moreover, when estimating a measurement model, for each variable, one item's loading or variance must be fixed to 1 (Ullman & Bentler, 2012). This could have caused some issues since it could have given more power to certain items than actually needed, making the results of the model less reliable, especially since adjustments have been made to the items. Also, there is an amount of variables which consist of only two items, where one item would have gotten too much or too little weight in determining the score for the variable. Hence, for this model, every item has the same weight in computing the score for the variable, and no loadings are estimated. Figure 3.1 depicts these latent variables as circles and connects each of these variables to their respective items, displayed as rectangles, which were used to compute a correct score for the latent variable. The second model, called a structural model, includes all the regressions that are to be tested in the model (Ullman & Bentler, 2012). Thus, the estimated model of this paper only consists of a structural model which has been defined and tested in RStudio version 4.2.3. All analyses of the Structural Equation Model were carried out using the "Lavaan" R package, introduced by Rosseel (2012). Prior to going more into detail about the different steps that were taken in the analysis process, it is important to formulate the structural model first. As already mentioned, the graphical representation of the complete research model can be found in Figure 3.1. The only thing left to do is to statistically define the structural model, as shown below:

Structural Model - Car Sharing

$$\begin{aligned}\mathrm{BI} = {} & \beta_{11}\mathrm{PU} + \beta_{12}\mathrm{PEOU} + \beta_{13}\mathrm{AT} + \beta_{14}\mathrm{SN} + \beta_{15}\mathrm{PBC} \\ & + \lambda_{11}\mathrm{Age} \\ & + \lambda_{12}\mathrm{Gender\_cat1} + \lambda_{13}\mathrm{Gender\_cat2} \\ & + \lambda_{14}\mathrm{Resid\_cat1} + \lambda_{15}\mathrm{Resid\_cat2} \\ & + \lambda_{16}\mathrm{DrFreq}\end{aligned}$$

$$
\begin{aligned}
&+ \zeta_2 \\
\mathrm{AT} &= \gamma_{11}\mathrm{PU} + \gamma_{12}\mathrm{PEOU} + \zeta_1
\end{aligned}
$$

Structural Model - Autonomous Vehicles

$$
\begin{aligned}
\mathrm{BI} = {} & \beta_{21}\mathrm{PU} + \beta_{22}\mathrm{PEOU} + \beta_{23}\mathrm{AT} + \beta_{24}\mathrm{SN} + \beta_{26}\mathrm{TRU} + \beta_{27}\mathrm{SE} + \beta_{28}\mathrm{PO} \\
& + \lambda_{21}\mathrm{Age} \\
& + \lambda_{22}\mathrm{Gender\_cat1} + \lambda_{23}\mathrm{Gender\_cat2} \\
& + \lambda_{24}\mathrm{Resid\_cat1} + \lambda_{25}\mathrm{Resid\_cat2} \\
& + \lambda_{26}\mathrm{DrFreq} \\
& + \lambda_{27}\mathrm{CS\_dummy} \\
& + \lambda_{28}\mathrm{DAS\_dummy} \\
& + \zeta_4 \\
AT = {} & \gamma_{21}\mathrm{PU} + \gamma_{22}\mathrm{PEOU} + \zeta_3
\end{aligned}
$$

In the analysis of the research model, four consecutive steps have been taken, hence four different models have been estimated for both the complete data set as well as the student data set. It is important to note that the same consecutive steps have been taken during the fitting procedure of the models for the two data sets. The first step in this process was to estimate the original model, as illustrated in Figure 3.1. The literature found some significant relationships between different independent variables (see overview in Appendices A.3 and A.4). Hence, in the second step of the process, the model was expanded by adding residual correlations between these specific pairs of variables aiming to improve the model's fit. Subsequently, variables which were proven to be insignificant in the previous two models were removed in the third step of the analysis process. In this paper, a p value $\leq .1$ was considered significant. This specific significance level (α) was adopted instead of the more commonly used level of $\alpha = .05$ due to the complexity and size of this paper's research model. More precisely, the following variables and residual correlations were kept in the third version of the research model:

- All significant variables and residual correlations with a p value $\leq .1$ in either the first or second version of the model
- Variables of which the p value decreased and came close to .1 when the residual correlations were added
- Variables which were particularly important for this research paper. More specifically, the variable *Behavioral Intention* (BI) of CS and the CS_dummy variable were kept for the analysis of the BI of AVs

Eventually, most of the variables and correlations that were kept because their p value was close to .1 turned out to be insignificant in the third version of the model. This is why in the final version of the model, model 4, only the statistically significant variables and residual correlations from model 3 were estimated. Hence, the final version of the model only consists of significant variables and significant residual correlations.

In each step of the analysis process, fit measures were computed in order to assess the evolution of the goodness of fit of the consecutive models. The fit measures are displayed in Table 3.7, where the following fit measures can be found for all estimated models: chi-squared (χ^2), degrees of freedom (df), p value, Comparative Fit Index (CFI), Tucker-Lewis Index (TLI), Root Mean Squared Error of Approximation ($RMSEA$), and Standardized Root Mean Square Residual ($SRMR$). These particular fit measures are reported because they represent the most commonly used fit measures in the literature when dealing with SEM (Schreiber, 2008). Hereby, the χ^2, $RMSEA$, and $SRMR$ are badness of fit tests, which means that the higher values for these indices, the worse the fit of the model. In general, when the ratio between χ^2 and df is ≤ 2 or 3, the model is considered to be a good fit. Furthermore, a $RMSEA$ and a $SRMR$ value $\leq .08$ are indications of a good fit. As opposed to the previously mentioned fit measures, CFI and TLI values $\geq .95$ indicate a good fit. Lastly, the model's p value indicates the deviation between the specified model and the perfectly fitting model. Thus, a large p value is preferred since this implies that the model does not significantly deviate from the perfectly fitting model (Schreiber, 2008).

When looking at the measures in Table 3.7, it becomes clear that the evolution of these measures is similar across both data sets. According to the fit measures, the fit of the first model, the original model, is the best one. Despite the fit measures being not too far away from the desired values for a good fit, many cut-off values are not achieved. In the second model, residual correlations were added to improve the model's fit, but surprisingly this worsened the model's fit. However, once insignificant variables are being removed from the model, these measures start to improve in model 3. The fit measures keep on improving when more insignificant variables and residuals are left out in model 4, but unfortunately, they do not reach the initial fit measures achieved by model 1. Still, according to Schreiber (2008), it is nearly impossible to have good fit measures and a perfectly identified model using an a priori method like SEM. Therefore, we are still satisfied with this final version of the model, and will report the insights resulting from this final model in the following chapter of the paper.

Once this final model was obtained, other analyses were carried out aiming to formulate interesting discoveries by executing the exact same procedure as before, but starting with different initial models. This was done starting with a model where the direct effects of *Perceived Usefulness* (PU) and *Perceived Ease of Use* (PEOU) on *Behavioral Intention* (BI) were excluded, and a model where the *Attitude* (AT) variable was simply left out. However, these models ended up having even worse fit measures than before, and thus are not worth reporting on. The only interesting observation was the sudden importance of some socio-demographic variables in the model without AT, whereas in this paper's final model almost no socio-demographic factors were proven to be significant. This led to additions that could be made to the previously obtained final model to try improving its fit. More specifically, the first step was to add interaction terms to the model between these significant socio-demographic factors and the AT variable. Unfortunately, as a result, the model's fit measures worsened even more. Thus, these interaction terms were removed, and instead, residual correlations were added between the same set of variables. Once more, the same thing happened and no interesting discoveries were made. Hence, after attempting to incorporate additional aspects into the model, the final model remained as it was, and no extra insights were found. An elaborate explanation of the results coming from this model will be given for the complete data set and the students-only data set in the next chapter of this paper. It is important to mention that the same four models have been estimated for the subset of non-students, which unfortunately led to very poor fit measures and thus was left out of the remaining parts of the study.

Table 3.7

Fit Measures

Model version	χ^2	*df*	χ^2/df	*p* value	*CFI*	*TLI*	*RMSEA*	*SRMR*
Good fit	-	-	$\leq$ 2 or 3	$\geq$ .05	$\geq$ .95	$\geq$ .95	$\leq$ .08	$\leq$ .08
Model 1: Original research model								
Complete data set	127.927	47	2.722	<.001	.904	.841	.092	.037
Student data set	84.224	45	1.872	<.001	.915	.860	.084	.035
Model 2: Adding residual correlations								
Complete data set	595.116	153	3.889	<.001	.702	.620	.120	.155
Student data set	325.376	142	2.291	<.001	.752	.682	.102	.135
Model 3: Removing irrelevant variables								
Complete data set	352.025	66	5.334	<.001	.784	.713	.146	.181
Student data set	140.939	64	2.202	<.001	.876	.836	.098	.140
Model 4 (Final model): Removing irrelevant variables from Model 3								
Complete data set	203.447	38	5.354	<.001	.860	.797	.147	.177
Student data set	122.596	48	2.554	<.001	.879	.836	.112	.157

Note. N = 202 (Complete data set), N = 125 (Student data set)

3.4.5 Extra Questions, Education, and Ranking

Next to statements which were used to measure latent variables, extra questions and statements were added to the survey to potentially gain additional insights (see 'Extra' in Tables 3.2 and 3.3). In the analysis process of these extra statements no complex statistical techniques, but instead descriptive measures and Student's t-tests were carried out. More specifically, Student's t-tests were performed in order to test whether two mean values significantly differed from one another, which could result in interesting findings. For instance, for the extra statements, the mean response score of the group of students was compared to the mean response value of the non-students. Also, further t-tests were conducted within the same data set to compare mean response values of different statements. It is important to highlight the main assumption that these tests are based on, which assumes the two samples, of which the mean scores are being compared, to be independent from one another. When performing these t-tests between the complete data set and the student data set, this assumption would not have been satisfied since a large fraction of the complete data set contains the students. This is why in this part of the analysis tests were carried out between the sample of students and non-students, unlike with the estimation of the model, where the students-only data set was compared to the complete data set. Moreover, reporting the differences between students and non-students was the logical choice. Note that technical issues occurred when recording the scores for these statements, which decreased the sample size for the students-only data set from 125 to 120, while the sample of non-students ($n = 77$) remained intact.

When designing and performing this part of the investigation, the same logic was applied for all tests. First, the mean values were calculated for the statements which looked interesting for further examination. By observing the obtained mean values, appropriate hypotheses could be developed, which then afterwards were tested in RStudio version 4.2.3. The decision was made to make use of one-sided t-tests since this will help us formulate more interesting findings. Two-sided t-tests help to assess whether two values are significantly different from one another, whereas one-sided t-tests allow us to examine whether one value is significantly larger/smaller than the other (Sharpe et al., 2010). The latter is more interesting for this study since the aim is to identify certain characteristics or groups who tend to be more/less open towards the studied technologies. In order to make this process more tangible, an example will be elaborated, where the exact steps are followed to compare the mean score of group x to the mean score of group y for a particular statement. To start, the mean score values are computed for each sample, namely $\overline{x}$ and $\overline{y}$. To make the next step easy to understand, imagine that we observe mean values where $\overline{x} > \overline{y}$, which would lead to the formulation of the following hypothesis:

$$\begin{cases} H_0 : \mu_x \leq \mu_y \\ H_A : \mu_x > \mu_y \end{cases}$$

This specific hypothesis was formulated since this paper is interested in finding out whether the population's mean of group x is indeed significantly larger than the population's mean of group y. For the t-tests, a significance level of $\alpha = .05$ (as opposed to the level of .1 in the previous section) is chosen, and if the formulated null hypothesis (H_0) is rejected, interesting findings can be observed. This same process was repeated each time it seemed interesting to compare two particular means. When performing these tests to compare different mean scores coming from the same sample, paired-samples t-tests were used. This is the exact same test that is adopted in case a comparison is made within one sample (Sharpe et al., 2010). Also, in the process of performing these paired-samples t-tests, the exact same steps, as explained before, were followed.

Before gathering the data for the analysis of the research model, specific actions were planned concerning the person's *Education*. The goal was to analyze whether the mean value of the *Behavioral Intention* (BI) of CS and AVs differed between students from different backgrounds. However, once the data was collected it became clear that the most useful comparison possible was the one between the group of business students and the group of non-business students since other fields of study were not represented well enough. As mentioned in Section 3.4.2, a dummy variable was created and added to the final model of both data sets to assess its significance. This was done in multiple ways. One way was to include *Education* as an additional explanatory variable in the final model, another option was to estimate different models where, each time, the dummy variable was included as an interaction term with another independent variable from the model. Nonetheless, in each of these models, the impact of this variable turned out to be insignificant which is why, once more, Student's t-tests were performed to fully cover this variable's effect. Here, the mean scores between the groups of business students and non-business students were compared, leading to interesting findings.

Lastly, the survey also contained ranking questions, where participants had to rank their preferences in transportation modes (AV, SAV, bike, by foot etc.). Just as with extra questions, five responses from the ranking were not recorded due to a technical issue, reducing the sample size for this question from 202 to 197 for the complete data set, and from 125 to 120 for the student data set. The sample size for the non-student data set remained intact. The purpose of this ranking is purely descriptive, but it is still interesting to see what the current preferred transportation modes are and if they differ when looking at students or non-students. For the ranking, the occurrence of the different options as the number one preferred transportation mode was counted, together with the occurrence of the different options in a respondent's top three. Hereby, 2 lists are created: one list with the amount of times a transportation mode was the most preferred by a respondent, and another list with the amount of times a transportation mode was in a respondent's top three. Doing so allows for a comparison, showing how a certain transportation mode looks attractive to certain people but quickly drops off in the ranking when looking at it from a general perspective.

Results

The previous chapter discussed this study's research aims, formulation of the hypotheses, and model development. In the following chapter, the focus lies on the results that came forth from the data. Firstly, the descriptive statistics, more specifically the socio-demographic characteristics of the survey's respondents are discussed. Secondly, the core results, namely the results from the Structural Equation Model for both the complete data set and the student data set are reviewed. Lastly, the results from the extra questions, the variable *Education*, and the ranking question are given.

4.1 Descriptive Results

First, the socio-demographic characteristics of the survey's respondents are discussed. As can be seen in Table 4.1, a total of 202 completed the survey, of which 125 (61.88%) were students, and 77 (38.12%) were non-students. As the age of non-students was measured on an interval scale, the mean age was estimated using interval mid-points and was 42.43, while the median age category for non-students was 36-45 years old. For students however, the mean age was 22.3 years old, with a standard deviation (SD) of 2.37. When it comes to gender, there were overall slightly more women (53.96%) than men (43.07%), and very few people that identify as a different gender or preferred not to say their gender (2.88%). The majority of respondents lived in urban or suburban areas (70.79%), whereas almost a third lived in a rural area (29.2%). When it comes to the possession of a driving license, almost four fifths (81.19%) of respondents possessed one. However, slightly less students (75.2%) had a driving license compared to non-students (90.91%). This difference could be caused by the fact that students have less time to practice for their driver's license, but still plan on getting theirs at a later age. Surprisingly, about a fifth (21.19%) of participants had already used a CS service, with double the fraction of non-students (31.17%) having used a CS service compared to students (15.2%). In the analysis of the iVOX data set (Section 2.5), only 1.5% of people indicated to have used a CS service, making the large amount of people with CS experience in this survey remarkable. Lastly, among students, there was a large amount of business students (56%) compared to other fields of study (44%) which is why, as mentioned in Section 3.4.5, no further distinction is made between the fields of study.

Table 4.1

Socio-Demographic Characteristics Respondents

Characteristic	Complete Data		Non-Students		Students	
	n	%	n	%	n	%
Total	202	100	77	38.12	125	61.88
Age						
≤ 17	1	0.5	0	0	1	0.8
18-25	137	67.82	17	22.08	120	96
26-35	12	5.94	9	11.69	3	2.4
36-45	17	8.42	16	20.78	1	0.8
46-55	16	7.92	16	20.78	0	0
56-65	15	7.43	15	19.48	0	0
≥ 66	4	1.98	4	5.19	0	0
Gender						
Male	87	43.07	21	27.27	66	52.8
Female	109	53.96	51	66.23	58	46.4
X	2	0.9	2	2.59	0	0
Prefer not to say	4	1.98	3	3.9	1	0.8
Place Of Residence						
Rural	59	29.2	25	32.47	34	27.2
Suburban	60	29.7	18	23.38	42	33.6
Urban	83	41.09	34	44.16	49	39.2
Driving License						
Yes	164	81.19	70	90.91	94	75.2
No	38	18.81	7	9.09	31	24.8
CS Experience						
Yes	43	21.29	24	31.17	19	15.2
No	157	77.72	53	68.83	104	83.2
I do not know	2	0.9	0	0	2	1.6
Business Student						
Yes	-	-	-	-	70	56
No	-	-	-	-	55	44

Note. $N = 202$

4.2 Results Structural Equation Model

Whereas the previous section of this chapter reviewed the descriptive results that came forth from the data, this section focuses on the results coming from the Structural Equation Model. First, outcomes from the Structural Equation Model from the complete data set are given, followed by the results from the students-only data set. As mentioned in Section 3.4.4, only the final model (model 4) for both the complete data set and the students-only data set is provided. Note that the chosen significance level (α) in this section of the paper is equal to $\alpha = .1$.

4.2.1 Results Complete Data Set

Table 4.2 shows which hypotheses were supported, together with the results that came forth from the Structural Equation Model. Significant residual correlations are presented in Table 4.3, and a visual overview of the final model for the complete data set is pictured by Figure 4.1. In this model, Hypothesis 1, which stated that the *Behavioral Intention* (BI) to use CS had a positive impact on the *Behavioral Intention* to use AVs, was not found statistically significant, though its p value was close to .1 (p = .128, visible in the rightmost column of Table 4.2). All other hypotheses included in the model were significant at $\alpha = .1$, the chosen significance level in Section 3.4.4.

For Car Sharing, all but two hypotheses were supported regarding the effect of a behavioral variable on the *Behavioral Intention* to use CS, as can be seen in Table 4.2. The hypotheses that were not supported, rather because they were insignificant in previous iterations of the model, were the direct effect of the *Perceived Ease Of Use* (PEOU) on BI (H4b) and the effect of *Subjective Norm* (SN) on BI (H5). Interestingly, the PEOU still had a significant indirect effect on BI through *Attitude* (AT) (p <.001), supporting Hypothesis 4c. Also the *Perceived Usefulness* (PU) had an indirect effect on BI through AT (H3c), and was larger than the same indirect effect of PEOU on BI. The behavioral variable that had the biggest direct impact on the BI of CS was *Attitude* with an estimate of .640 (p <.001, Hypothesis 2), followed by the *Perceived Usefulness* (PU) that had an estimate of .159 (p = .007, Hypothesis 3b). Each of these discussed estimates should be interpreted in a standardized sense. Thus, the estimate of .640 for AT means that, if the AT increases with one standard deviation (*SD*), the BI of CS will, on average, increase with .640 standard deviations (*SD*). Analogously, the equivalent interpretation can be formulated for the direct impact of PU, meaning that the BI of CS will increase with .159 *SD* on average, when there is an increase of one *SD* in PU. Furthermore, both Hypothesis 3a and 4a were supported, meaning that both PU (p <.001) and PEOU (p <.001) had a positive influence on the *Attitude* towards CS, where PU had the larger influence with an estimate of .523. *Perceived Behavioral Control* (PBC), a variable only included for CS, had a significant effect on the BI, supporting Hypothesis 6 with a p value of p = .008. This last variable has the lowest impact on the BI of CS, with an estimate of .120 meaning that the BI, on average, increases with .120 *SD* when PBC increases with one *SD*.

In the case of AVs, the following three hypotheses were not supported because they were insignificant in previous iterations of the research model: the direct effect of PEOU on BI (H4b), the effect of *Self-Efficacy* (SE) on BI (H8), and the effect of *Psychological Ownership* (PO) on BI (H9), shown in Table 4.2. As with CS, the variable having the highest direct influence on the BI to use AVs was *Attitude* (H2), with an estimate of .551 (p <.001). This estimate can again be interpreted as follows: The BI of AVs will, on average, increase with .551 *SD* when AT increases with one *SD*. Moreover, similar to CS, PU and PEOU had a significant effect on *Attitude* (H3a and H4a respectively), with PU again having the larger effect (estimate = .672, p <.001), to be interpreted analogously as before. Their indirect effects on BI of AVs through *Attitude*, formulated by Hypothesis 3c and 4c, were also found significant, with the indirect effect of PU being almost four times as large than that from PEOU. Additionally, the effect of *Trust* on BI (H7), which was only measured for AVs, was supported by the data, p <.001.

Comparing the results from both CS and AVs, it was noticeable that similar conclusions were formulated for the equivalent hypotheses across CS and AVs. However, there is one exception, namely the effect of the *Subjective Norm* (SN) on BI (H5), which was not included in the final model for CS despite being supported for AVs (p = .001). Interestingly for both, the direct effect of PU on BI was significant (H3b), yet the direct effect of PEOU on BI was not proven to be significant.

Looking at the residual correlations in Table 4.3, we can see that the residuals for *Perceived Usefulness* (PU) and *Perceived Ease Of Use* (PEOU) were correlated for both CS and AVs, as was suggested by the literature. Furthermore, some other independent variables for AVs had correlating residuals. In this case, the residuals of *Subjective Norm* (SN) were significantly correlated with the residuals of PU, and the same holds between *Trust* (TRU) and PU, and TRU and PEOU. All residual correlations were significant at the $\alpha = .1$ level.

4.2.2 Results Students Data Set

The results coming from the students-only data set can be found in Tables 4.4 and 4.5, with a visual representation of the results shown by Figure 4.2. As opposed to the complete data set, Hypothesis 1 was supported, meaning that the *Behavioral Intention* (BI) of CS had a positive significant impact on the BI of AVs, p =.067. Once again, all other hypotheses included in the final model were significant at the $\alpha = .1$ level.

For CS, the same results as for the complete data set were obtained, except for the direct effect of *Perceived Usefulness* (PU) on *Behavioral Intention* (BI) (H3b) which was not significant in previous iterations of the model and thus not included in the final model (see Table 4.4). Likewise, the direct effect of *Perceived Ease Of Use* (PEOU) on BI and the effect of *Subjective Norm* (SN) on BI were not included in the final model for CS. Furthermore, Hypothesis 3a and 4a were supported, and once again, the effect

Table 4.2

Results Complete Data Set

Effect	Hypothesis	Estimate	*SE*	90% CI *LL*	90% CI *UL*	*p*
Behavioral Intention CS and AV						
BI (CS) → BI (AV)	H1	.059	.039	-.005	.122	.128
Car Sharing						
AT → BI	H2	.640	.052	.554	.726	<.001
PU → AT	H3a	.523	.049	.443	.604	<.001
PU → BI	H3b	.159	.059	.061	.256	.007
PU → AT → BI	H3c	.335	.042	.266	.404	<.001
PEOU → AT	H4a	.303	.053	.215	.391	<.001
PEOU → BI	H4b	-	-	-	-	-
PEOU → AT → BI	H4c	.194	.038	.131	.257	<.001
SN → BI	H5	-	-	-	-	-
PBC → BI	H6	.120	.045	.045	.194	.008
Autonomous Vehicles						
AT → BI	H2	.551	.054	.463	.639	<.001
PU → AT	H3a	.672	.041	.604	.739	<.001
PU → BI	H3b	.145	.064	.039	.250	.024
PU → AT → BI	H3c	.370	.043	.300	.441	<.001
PEOU → AT	H4a	.145	.052	.060	.229	.005
PEOU → BI	H4b	-	-	-	-	-
PEOU → AT → BI	H4c	.080	.029	.031	.128	.007
SN → BI	H5	.138	.042	.069	.206	.001
TRU → BI	H7	.216	.049	.136	.296	<.001
SE → BI	H8	-	-	-	-	-
PO → BI	H9	-	-	-	-	-

Note. Values based on standardized solution of the SEM. Effects and hypotheses not included in the final model have "-" as values. $N = 202$, *SE* = Standard Error, CI = Confidence Interval, *LL* = Lower Limit, *UL* = Upper Limit.

Table 4.3

Significant Residual Correlations Complete Data Set

Variables		Estimate	*SE*	90% CI		*p*
				LL	*UL*	
Car Sharing						
PU	PEOU	.389	.060	.291	.487	<.001
Autonomous Vehicles						
PU	PEOU	.407	.056	.315	.499	<.001
SN	PU	.299	.052	.213	.384	<.001
TRU	PU	.578	.045	.504	.651	<.001
TRU	PEOU	.531	.051	.447	.614	<.001

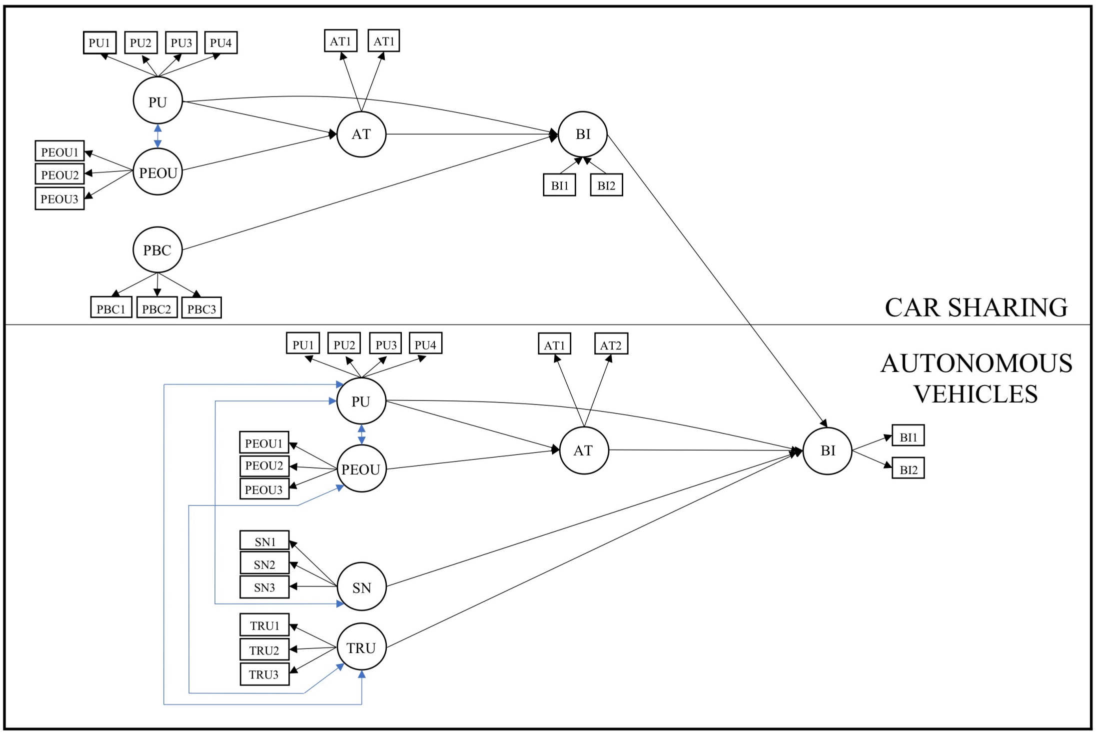
Note. Values based on standardized solution of the SEM. $N = 202$, *SE* = Standard Error, CI = Confidence Interval, *LL* = Lower Limit, *UL* = Upper Limit.

of PU on *Attitude* (AT) was larger than the effect of PEOU on AT. The same goes for the indirect effects of both variables (H3c and H4c) on BI, both were significant and the effect of PU was twice as big than that of PEOU. The *Perceived Behavioral Control* (PBC) had a significant impact on BI, but was larger for students (estimate = .158) than for the complete data set (estimate = .120). Once more, the largest direct effect of a variable on the BI was AT (H2), with an estimate of .692. The interpretation of this estimate is the same as before, meaning that if the AT towards CS increases with one *SD*, on average, the BI of CS increases with .692 *SD*.

With regards to AVs, the results for the students-only data set and the complete data set were almost the same, as shown in Table 4.4. There is a difference however, one that considers the direct effects of *Perceived Usefulness* (PU) and *Perceived Ease of Use* (PEOU) on *Behavioral Intention* (BI), Hypothesis 3b and Hypothesis 4b respectively. In the complete model, Hypothesis 3b was supported and Hypothesis 4b was left out of the model, whereas for the students-only model the opposite was true. Moreover, in the students-only data set, *Attitude* (AT) had the largest direct influence on BI (H2), with an estimate of .566. Thus, the BI to use AVs will, on average, increase with .566 *SD* when the AT towards AVs increases with one *SD*. Once more, the direct effect of PU on AT and the indirect effect of PU on BI were larger than the equivalent effects for PEOU. Of the three hypotheses formulated for AVs specifically, only *Trust* (TRU) was proven to be significant (H7, $p = .049$). At the bottom of Table 4.4, an extra effect that was not hypothesized can be found, namely the effect of having used a CS service on the BI of AVs. Here, having used a CS service in the past proved to be significant on the BI to use AVs for students, with a p value of $p = .066$. Unfortunately, no other socio-demographic variable was found important in any of the other models which contradicts some studies

Figure 4.1

Final Model Complete Data Set



in the literature.

When taking the results of CS and AVs together, we can see that the hypotheses supported for both were very similar, except for H5, which was supported for AVs but left out in the final model for CS.

The residual correlations significant at the $\alpha = .1$ level can be found in Table 4.5, and were similar to those for the complete data set. Again, as expected, *Perceived Usefulness* (PU) and *Perceived Ease Of Use* (PEOU) had significant correlating residuals for CS and AVs ($p = .008$ and $p < .001$ respectively). Other independent variables for AVs had multiple significant residual correlations between them, namely *Subjective Norm* (SN) and PU, *Trust* (TRU) and PU, and TRU and PEOU.

The next section of this chapter goes over the extra questions, looks at the effect of *Education*, and discusses the outcomes of the ranking question asked in the survey.

Table 4.4

Results Students Data Set

Effect	Hypothesis	Estimate	*SE*	90% CI *LL*	90% CI *UL*	*p*
Behavioral Intention CS and AV						
BI (CS) → BI (AV)	H1	.098	.054	.010	.187	.067
Car Sharing						
AT → BI	H2	.692	.046	.616	.768	<.001
PU → AT	H3a	.503	.063	.400	.607	<.001
PU → BI	H3b	-	-	-	-	-
PU → AT → BI	H3c	.348	.052	.263	.434	<.001
PEOU → AT	H4a	.294	.069	.181	.408	<.001
PEOU → BI	H4b	-	-	-	-	-
PEOU → AT → BI	H4c	.204	.050	.121	.286	<.001
SN → BI	H5	-	-	-	-	-
PBC → BI	H6	.158	.062	.056	.261	.011
Autonomous Vehicles						
AT → BI	H2	.566	.057	.472	.660	<.001
PU → AT	H3a	.695	.048	.616	.774	<.001
PU → BI	H3b	-	-	-	-	-
PU → AT → BI	H3c	.393	.051	.309	.477	<.001
PEOU → AT	H4a	.148	.062	.046	.251	.018
PEOU → BI	H4b	.179	.066	.071	.287	.006
PEOU → AT → BI	H4c	.084	.036	.025	.143	.019
SN → BI	H5	.177	.056	.086	.269	.001
TRU → BI	H7	.132	.067	.022	.242	.049
SE → BI	H8	-	-	-	-	-
PO → BI	H9	-	-	-	-	-
Other						
CS_dummy → BI (AV)	/	.098	.053	.010	.186	.066

Note. Values based on standardized solution of the SEM. Effects and hypotheses not included in the final model have "-" as values. $N = 125$, *SE* = Standard Error, CI = Confidence Interval, *LL* = Lower Limit, *UL* = Upper Limit.

Table 4.5

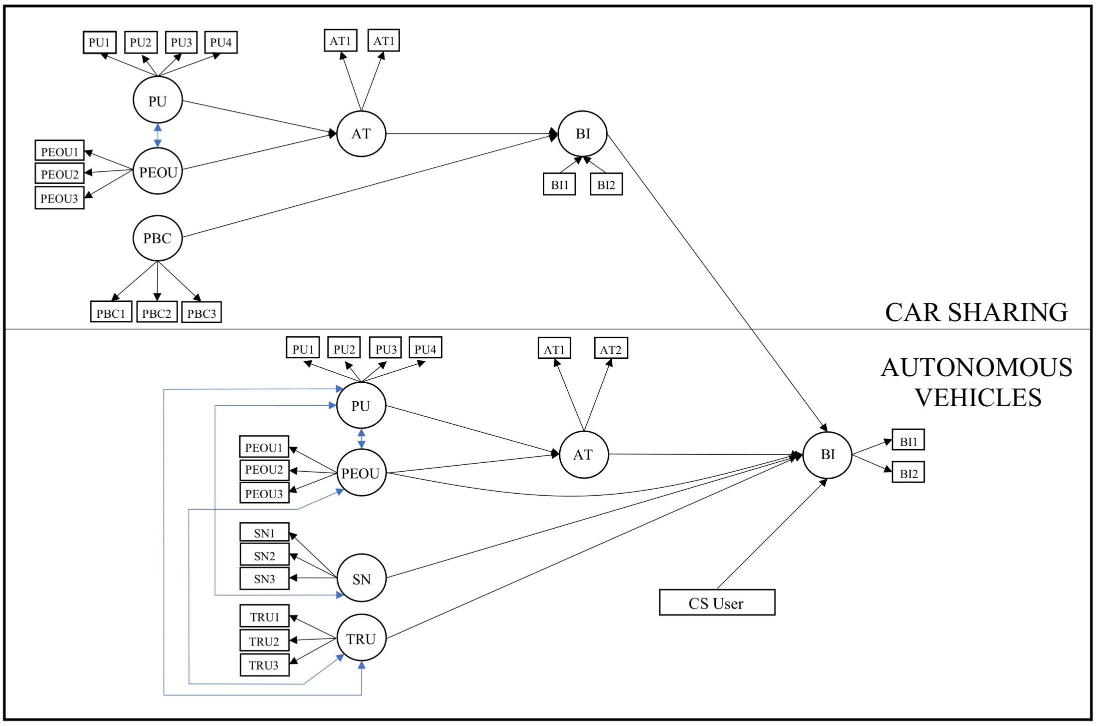
Significant Residual Correlations Student Data Set

Variables		Estimate	*SE*	90% CI		*p*
				LL	*UL*	
Car Sharing						
PU	PEOU	.225	.085	.085	.365	.008
Autonomous Vehicles						
PU	PEOU	.373	.073	.254	.492	<.001
SN	PU	.332	.068	.221	.443	<.001
TRU	PU	.516	.062	.415	.618	<.001
TRU	PEOU	.545	.063	.442	.649	<.001

Note. Values based on standardized solution of the SEM. N = 125, *SE* = Standard Error, CI = Confidence Interval, *LL* = Lower Limit, *UL* = Upper Limit.

Figure 4.2

Final Model Student Data Set



4.3 Results Extra Questions, Education, and Ranking

As discussed in Section 3.4.5, other analyses were performed next to examining the research model to discover additional findings. In this process, a deeper dive was taken into the extra statements, the *Education* variable, and the ranking question that was asked in the survey. For the Student's t-tests that were carried out in this part, the significance level was set to $\alpha = .05$ instead of $\alpha = .1$ used in Section 4.2.

Unfortunately, out of the many Student's t-tests that were performed, only a few turned out to be significant and led to interesting findings, as summarized in Table 4.6. In the part about *Perceived Usefulness*, the survey asked the respondents whether they agree with the following two statements: "*I think CS is better and more convenient than my current main form of travel.*" (CS_PU2), and "*I think CS is better and more convenient than owning a regular car.*" (CS_PU_Extra), shown by the first pair in Table 4.6. The mean response value for the second statement was significantly larger than for the first statement ($p < .001$) in the non-student data set. Based on this finding, it could be argued that, generally speaking, people acknowledge CS to be better and more convenient than regular cars. However, when CS is compared to their current main form of travel, people tend to be more negative towards CS even though, according to Derauw et al. (2019), the main form of travel in Belgium is the regular car. Interestingly, as can be seen by the second pair in Table 4.6, the exact same conclusion can be formulated when looking at the equivalent statements for AVs. Here too, the non-students score significantly ($p < .001$) higher on the statement where AVs are compared to regular cars (AV_PU2) than the statement where AVs are compared to the non-students' main form of travel (AV_PU_Extra).

When comparing the set of students to the set of non-students, an additional finding is discovered. The mean score for statement AV_PO_Extra1 (see Table 3.3) is significantly higher ($p = .011$) for the set of non-students. Thus, non-students would opt faster for an SAV compared to students. Furthermore, the customization of a *Shared Autonomous Vehicle* (SAV) seems to be of crucial importance for the case of students since the t-test was significant and the null hypothesis was rejected, as can be seen by the fourth pair in Table 4.6. In this part of the analysis, the t-test compares the mean response values of students for the two extra statements included for the *Psychological Ownership* (PO) variable. The first statement aims to find out if students would rather have SAVs instead of privately owned AVs. The second statement asks the same question, but specifies that the SAV could be automatically customized to the user's preferences. Since the null hypothesis was rejected, this leads to the (particularly interesting) conclusion that students will generally opt for an SAV, instead of an AV, in case the SAV can be customized to their preferences. Building on this, the fifth hypothesis in Table 4.6 dives deeper into the group of students, where it showed that business students tend to have a higher *Behavioral Intention* (BI) for AVs than non-business students. Hence, business students are generally more accepting of the technology compared to students from non-business backgrounds.

Table 4.6

T-tests

Pair		Sample	n	Sample Mean	Hypothesis Formulation	t-statistic	p
x:	CS_PU2	Non-students	77	2.468	$H_0 : \mu_x \geq \mu_y$	- 4.709	$< .001$
y:	CS_PU_Extra	Non-students	77	3.078	$H_A : \mu_x < \mu_y$		
x:	AV_PU2	Non-students	77	2.792	$H_0 : \mu_x \geq \mu_y$	- 4.905	$< .001$
y:	AV_PU_Extra	Non-students	77	3.260	$H_A : \mu_x < \mu_y$		
x:	AV_PO_Extra1	Students	120	2.875	$H_0 : \mu_x \geq \mu_y$	- 2.328	.011
y:	AV_PO_Extra1	Non-students	77	3.286	$H_A : \mu_x < \mu_y$		
x:	AV_PO_Extra1	Students	120	2.875	$H_0 : \mu_x \geq \mu_y$	- 4.09	$< .001$
y:	AV_PO_Extra2	Students	120	3.233	$H_A : \mu_x < \mu_y$		
x:	AV_BI	Business Students	70	3.378	$H_0 : \mu_x \leq \mu_y$	2.146	.017
y:	AV_BI	Non-business Students	55	3.009	$H_A : \mu_x > \mu_y$		

Note. All hypotheses significant on $\alpha - level = .05$

As stated in Section 3.4.5, respondents were asked to rank their preferred modes of transportation. Table 4.7 shows the ranking for the complete data set, with in the left columns the most preferred transportation mode and in the right columns the occurrence of a transportation mode in a respondent's top three. As can be seen in Table 4.7, traveling by bike was the most preferred transportation mode across all respondents, with more than a fifth of respondents ranking it the highest (21.13%), followed closely by AVs (20.30%) and SAVs (17.26%). Surprisingly, when looking at the occurrence of a transportation mode in the respondents' top three, the ranking is very different. Instead of AVs and SAVs being ranked highly, they are now ranked third and second to last. Traveling with a regular car, using public transport, and traveling by bike, which are the most common ways of travel these days, are ranked the highest. For the student data set, the results are very similar as shown in Table 4.8. The top three for the most preferred transportation mode is the same though "Bike" is ranked third instead of first as with the complete data set. For the occurrence of a transportation mode in a respondent's top three, the ranking is exactly the same for both data sets. When looking at the results from the non-students, shown in Table 4.9, we can see that non-students' most preferred transportation mode differed compared to those in the complete and student data set. The top three of non-students' most preferred transportation mode consists of traveling

Table 4.7

Ranking Complete Data Set

Most Preferred TM	n	%	TM In Top 3	n	%
Bike	42	21.13	Regular Car	110	18.61
AV	40	20.30	Public Transport	102	17.26
SAV	34	17.26	Bike	100	16.92
By Foot	24	12.18	Car Sharing	80	13.54
Regular Car	19	9.64	By Foot	79	13.37
Public Transport	19	9.64	SAV	69	11.68
Car Sharing	17	8.63	AV	47	7.95
Other	2	1.02	Other	4	0.68

Note. $N = 197$, N for top three is $3N = 591$, TM = Transportation Mode, "Other" includes: electric scooter and moped.

by bike, by foot, and using an AV. With regards to the occurrence of a transportation mode in a non-students' top three, the results were exactly the same as for the complete and student data set.

Table 4.8

Ranking Student Data Set

Most Preferred TM	n	%	TM In Top 3	n	%
AV	27	22.50	Regular Car	66	18.33
SAV	25	20.83	Public Transport	58	16.11
Bike	23	19.17	Bike	57	15.83
Regular Car	12	10	Car Sharing	52	14.44
By Foot	11	9.17	By Foot	49	13.61
Public Transport	11	9.17	SAV	47	13.06
Car Sharing	11	9.17	AV	31	8.61
Other	0	0	Other	0	0

Note. $N = 120$, N for top three is $3N = 360$, TM = Transportation Mode, "Other" includes: electric scooter and moped.

Table 4.9

Ranking Non-Student Data Set

Most Preferred TM	n	%	TM In Top 3	n	%
Bike	19	24.68	Regular Car	44	19.05
By Foot	13	16.88	Public Transport	44	19.05
AV	13	16.88	Bike	43	18.61
SAV	9	11.69	By Foot	30	12.99
Public Transport	8	10.39	CS	28	12.12
Regular Car	7	9.09	SAV	22	9.52
CS	6	7.79	AV	16	6.93
Other	2	2.60	Other	4	1.73

Note. $N = 77$, N for top three is $3N = 231$, TM = Transportation Mode, "Other" includes: electric scooter and moped.

Discussion

In the previous chapter, the results were reported in detail. The following and also last chapter of this paper first goes over the representativeness of the data, followed by a discussion of the results found in Chapter 4. In addition, based on these results, advice to policy makers is given. Furthermore, the limitations encountered in this study are reviewed, as well as recommendations for future research that studies CS and AV acceptance.

5.1 Representativeness of the Data Set

Before discussing the eye-catching results that came forth from the analysis, it is important to assess the representativeness of the collected data. During this process, the socio-demographic characteristics of the respondents were compared to the official numbers for the Belgian population since the survey has been published in Belgium. When doing so, it became clear which groups are under or over-represented. For instance, the survey did not reach the group of people under the age of 17 (.5%) and the group of people above the age of 66 (1.98%) sufficiently. This is because, according to the numbers made public by Statbel (2022), these groups represent approximately 22% and 20% of the Belgian population, respectively. Thus, there is a lack of people from these age groups in the data. Moreover, even without considering the data from Statbel (2022), it was obvious that Age category of 18-25 is over-represented since the survey mainly reached students. Next, when considering the *Gender* of a person, the survey seems to have performed fairly well since the distribution was close to an even distribution with women being slightly over-represented, similar to the data from Statbel (2022).

In addition, according to the data from the World Bank, 98.12% of the Belgian population lives in urban areas, and the remaining 1.88% in rural areas (World Bank, n.d.). Unfortunately, no data was found concerning numbers from suburban locations. Still, since World Bank (n.d.) makes no distinction between urban and suburban areas, it could be reasoned that the immense percentage of 98.12% contains both. This means that there was a substantial over-representation of people from rural regions. However, no exact definition was given in the survey for terms like urban, suburban and rural, and this was left to the respondents' interpretation, whereas official reports from statistical offices such as World Bank (n.d.) adopt specific definitions to make this distinction. This difference in approach makes the comparison of the data to the official published numbers potentially obsolete. When considering the proportion of people with a Driving License, the survey provided an appropriate representation, where 81% of respondents stated to be in possession of one, whereas Dewulf and Lequeux (2018) published this proportion to be 88%. Lastly, as expected, it was not possible to split the group of students into different fields of study since any field different from business was under-represented.

5.2 Discussion of the Results

5.2.1 Structural Equation Model

The research question of this paper was: "How Do Car Sharers and Non-Car Sharers View the Trends in Self-Driving/Autonomous Transport?", which could be answered by Hypothesis 1 (see Section 3.2.1). Unfortunately, this hypothesis was close to, but not significant at $\alpha = .1$ for the complete data set ($p = .128$), though it was proven to be significant for the student data set ($p = 0.67$). This means that, for students, engaging with CS raises their acceptance of AVs, which is interesting because it answers the research question in the case of that particular population group. In line with the results from this research, a previous study by Curtale et al. (2022) suggested that the *Behavioral Intention* (BI) of Electric Car Sharing (ECS) services has a positive impact on the BI to use Autonomous Electric Car Sharing services (AECS), though their research focus was much more narrow than this paper's focus. By looking at the results of Curtale et al. (2022) and the results of this paper, it could be argued that a possible significant relationship between the BI of CS and the BI of AVs does exist in general, but was not found due to limitations with the data.

Attitude was a behavioral variable which was found very important for both CS and AVs in both the complete and the student data set. This result seems logical, since a person that has a more positive attitude towards CS or AVs is also much more likely to use those technologies. However, a big part of the literature does not include *Attitude* (AT) and its effect on the *Behavioral Intention*, except for a paper from Müller (2019), who found a positive relationship between AT and BI for both CS and AVs. Despite the final version of the TAM (Venkatesh & Davis, 1996) not including AT anymore and the general exclusion of this variable in the literature, it is suggested that future research still includes this variable as it seems to be key for these technologies.

There are two other variables that have a large influence on the *Attitude* (AT), namely the *Perceived Usefulness* (PU) and *Perceived Ease Of Use* (PEOU). First, the effect of PU is discussed. As suggested by the results, the PU is a very important variable that influences AT directly for both CS and AVs, shown by Hypothesis 3a. Moreover, PU influences the BI directly (H3b) and indirectly through AT (H3c), though the results from the students-only data set do not support the former relationship. To increase people's

PU, advertisements that emphasise the usefulness of CS and AVs could be made. More specifically for CS, highlighting that CS can save money or that CS is very flexible could be possible messages to be put in the advertisements. In the case of AVs, pointing out that they help you save time and are able to solve traffic congestion problems are two examples of its usefulness, though it will take a longer time to convince people since AVs are not on the market yet. The importance of PU's effect on AT was also highlighted in a paper by Müller (2019), who found that PU influences AT positively for both CS and AVs. Moreover, the positive effect of PU on BI was confirmed by multiple studies, such as Y. Liu and Yang (2018) confirming this relationship for CS, and Baccarella et al. (2021) and Lee et al. (2019) finding this relationship for AVs. Besides the PU being a crucial part of the final model, significant positive residual correlations were found between PU and other variables, as can be seen in Tables 4.3 and 4.5. More specifically, the analysis showed that the residuals of PU were significantly correlated with those of PEOU for both CS and AVs, and with those of *Subjective Norms* (SN) and *Trust* (TRU) for the case of AVs. Interestingly, the same conclusions can be formulated concerning all obtained residual correlations for the complete data set and students-only data set. Moreover, the interpretation of residual correlations goes as follows: A significant residual correlation means that the unexplained parts of the variables' effects correlate with each other. This observation leads to the conclusion that there might be some overlap between the set of variables, implying a potential relationship between said variables. Using this logic and the findings from the literature, this suggests that both CS and AVs are potentially perceived more useful when someone thinks they are easy to use. The exact relationships found in the literature are shown in Appendices A.3 and A.4. Also, according to the obtained residual correlations, the influence of other people and how trustworthy an AV is seems to affect how useful someone perceives an AV in the adoption process of AVs.

The second variable that influences *Attitude* directly is the *Perceived Ease Of Use*, which also has an indirect effect on the BI through AT. Furthermore, the direct effect of PEOU on BI was also tested, but was only significant in the case of AVs in the students-only data set. To stimulate the PEOU of both technologies, one could market different features of CS and AVs that make them easy to use. By stressing the user-friendliness of a CS app and having shared cars parked everywhere, it is possible to increase the PEOU of CS. Autonomous Vehicles (AVs), despite them not being widely available yet, can be promoted as something that requires very little effort to use, only needing the press of a few buttons to get to your destination. The results in this research contribute to the findings from the literature. More specifically, the direct effect of PEOU on AT is supported in a study by Müller (2019) who finds this relationship for CS as well as for AVs, though Haldar and Goel (2019) do not find support for this relationship. Furthermore, the literature finds evidence for the PEOU's direct effect on BI, with Y. Liu and Yang (2018), Tran et al. (2019), and others proving this for CS, and Xu et al. (2018) among others for AVs. Also, the PEOU influences the PU according to the literature, where Haldar and Goel (2019), Y. Liu and Yang (2018), and Müller (2019) suggest this finding for CS, and Baccarella et al. (2021), Lee et al. (2019), Müller (2019), and Panagiotopoulos and Dimitrakopoulos (2018) for AVs. Based on these findings, residual correlations were added to the model concerning these specific variables. The obtained residual correlations in Tables 4.3 and 4.5 show that for both CS and AVs, the residuals of PU and PEOU are correlated, as discussed in previous paragraph. Moreover, the results show a significant positive correlation between the residuals of the variables PEOU and TRU. This suggests a potential relationship between the variables, i.e., a relationship could exist between how much a person trusts AVs and how easy he or she thinks AVs are to use. When comparing PU to PEOU, we can see that the results from this paper suggest that the effects of PU are larger than the same effects of PEOU, hence to promote CS or AV use, one should focus more on communicating the usefulness of the technologies.

Another variable that seemed important was *Subjective Norm* (SN), though only for AVs and not for CS. In other words, the influence of other people on an individual has an impact on that person's BI for AVs, but not for CS, according to the data. When applying this finding to the real world, one could for example use a celebrity to raise AV acceptance, though surprisingly, the same can not be achieved for CS. Also, manufacturers of AVs could organize networking events around the topic of AVs. People who participate in these events could then further inform their close ones about AVs. This result contradicts the findings of Curtale et al. (2021) and Mattia et al. (2019) who do find a positive relationship between the SN and BI for CS. For AVs however, the findings from this study are consistent with those from Du et al. (2021), Leicht et al. (2018), Panagiotopoulos and Dimitrakopoulos (2018), and Zhu et al. (2020). As mentioned before, the residuals of SN and PU are correlated for AVs, indicating that a relationship could exist between them, which was already mentioned by Zhu et al. (2020) who found a positive impact of the SN on the PU.

There is one variable that was measured for CS only, namely the *Perceived Behavioral Control* (PBC). The result that came forth from the data, more specifically the significant positive relationship of PBC on the BI of CS, is consistent with Mattia et al. (2019) who found the same result. Thus, to encourage people to use CS it is possible to manipulate the PBC by, for example, advertising CS as a travel solution available to anyone, offering it at a low cost, or providing more shared cars so people have more access to CS. In this case, the goal in mind is to show people that there are very few barriers preventing them to use CS, and that nothing out of their control could stop them from using it.

Three variables were included for AVs only, two of which were left out of the final model, *Self-Efficacy* (SE) and *Psychological Ownership* (PO) to be more specific. Firstly, *Self-Efficacy* was not proven to be significantly related to BI in the final model, contradicting findings by Du et al. (2021), Lee et al. (2019), and Zhu et al. (2020), who did find a positive significant relationship between SE and BI. However, it could be argued that this paper did not find this relationship to be significant due to the low Cronbach's alpha of this variable. Secondly, *Psychological Ownership* was also not included in the final model because it was deemed insignificant in previous iterations of the model. This outcome is opposite to that of Lee et al. (2019) who found a positive relationship between PO and BI, though their study focused exclusively on SAVs, which was not the case for this research.

Trust (TRU) was the only variable included solely for AVs that had a significant influence on BI, confirming the findings by Du et al. (2021), P. Liu et al. (2019), Panagiotopoulos and Dimitrakopoulos (2018), and Xu et al. (2018) who found *Trust* to be an important variable for AV acceptance. Moreover, *Trust* had significantly correlating residuals with PU, suggesting a potential relationship between the level of trust in AVs and the PU of the technology. Building on this, the same conclusion can be formulated for TRU and PEOU, i.e., a relation could exist between the amount of trust in AVs and the ease of use of the technology, as perceived by the individual. These potential relationships are confirmed by the literature where Xu et al. (2018) concluded both relationships to be significant. It is hard to make people trust AVs right now since it is not possible to experience traveling in an AV, except for a few places such as San Francisco where Waymo, Google's AV company (see Introduction), is active. However, AV manufacturers should focus on creating a car that puts safety first, with plenty of fail-safe systems, a good Automatic Driving System (ADS) that controls the car, and make the car crash-safe to prevent injuries as much as possible. By being more transparent about safety and explaining the workings of the AVs, people will trust AVs more when they get to use the cars, and will use them more once they realize AVs are trustworthy.

Unfortunately, despite much of the literature finding significant relationships coming from the socio-demographic variables, this paper did not find evidence for such relationships. The only significant influence of a socio-demographic characteristic was found in the students data set, namely the influence of CS dummy on the BI of AVs. This result suggests that for students in general, having past experience with a CS service would make them more likely to use an AV.

5.2.2 Extra Tests

Besides investigating the research question using Structural Equation Modeling (SEM), extra tests were performed to provide other findings. Of many different tests conducted, five were found significant, as can be seen in Table 4.6. The first two tests in Table 4.6 considered the comparison of CS and AVs to a regular car, and to a person's main form of travel. Here, within the non-students group, respondents scored significantly lower on the statement where CS and AVs were being compared to their main form of travel. This suggests that they are not ready to replace their main form of travel with either (or both) of the technologies. In theory, the scores for both statements should have been approximately the same since, according to Derauw et al. (2019), the main form of travel in Belgium is the regular car. Surprisingly, this was not the case and even a significant difference was found between these scores. Test number three compared students and non-students and their preference between buying an AV or using an SAV. The result from this test shows that students are less in favour of using SAVs compared to non-students, though there is an interesting aspect that could raise students' acceptance of SAVs. This is shown by the fourth test, that compares students' preference of using SAVs over buying an AV. Here, one of the statements simply asked the respondent whether they would prefer to make use of an SAV over a private AV, and no further specifications were given regarding the SAV. However, the second statement specified that it would be possible to customize the SAV to the user's preferences even before the person has entered the vehicle. The result from this test shows that, when SAVs can be customized beforehand, students would prefer SAVs over AVs more than when this customization was not mentioned. Thus, even though students are generally less accepting of SAVs compared to non-students, their acceptance can be influenced by making sure the vehicles are customizable beforehand. Lastly, a comparison between business and non-business students was made regarding the BI of AVs, and interestingly it was observed that the BI to use AVs of business students was higher than that of non-business students. Therefore, it can be said that, according to the data, business students would be more open to use AVs as opposed to non-business students.

5.2.3 Ranking

Finally, a ranking was made to see how a transportation mode ranks as someone's most preferred form of travel versus the occurrence of a transportation mode in a person's top three. The results were very similar for both the complete and the students data set. In general, it can be said that bikes, AVs, and SAVs are ranked highest when it comes to the most preferred transportation mode. However, when looking at the appearance of a transportation mode in the respondents' top three, more popular modes of travel are ranked highest, namely a regular car, public transport, and bike. This result could be caused by the fact that many people would prefer an AV or SAV, but that those quickly drop off in terms of preference when looking more generally, and that people still prefer more common transportation modes. However, the results differed slightly for the non-student data set. In their case, the most preferred transportation modes were traveling by bike, by foot, or using an AV. This result suggests that non-students still choose traditional transportation modes over newer ones, which could possibly be caused by the fact that the non-student group was older compared to the student group. However, the results for the occurrence of a transportation mode in their top three was consistent with that of the complete data set and student data set.

5.3 Limitations and Future Research

In the previous chapters of the paper, an elaborate explanation was given about this model's research design and results, followed by an in-depth discussion of these results. Now, it is necessary to assess this paper's limitations and formulate potential solutions to them for further research. Moreover, a lot of things still need to be analyzed in the future, which is why suggestions will be provided for future research in this last part of the study.

To start, it is important to pay attention to the potential limitations caused by the characteristics of the collected data. As already mentioned in previous sections of the paper, the size of the data is quite limited causing a few implications for the analysis and interpretation of the results. Another important aspect is the data set's representativeness discussed in Section 5.1, where it became clear that some groups of the population were over- or under-represented. It appeared that young-adults under the age of 17, and seniors above the age of 66 were not represented well enough by the data, even though they make up a large portion of our population. On the contrary, the age category of 18-25 represented more than 50% of the respondents, consisting mainly of students, which led to the decision to go more in depth into this subset of the data set. Since interesting findings came forth from the students-only data set, it might be useful to conduct a separate study aimed specifically at students and their perspective, where it is made sure that enough students are included from different fields of study, something this paper's survey failed to achieve. Another mistake that was made was the unspecified measurement of a person's place of residence. As was discussed in Section 5.1, it is difficult to assess the representativeness of the data when looking at a person's place of residence since this was measured in an ambiguous manner. Moreover, the main hypothesis of this study was unfortunately proven to be insignificant for the complete data set ($p = .128$), whereas this hypothesis was significant for the students-only data set ($p = .067$). By looking at this comparison and seeing how close the p value was to the significance level (α) of .1, it could be argued that, if a bigger audience was reached with the survey, this relationship could have been found to be significant. When taking all of this together, it becomes clear that it is important for future research to conduct this study on a much larger scale, where it is made sure that every part of the population is represented well enough. It might also be smart to take a look at reports from official statistical offices before collecting the data in order to make sure the data is collected in such a way to make comparison possible.

Moreover, the designed Structural Equation Model and its characteristics should be considered as well. As was mentioned in Section 3.4.3, some variables had quite low ($< .70$) Cronbach's alphas. More specifically, this was the case for *Perceived Ease of Use* (PEOU), *Perceived Behavioral Control* (PBC), and *Self-Efficacy* (SE). According to Bujang et al. (2018), these low values could have been caused by the small sample size, which another reason to suggest future research to be on a much larger scale. Additionally, for the context of this study, adjustments were made to the items included in the survey, potentially reducing these Cronbach's alphas even more. In every study, it is important to include the correct items that will measure what the study aims to measure, hence it is advised to investigate this more in depth and develop items specifically for the aim of measuring variables in the context of CS and AVs. Another issue in this paper was that the obtained fit measures of the final Structural Equation Model did not reach the favorable cut-off values, as can be seen in Table 3.7. Once again, this shows the importance of having a sufficiently large data set since, according to Schreiber (2008), a small data set could lead to non-satisfactory fit measures for the constructed model. Furthermore, the acceptance of CS and AVs should be assessed more in depth, meaning that it needs to be studied by making use of state-of-the-art statistical tools where more details are considered. On the contrary, doing more general analyses might also be of great use within this field. For instance, it might be interesting to carry out a Principal Factor Analysis to categorize different variables into more general fields, which could be a better approach than going in detail as in this paper. After all, the paper is trying to explain and predict human behavior which is an (nearly) impossible task, thus the answer might be found in more general analyses instead of estimations of detailed models containing many (similar) variables. If Structural Equation Modeling (SEM) is still chosen in further research within this field, then it is advised to do a more thorough assessment of the existing literature since a SEM is an a priori method where the model is first constructed and then fitted. Hereby, it is essential to have a complete overview of the existing literature in order to make sure an appropriate model is constructed.

Furthermore, in this paper, none of the socio-demographic factors were proven to be significant for the acceptance of these technologies despite many studies finding evidence for their relevance. Thus, the socio-demographic factors might have been included or measured inappropriately in this study and a better assessment of these factors is needed. Another interesting idea for future research might be to analyse this research question via an observational study. In this study, one group would gain access to free CS for some time, while the other group would not receive this treatment. At the end of this period, the same questions concerning AVs could be asked to both groups in order to measure their level of acceptance of AVs, which could identify the existence of a significant difference between the groups' acceptance. This could help analyze this research question more in depth by assessing whether this effect practically takes place instead of looking at the effect in theoretical models. Speaking of practicalities, it is also useful to study what influences the independent variables themselves. By doing so, even better approaches could be designed to increase the acceptance of both technologies, focusing on the most relevant variables.

Lastly, the data collected by iVOX was, unfortunately, outdated and not in line with the exact research purpose of this paper. Hence, it was difficult to interpret the insights coming from this data and comparing them to our study in a logical manner. The analysis of the iVOX data seems like an intermezzo in this paper and is not coherent with the rest of the paper.

Bibliography

Abraham, H., Lee, C., Brady, S., Fitzgerald, C., Mehler, B., Reimer, B., & Coughlin, J. F. (2017). Autonomous vehicles and alternatives to driving: Trust, preferences, and effects of age. *Proceedings of the transportation research board 96th annual meeting*, 8–12.

Acheampong, R. A., & Cugurullo, F. (2019). Capturing the behavioural determinants behind the adoption of autonomous vehicles: Conceptual frameworks and measurement models to predict public transport, sharing and ownership trends of self-driving cars. *Transportation research part F: traffic psychology and behaviour*, *62*, 349–375. https://doi.org/10.1016/j.trf.2019.01.009

Acheampong, R. A., & Siiba, A. (2020). Modelling the determinants of car-sharing adoption intentions among young adults: The role of attitude, perceived benefits, travel expectations and socio-demographic factors. *Transportation*, *47*(5), 2557–2580. https://doi.org/10.1007/s11116-019-10029-3

Ajzen, I. (1980). *Understanding attitudes and predicting social behavior*. Prentice Hall.

Ajzen, I. (1991). The theory of planned behavior. *Organizational behavior and human decision processes*, *50*(2), 179–211. https://doi.org/10.1016/0749-5978(91)90020-T

Anderson, J. M., Nidhi, K., Stanley, K. D., Sorensen, P., Samaras, C., & Oluwatola, O. A. (2014). *Autonomous vehicle technology: A guide for policymakers*. Rand Corporation. https://doi.org/10.7249/RR443-2

Baccarella, C. V., Wagner, T. F., Scheiner, C. W., Maier, L., & Voigt, K.-I. (2021). Investigating consumer acceptance of autonomous technologies: The case of self-driving automobiles. *European Journal of Innovation Management*, *24*(4), 1210–1232. https://doi.org/10.1108/EJIM-09-2019-0245

Bandura, A. (1986). Social foundations of thought and action. *Englewood Cliffs, NJ*, *1986*(23-28).

Bimbraw, K. (2015). Autonomous cars: Past, present and future a review of the developments in the last century, the present scenario and the expected future of autonomous vehicle technology. *2015 12th International Conference on Informatics in Control, Automation and Robotics (ICINCO)*, *01*, 191–198. https://doi.org/10.5220/0005540501910198

Bujang, M. A., Omar, E. D., & Baharum, N. A. (2018). A review on sample size determination for cronbach's alpha test: A simple guide for researchers. *The Malaysian* *journal of medical sciences: MJMS*, *25*(6), 85. https://doi.org/10.21315/mjms2018.25.6.9

Burkhardt, J. E., & Millard-Ball, A. (2006). Who is attracted to carsharing? *Transportation research record*, *1986*(1), 98–105. https://doi.org/10.1177/0361198106198600113

Carmen, R., Rousseau, S., Eyckmans, J., Chapman, D., Van Acker, K., Van Ootegem, L., & Bachus, K. (2019). *Car-sharing in Flanders* (tech. rep.). Circular Economy Policy Research Center.

Carsharing Association. (n.d.). What is Car Sharing? Retrieved April 6, 2023, from https://carsharing.org/about/

Carteni, A. (2020). The acceptability value of autonomous vehicles: A quantitative analysis of the willingness to pay for shared autonomous vehicles (savs) mobility services. *Transportation Research Interdisciplinary Perspectives*, *8*, 100224. https://doi.org/10.1016/j.trip.2020.100224

Cortina, J. M. (1993). What is coefficient alpha? an examination of theory and applications. *Journal of applied psychology*, *78*(1), 98. https://doi.org/10.1037/0021-9010.78.1.98

Cover, T., & Hart, P. (1967). Nearest neighbor pattern classification. *IEEE Transactions on Information Theory*, *13*(1), 21–27. https://doi.org/10.1109/TIT.1967.1053964

Cronbach, L. J. (1951). Coefficient alpha and the internal structure of tests. *Psychometrika*, *16*(3), 297–334. https://doi.org/10.1007/BF02310555

Curtale, R., Liao, F., & Rebalski, E. (2022). Transitional behavioral intention to use autonomous electric car-sharing services: Evidence from four european countries. *Transportation Research Part C: Emerging Technologies*, *135*, 103516. https://doi.org/10.1016/j.trc.2021.103516

Curtale, R., Liao, F., & van der Waerden, P. (2021). User acceptance of electric car-sharing services: The case of the netherlands. *Transportation Research Part A: Policy and Practice*, *149*, 266–282. https://doi.org/10.1016/j.tra.2021.05.006

Davis, F. D. (1985). *A technology acceptance model for empirically testing new end-user information systems: Theory and results* (Doctoral dissertation). Massachusetts Institute of Technology.

Davis, F. D., Bagozzi, R. P., & Warshaw, P. R. (1989). User acceptance of computer technology: A comparison of two theoretical models. *Management science*, *35*(8), 982–1003. https://doi.org/10.1287/mnsc.35.8.982

Delacre, M., Lakens, D., & Leys, C. (2017). Why psychologists should by default use welch's t-test instead of student's t-test. *International Review of Social Psychology*, *30*(1). https://doi.org/10.5334/irsp.82

Derauw, S., Gelaes, S., & Pauwels, C. (2019). *Enquête Monitor over de Mobiliteit van de Belgen* (tech. rep.). VIAS Institute.

Dewulf, M., & Lequeux, Q. (2018). *Statistisch Rapport 2018 Rijvaardigheid en Rijgeschiktheid* (tech. rep.). VIAS Institute.

Du, H., Zhu, G., & Zheng, J. (2021). Why travelers trust and accept self-driving cars: An empirical study. *Travel behaviour and society*, *22*, 1–9. https://doi.org/10.1016/j.tbs.2020.06.012

Efthymiou, D., Antoniou, C., & Waddell, P. (2013). Factors affecting the adoption of vehicle sharing systems by young drivers. *Transport policy*, *29*, 64–73. https://doi.org/10.1016/j.tranpol.2013.04.009

Emzivat, Y., Ibanez-Guzman, J., Martinet, P., & Roux, O. H. (2017). Dynamic driving task fallback for an automated driving system whose ability to monitor the driving environment has been compromised. *2017 IEEE Intelligent Vehicles Symposium (IV)*, 1841–1847. https://doi.org/10.1109/IVS.2017.7995973

Fagnant, D. J., & Kockelman, K. (2015). Preparing a nation for autonomous vehicles: Opportunities, barriers and policy recommendations. *Transportation Research Part A: Policy and Practice*, *77*, 167–181. https://doi.org/10.1016/j.tra.2015.04.003

Fagnant, D. J., & Kockelman, K. M. (2018). Dynamic ride-sharing and fleet sizing for a system of shared autonomous vehicles in austin, texas. *Transportation*, *45*, 143–158. https://doi.org/10.1007/s11116-016-9729-z

Filezwaarte. (2023). Retrieved April 5, 2023, from https://www.vlaanderen.be/statistiek-vlaanderen/mobiliteit/filezwaarte

Haldar, P., & Goel, P. (2019). Willingness to use carsharing apps: An integrated tpb and tam. *International Journal of Indian Culture and Business Management*, *19*(2), 129–146. https://doi.org/10.13140/RG.2.2.34379.23843

Hohenberger, C., Spörrle, M., & Welpe, I. M. (2016). How and why do men and women differ in their willingness to use automated cars? the influence of emotions across different age groups. *Transportation Research Part A: Policy and Practice*, *94*, 374–385. https://doi.org/10.1016/j.tra.2016.09.022

Hulse, L. M., Xie, H., & Galea, E. R. (2018). Perceptions of autonomous vehicles: Relationships with road users, risk, gender and age. *Safety science*, *102*, 1–13. https://doi.org/10.1016/j.ssci.2017.10.001

Khan, A. (2017). Modelling human factors for advanced driving assistance system design. *Advances in Human Aspects of Transportation: Proceedings of the AHFE 2016 International Conference on Human Factors in Transportation, July 27-31, 2016, Walt Disney World®, Florida, USA*, 3–14. https://doi.org/10.1007/978-3-319-41682-3_1

König, M., & Neumayr, L. (2017). Users' resistance towards radical innovations: The case of the self-driving car. *Transportation research part F: traffic psychology and behaviour*, *44*, 42–52. https://doi.org/10.1016/j.trf.2016.10.013

Krueger, R., Rashidi, T. H., & Rose, J. M. (2016). Preferences for shared autonomous vehicles. *Transportation research part C: emerging technologies*, *69*, 343–355. https://doi.org/10.1016/j.trc.2016.06.015

Kuderer, M., Gulati, S., & Burgard, W. (2015). Learning driving styles for autonomous vehicles from demonstration. *2015 IEEE international conference on robotics and automation (ICRA)*, 2641–2646. https://doi.org/10.1109/ICRA.2015.7139555

Kyriakidis, M., Happee, R., & de Winter, J. C. (2015). Public opinion on automated driving: Results of an international questionnaire among 5000 respondents. *Transportation research part F: traffic psychology and behaviour*, *32*, 127–140. https://doi.org/10.1016/j.trf.2015.04.014

Le Vine, S., Zolfaghari, A., & Polak, J. (2014). Carsharing: Evolution, challenges and opportunities. *Scientific advisory group report*, *22*, 218–229.

Lee, J., Lee, D., Park, Y., Lee, S., & Ha, T. (2019). Autonomous vehicles can be shared, but a feeling of ownership is important: Examination of the influential factors for intention to use autonomous vehicles. *Transportation Research Part C: Emerging Technologies*, *107*, 411–422. https://doi.org/10.1016/j.trc.2019.08.020

Leicht, T., Chtourou, A., & Youssef, K. B. (2018). Consumer innovativeness and intentioned autonomous car adoption. *The Journal of High Technology Management Research*, *29*(1), 1–11. https://doi.org/10.1016/j.hitech.2018.04.001

Litman, T. (2000). Evaluating Carsharing Benefits. *Transportation Research Record: Journal of the Transportation Research Board*, *1702*(1), 31–35. https://doi.org/10.3141/1702-04

Litman, T. (2016). *Parking management: Strategies, evaluation and planning*. Victoria Transport Policy Institute Victoria, BC, Canada.

Litman, T. (2017). *Autonomous vehicle implementation predictions*. Victoria Transport Policy Institute Victoria, BC, Canada.

Liu, P., Yang, R., & Xu, Z. (2019). Public acceptance of fully automated driving: Effects of social trust and risk/benefit perceptions. *Risk Analysis*, *39*(2), 326–341. https://doi.org/10.1111/risa.13143

Liu, Y., & Yang, Y. (2018). Empirical examination of users' adoption of the sharing economy in china using an expanded technology acceptance model. *Sustainability*, *10*(4), 1262. https://doi.org/10.3390/su10041262

Marangunić, N., & Granić, A. (2015). Technology acceptance model: A literature review from 1986 to 2013. *Universal access in the information society*, *14*(1), 81–95. https://doi.org/10.1007/s10209-014-0348-1

Martinez, L. M., & Viegas, J. M. (2017). Assessing the impacts of deploying a shared self-driving urban mobility system: An agent-based model applied to the city of lisbon, portugal [Connected and Automated Vehicles: Effects on Traffic, Mobility and Urban Design]. *International Journal of Transportation Science and Technology*, *6*(1), 13–27. https://doi.org/10.1016/j.ijtst.2017.05.005

Matthijs, J., Rodenbach, J., Ryvers, S., & Seeuws, B. (2022). *Jaarrapport Autodelen 2021* (tech. rep.). Autodelen.net.

Mattia, G., Mugion, R. G., & Principato, L. (2019). Shared mobility as a driver for sustainable consumptions: The intention to re-use free-floating car sharing. *Journal of Cleaner Production*, *237*, 117404. https://doi.org/10.1016/j.jclepro.2019.06.235

Merfeld, K., Wilhelms, M.-P., Henkel, S., & Kreutzer, K. (2019). Carsharing with shared autonomous vehicles: Uncovering drivers, barriers and future developments–a four-stage delphi study. *Technological Forecasting and Social Change*, *144*, 66–81. https://doi.org/10.1016/j.techfore.2019.03.012

Michon, J. A. (1985). A critical view of driver behavior models: What do we know, what should we do? *Human behavior and traffic safety*, 485–524. https://doi.org/10.1007/978-1-4613-2173-6_19

Millard-Ball, A., Murray, G., & ter Schure, J. (2006). *Carsharing as parking management strategy* (tech. rep.).

Müller, J. M. (2019). Comparing technology acceptance for autonomous vehicles, battery electric vehicles, and car sharing—a study across europe, china, and north america. *Sustainability*, *11*(16), 4333. https://doi.org/10.3390/su11164333

Namazu, M., MacKenzie, D., Zerriffi, H., & Dowlatabadi, H. (2018). Is carsharing for everyone? understanding the diffusion of carsharing services. *Transport Policy*, *63*, 189–199. https://doi.org/10.1016/j.tranpol.2017.12.012

On-Road Automated Driving (ORAD) Committee. (2021). *Taxonomy and definitions for terms related to driving automation systems for on-road motor vehicles*. https://doi.org/10.4271/J3016_202104

Pakusch, C., Stevens, G., & Bossauer, P. (2018). Shared autonomous vehicles: Potentials for a sustainable mobility and risks of unintended effects. *ICT4S*, 258–269. https://doi.org/10.29007/rg73

Panagiotopoulos, I., & Dimitrakopoulos, G. (2018). An empirical investigation on consumers' intentions towards autonomous driving. *Transportation research part C: emerging technologies*, *95*, 773–784. https://doi.org/10.1016/j.trc.2018.08.013

Prieto, M., Baltas, G., & Stan, V. (2017). Car sharing adoption intention in urban areas: What are the key sociodemographic drivers? *Transportation Research Part A: Policy and Practice*, *101*, 218–227. https://doi.org/10.1016/j.tra.2017.05.012

Rabbitt, N., & Ghosh, B. (2013). A study of feasibility and potential benefits of organised car sharing in Ireland. *Transportation Research Part D: Transport and Environment*, *25*, 49–58. https://doi.org/10.1016/j.trd.2013.07.004

Rahimi, A., Azimi, G., Asgari, H., & Jin, X. (2020b). Adoption and willingness to pay for autonomous vehicles: Attitudes and latent classes. *Transportation Research Part D: Transport and Environment*, *89*, 102611. https://doi.org/10.1016/j.trd.2020.102611

Rahimi, A., Azimi, G., & Jin, X. (2020a). Examining human attitudes toward shared mobility options and autonomous vehicles. *Transportation research part F: traffic psychology and behaviour*, *72*, 133–154. https://doi.org/10.1016/j.trf.2020.05.001

Rodenbach, J., Mathis, J., Chicco, A., Diana, M., Wells, P., & Beccaria, S. (2018). Car sharing in europe: A multidimensional classification and inventory. *Deliverable D2*, *1*.

Rosseel, Y. (2012). Lavaan: An r package for structural equation modeling. *Journal of statistical software*, *48*, 1–36.

Schlüter, J., & Weyer, J. (2019). Car sharing as a means to raise acceptance of electric vehicles: An empirical study on regime change in automobility. *Transportation*

Research Part F: Traffic Psychology and Behaviour, *60*, 185–201. https://doi.org/10.1016/j.trf.2018.09.005

Schreiber, J. B. (2008). Core reporting practices in structural equation modeling. *Research in social and administrative pharmacy*, *4*(2), 83–97. https://doi.org/10.1016/j.sapharm.2007.04.003

Sharpe, N. R., De Veaux, R. D., Velleman, P. F., & Wright, D. (2010). *Business statistics*. Addison Wesley Boston, MA.

Statbel. (2022). Structuur van de bevolking — Statbel. Retrieved May 5, 2023, from https://statbel.fgov.be/nl/themas/bevolking/structuur-van-de-bevolking#news

Taherdoost, H. (2019). What is the best response scale for survey and questionnaire design; review of different lengths of rating scale/attitude scale/likert scale. *Hamed Taherdoost*, 1–10.

Thurner, T., Fursov, K., & Nefedova, A. (2022). Early adopters of new transportation technologies: Attitudes of russia's population towards car sharing, the electric car and autonomous driving. *Transportation Research Part A: Policy and Practice*, *155*, 403–417. https://doi.org/10.1016/j.tra.2021.11.006

Tientrakool, P., Ho, Y.-C., & Maxemchuk, N. F. (2011). Highway capacity benefits from using vehicle-to-vehicle communication and sensors for collision avoidance. *2011 IEEE Vehicular Technology Conference (VTC Fall)*, 1–5. https://doi.org/10.1109/VETECF.2011.6093130

Tran, V., Zhao, S., Diop, E. B., & Song, W. (2019). Travelers' acceptance of electric carsharing systems in developing countries: The case of china. *Sustainability*, *11*(19), 5348. https://doi.org/10.3390/su11195348

Ullman, J. B., & Bentler, P. M. (2012). Structural equation modeling. *Handbook of Psychology, Second Edition*, *2*. https://doi.org/10.1002/9781118133880.hop202023

Venkatesh, V., & Bala, H. (2008). Technology acceptance model 3 and a research agenda on interventions. *Decision sciences*, *39*(2), 273–315. https://doi.org/10.1111/j.1540-5915.2008.00192.x

Venkatesh, V., & Davis, F. D. (1996). A model of the antecedents of perceived ease of use: Development and test. *Decision sciences*, *27*(3), 451–481. https://doi.org/10.1111/j.1540-5915.1996.tb00860.x

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS quarterly*, 425–478. https://doi.org/10.2307/30036540

Venkatesh, V., Thong, J. Y., & Xu, X. (2012). Consumer acceptance and use of information technology: Extending the unified theory of acceptance and use of technology. *MIS quarterly*, 157–178. https://doi.org/10.2307/41410412

Voertuigenpark — Statbel. (2022). Retrieved April 5, 2023, from https://statbel.fgov.be/nl/themas/mobiliteit/verkeer/voertuigenpark

World Bank. (n.d.). World Bank Open Data Belgium. Retrieved May 5, 2023, from https://data.worldbank.org

Xu, Z., Zhang, K., Min, H., Wang, Z., Zhao, X., & Liu, P. (2018). What drives people to accept automated vehicles? findings from a field experiment. *Transportation* *research part C: emerging technologies*, *95*, 320–334. https://doi.org/10.1016/j.trc.2018.07.024

Zhu, G., Chen, Y., & Zheng, J. (2020). Modelling the acceptance of fully autonomous vehicles: A media-based perception and adoption model. *Transportation research part F: traffic psychology and behaviour*, *73*, 80–91. https://doi.org/10.1016/j.trf.2020.06.004

Appendix A

Summarizing Tables

Appendix A shows different tables summarizing information from this paper. Table A.1 contains a list of acronyms used in this paper, which are sorted alphabetically. Also, the context in which these acronyms are used is given. In Table A.2, a comparison between the different frameworks, discussed in 2.1, is given to provide an overview of the variables in each framework and to compare how different variables from different frameworks relate to each other.

Tables A.3 and A.4 give an overview of the relationships between different behavioral variables discussed in Chapter 2, what type of relationship was found (if any was found), and in which paper the type of relationship was found. The same type of summary for the socio-demographic variables is shown in Table A.5.

Table A.1

List of Acronyms

Acronym	Meaning	Context
ADS	Automated Driving System	AVs
AECS	Autonomous Electric Car Sharing	AVs & CS
AT	Attitude	TAM
AV	Autonomous Vehicle	
BI	Behavioral Intention	TAM & UTAUT
CS	Car Sharing	
DDT	Dynamic Driving Task	AVs
ECS	Electric Car Sharing	CS
EE	Effort Expectancy	UTAUT
ENV	Environmental Protection	Müller (2019)
EV	Electric Vehicle	
FC	Facilitating Conditions	UTAUT
HOV	Human Operated Vehicle	
INV	Innovativeness	Müller (2019)
NOV	Novelty Seeking	Extension
ODD	Operational Design Domain	AVs
ORAD	On-Road Automated Driving	AVs
OU	Objective Usability	TAM 3
PB	Perceived Benefits	Extension
PBC	Perceived Behavioral Control	TPB
PE	Perceived Enjoyment	Extension
PEOU	Perceived Ease of Use	TAM
PEX	Performance Expectancy	UTAUT
PO	Psychological Ownership	Extension
PR	Perceived Risk	Extension
PS	Perceived Safety	Extension
PU	Perceived Usefulness	TAM
SAE	Society of Autonomous Engineers	AVs
SAV	Shared Autonomous Vehicle	
SCT	Social Cognitive Theory	Behavioral models
SE	Self-Efficacy	SCT
SEM	Structural Equation Modelling	Research method
SI	Social Influence	UTAUT
SN	Subjective Norm	TPB
TAM	Technology Acceptance Model	Acceptance models
TPB	Theory of Planned Behavior	Acceptance models
TRA	Theory of Reasoned Action	Behavioral models
TRU	Trust	Extension
UTAUT	Unified Theory of Acceptance and Use of Technology	Acceptance models
WTU	Willingness to Use	Extension

Table A.2

Framework Comparison Table

TPB	TAM	UTAUT
Attitude Towards the Behavior	Attitude Towards Using (Removed in 1996)	-
Subjective Norm (SN)	-	Social Influence (SI)
Perceived Behavioral Control (PBC)	-	Facilitating Conditions (FC)
Intention	Behavioral Intention (BI) (Added in 1989)	Behavioral Intention (BI)
-	Perceived Usefulness (PU)	Performance Expectancy (PEX)
-	Perceived Ease Of Use (PEOU)	Effort Expectancy (EE)
-	-	Other Moderators
Behavior	Actual System Use	Use Behavior

Table A.3

Summary of Behavioral Variables - Part 1

Car Sharing

Variables	Relationship Type	Model	Papers
Perceived Usefulness → Behavioral Intention	Positive relationship (+)	TAM UTAUT	Liu and Yang (2018) Curtale et al. (2021)* Tran et al. (2019)*
Perceived Ease of Use → Behavioral Intention	Positive relationship (+)	TAM UTAUT	Liu and Yang (2018) Tran et al. (2019)*
	No relationship	UTAUT	Curtale et al. (2021)*
Perceived Ease of Use → Perceived Usefulness	Positive relationship (+)	TAM	Müller (2019) Haldar and Goel (2019) Liu and Yang (2018)
Perceived Usefulness → Attitude	Positive relationship (+)	TAM	Müller (2019) Haldar and Goel (2019)
Perceived Ease of Use → Attitude	Positive relationship (+)	TAM	Müller (2019)
	No relationship	TAM	Haldar and Goel (2019)
Attitude → Behavioral Intention	Positive relationship (+)	TAM TPB	Müller (2019) Mattia et al. (2019)
Trust → Perceived Usefulness	No relationship	Extended TAM	Liu and Yang (2018)
Trust → Perceived Ease of Use	No relationship	Extended TAM	Liu and Yang (2018)
Trust → Behavioral Intention	No relationship	Extended TAM Extended UTAUT	Liu and Yang (2018) Curtale et al. (2021)

* Proven with equivalent variables from other models

Autonomous Vehicles

Variables	Relationship Type	Model	Papers
Perceived Usefulness → Behavioral Intention	Positive relationship (+)	TAM UTAUT Other	Baccarella et al. (2021) Lee et al. (2019) Panagiotopoulos and Dimitrakopoulos (2018) Xu et al. (2018) Leicht et al. (2018)* Zhu et al. (2020)
Perceived Ease of Use → Behavioral Intention	Positive relationship (+)	TAM UTAUT	Panagiotopoulos and Dimitrakopoulos (2018) Xu et al. (2018) Leicht et al. (2018)*
	No relationship	TAM	Baccarella et al. (2021) Lee et al. (2019)
Perceived Ease of Use → Perceived Usefulness	Positive relationship (+)	TAM	Baccarella et al. (2021) Lee et al. (2019) Müller (2019) Panagiotopoulos and Dimitrakopoulos (2018)
Perceived Usefulness → Attitude	Positive relationship (+)	TAM	Müller (2019)
Perceived Ease of Use → Attitude	Positive relationship (+)	TAM	Müller (2019)
Attitude → Behavioral Intention	Positive relationship (+)	TAM	Müller (2019)
Trust → Perceived Usefulness	Positive relationship (+)	UTAUT	Xu et al. (2018)
Trust → Perceived Ease of Use	Positive relationship (+)	UTAUT	Xu et al. (2018)
Trust → Behavioral Intention	Positive relationship (+)	UTAUT Extended TAM Other	Xu et al. (2018) Panagiotopoulos and Dimitrakopoulos (2018) Du et al. (2021) Liu et al. (2019)
Perceived Risk → Behavioral Intention	Negative relationship (-)	Other	Lee et al. (2019) Zhu et al. (2020)
	No relationship	Other	Liu et al. (2019)
Perceived Safety → Behavioral Intention	Positive relationship (+)	Other	Xu et al. (2018)
Trust → Perceived Risk	Negative relationship (-)	Other	Liu et al. (2019)
Trust → Perceived Benefits	Positive relationship (+)	Other	Liu et al. (2019)

* Proven with equivalent variables from other models

Table A.4

Summary of Behavioral Variables - Part 2

Car Sharing

Variables	Relationship type	Model	Papers
Subjective Norm → Perceived Usefulness	Positive relationship (+)	Extended TAM	Liu and Yang (2018)
Subjective Norm → Perceived Ease of Use	Positive relationship (+)	Extended TAM	Liu and Yang (2018)
Subjective Norm → Behavioral Intention	Positive relationship (+)	TPB UTAUT	Mattia et al. (2019) Curtale et al. (2021)*
	No relationship	UTAUT	Tran et al. (2019)*
Subjective Norm → Trust	Positive relationship (+)	Extended TAM	Liu and Yang (2018)
Perceived Behavioral Control → Behavioral Intention	Positive relationship (+)	TPB	Mattia et al. (2019)
Perceived Enjoyment → Perceived Usefulness	Positive relationship (+)	Extended TAM	Müller (2019)
Perceived Enjoyment → Perceived Ease of Use	Positive relationship (+)	Extended TAM	Müller (2019)
Perceived Enjoyment → Behavioral Intention	Positive relationship (+)	Extended UTAUT	Tran et al. (2019)

* Proven with equivalent variables from other models

Autonomous Vehicles

Variables	Relationship type	Model	Papers
Subjective Norm → Perceived Usefulness	Positive relationship (+)	TPB	Zhu et al. (2020)
Subjective Norm → Perceived Ease of Use	Positive relationship (+)	TPB	Acheampong and Cugurullo (2019) Zhu et al. (2020)
Subjective Norm → Behavioral Intention	Positive relationship (+)	Extended TAM UTAUT	Panagiotopoulos and Dimitrakopoulos (2018)* Leicht et al. (2018)*
		TPB Other	Zhu et al. (2020) Du et al. (2021)
Subjective Norm → Perceived Behavioral Control	Positive relationship (+)	TPB	Acheampong and Cugurullo (2019)
Subjective Norm → Perceived Benefits	Positive relationship (+)	TPB	Acheampong and Cugurullo (2019)
Anxiety → Perceived Usefulness	No relationship	Extended TAM	Baccarella et al. (2021)
Anxiety → Perceived Ease of Use	Negative relationship (-)	Extended TAM	Baccarella et al. (2021)
Anxiety → Perceived Usefulness → Behavioral Intention	Negative relationship (-)	Extended TAM	Baccarella et al. (2021)
Anxiety → Perceived Ease of Use → Behavioral Intention	Negative relationship (-)	Extended TAM	Baccarella et al. (2021)
Anxiety → Behavioral Intention	Negative relationship (-)	Other	Hohenberger et al. (2016)
Self Efficacy → Perceived Usefulness	Positive relationship (+)	Other	Zhu et al. (2020)
Self Efficacy → Perceived Ease of Use	Positive relationship (+)	UTAUT	Lee et al. (2019)
Self Efficacy → Behavioral Intention	Positive relationship (+)	UTAUT Other	Lee et al. (2019) Du et al. (2021) Zhu et al. (2020)
Perceived Enjoyment → Perceived Usefulness	Positive relationship (+)	Extended TAM	Müller (2019)
Perceived Enjoyment → Perceived Ease of Use	Positive relationship (+)	Extended TAM	Müller (2019)
Pleasure → Behavioral Intention	Positive relationship (+)	Other	Hohenberger et al. (2016)
Novelty Seeking → Perceived Usefulness → Behavioral Intention bhj	Positive relationship (+)	Extended TAM	Baccarella et al. (2021)
Psychological Ownership → Behavioral Intention	Positive relationship (+)	Other	Lee et al. (2019)

* Proven with equivalent variables from other models

Table A.5

Summary of Socio-Demographic Factors

Variable	Impact	Papers
Age		
Car Sharing	Negative impact (-)	Curtale et al. (2021)
		Prieto et al. (2017)
		Rahimi et al. (2020a)
		Thurner et al. (2022)
	No impact	Efthymiou et al. (2013)
Autonomous Vehicles	Negative impact (-)	Khan (2017)
		König and Neumayr (2017)
		Rahimi et al. (2020a)
		Rahimi et al. (2020b)
		Thurner et al. (2022)
		Acheampong and Cugurullo (2019)*
Gender		
Car Sharing	Negative impact (-) (Female)	Acheampong and Siiba (2020)
		Burkhardt and Millard-Ball (2006)
		Prieto et al. (2017)
		Rahimi et al. (2020a)
	No impact	Curtale et al. (2021)
		Thurner et al. (2022)
Autonomous Vehicles	Negative impact (-) (Female)	Khan (2017)
		König and Neumayr (2017)
		Liu et al., 2019
		Thurner et al. (2022)
Place of Residence		
Car Sharing	Positive impact (+) (City)	Prieto et al. (2017)
		Thurner et al. (2022)
	No impact	Rahimi et al. (2020a)
Autonomous Vehicles	Positive impact (+) (City)	König and Neumayr (2017)
		Rahimi et al. (2020b)
		Thurner et al. (2022)
Income		
Car Sharing	Positive impact (+)	Curtale et al. (2021)
	Negative impact (-)	Efthymiou et al. (2013)
	No impact	Thurner et al. (2022)
Autonomous Vehicles	Positive impact (+)	Rahimi et al. (2020b)
	Negative impact (-) for middle class	Rahimi et al. (2020a)
	No impact	Thurner et al. (2022)
Education		
Car Sharing	Positive impact (+)	Prieto et al. (2017)
		Rahimi et al. (2020a)
	Negative impact (-)	Acheampong and Siiba (2020)

Variable	Impact	Papers
	No impact	Curtale et al. (2021)
		Efthymiou et al. (2013)
		Thurner et al. (2022)
Autonomous Vehicles	Postive impact (+)	Acheampong and Siiba (2020)*
	No impact	Thurner et al. (2022)
Household Size		
Car Sharing	Positive impact (+)	Thurner et al. (2022)
Autonomous Vehicles	Positive impact (+)	Rahimi et al. (2020b)
		Thurner et al. (2022)
	Negative impact (-)	Rahimi et al. (2020a)
Car Ownership		
Car Sharing	No impact	Thurner et al. (2022)
Autonomous Vehicles	No impact	Thurner et al. (2022)
Car Usage		
Autonomous Vehicles	Negative impact (-)	König and Neumayr (2017)
		Rahimi et al. (2020b)
Usage of automation assistance system		
Autonomous Vehicles	Positive impact (+)	König and Neumayr (2017)
		Kyriakidis et al. (2015)
Environmental attitude		
Car Sharing	Positive impact (+)	Efthymiou et al. (2013)
	No impact	Acheampong and Siiba (2020)
Daily Distance		
Car Sharing	Positive impact (+)	Rahimi et al. (2020a)

* Indirect impact

Appendix B

Survey iVOX

Table B.1 in Appendix B shows the different questions asked in the survey made by iVOX, whether they are included in the analysis, and other remarks about those questions.

Table B.1

iVOX Survey Questions

Question	Description	Included?	Other Remarks
Employment	How can you describe your job?	X	
Family Situation	What is your family situation?		
Household Size	How many people live in your houshold, including yourself?	X	
Driving License	Do you possess a driving license B?	X	
Household Driving Licenses	How many people in your household possess a driving license B, including yourself?		
Household Employment	How many people in your household have a job, including yourself?		
Household Income	What is your net househould income?		
CS Member	Are you member or a customer of a Car Sharing organisation?	X	
CS Organisation	Of which Car Sharing organisation are you a member or customer of?		Only asked to people who answered "Yes" in V8
Likelihood To Become Member	How likely are you to become a member of a Car Sharing service?		Only asked to people who answered "No" in V8
Transportation Modes	How often did you make use of the following transportation modes in the past month?		
Cars In Household	How many cars are currently in your household (including company cars)?	X	

Table B.1

iVOX Survey Questions

Question	Description	Included?	Other Remarks
CS Convenience, Features, and Parking	To what extent would the following aspects of Car Sharing convince you to use Car Sharing?	X	Only asked to people who answered ”No” in V8
CS Convenience, Features, and Parking	To what extent do you find the following aspects of Car Sharing important as a Car Sharing user?	X	Only asked to people who answered ”Yes” in V8
Subscriptions	Which of the following statements apply to you?	X	Statements are related to subscriptions public transport, shared bikes etc.
CS Platform	To what extent do you agree with the following statements?	X	Statements about sharing platforms, each statements has different options for the features of a sharing platform
CS Platform Ranking	Which of the following aspects of a sharing platform do you find most important?		
Platform WTP	Would you be willing to pay for a sharing platform?	X	
AV_Q1, AV_Q2, AV_Q3	To what extent do you agree with the following statements?	X	Various statements about Autonomous Vehicles
Gender	What is your gender?	X	
Birth Year	What is your birth year?	X	Used to derive the age of the respondent (Age = 2019 - birth year)
Diploma	What is your highest attained educational degree?	X	
Postal Code	What is your postal code?		
Province	In what province do you live?		
Urbanisation	How would you describe the area you live in?	X	

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