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ADOPTION AND ACCEPTANCE OF AUTONOMOUS VEHICLES

Master's Thesis 2019

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ABSTRACT

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This is a deductive, explanatory study that discusses the technology acceptance and innovation diffusion of autonomous vehicles (AVs). The purpose of the study was to understand whether there exists a sufficient level of acceptance towards the AV technology among consumers for this innovation to begin diffusing into the society. Relevant literature and prior studies on adoption, acceptance, and impacts of the AV technology were reviewed. Empirical research was conducted exploiting quantitative research methods. An online questionnaire was utilized to measure the acceptance of 300 respondents towards AVs using predictor items taken from the Car technology acceptance model (CTAM) and Innovation diffusion theory. The survey results were analyzed using a multiple linear regression model that measured intentions to use AVs, and binary logistic regression that measured willingness to pay (WTP). The main findings include that respondents overall had a slightly favorable view towards AVs. Clear majority of the respondents thought that AVs will be safer and better drivers than regular vehicles. 67.7 percent expressed interest to take a ride in an AV while on average the WTP for a fully autonomous driving system on top of the base price of a vehicle was 3 592 euros. Safety, compatibility and relative advantage had the highest influence on intentions to use and WTP, while demographic variables had a negligible effect. The low level of prior experiences of AVs among the respondents limits the reliability of the results of the study. It is thus likely that the acceptance towards fully autonomous vehicles changes once this technology becomes available to consumers.

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Tämä on deduktiivinen, selittävä tutkimus, joka käsittelee autonomisten ajoneuvojen (AV) käyttöönottohalukkuutta ja innovaatioiden diffuusiota. Tutkimuksen tarkoituksena oli selvittää esiintyykö kuluttajien keskuudessa riittävästi hyväksyntää ja käyttöhalukkuutta AV-teknologiaa kohtaan, jotta sen diffuusioprosessi voi käynnistyä. Kirjallisuuskatsaus käsitteli innovaatioiden käyttöönoton ja hyväksyttävyyden teoriaa ja aiempia tutkimuksia AV-teknologian vaikutuksista ja hyväksyttävyydestä. Empiirinen tutkimus toteutettiin kvantitatiivisin menetelmin. Kuluttajien AV-teknologian käyttöhalukkuutta mitattiin 300 vastaajan kyselyllä, jossa hyväksyntää ennustavat muuttujat oli valittu Car technology acceptance model eli CTAM-mallista ja innovaatioiden diffuusion teoriasta. Käyttöaikomuksia analysoitiin usean selittäjän lineaarisella regressiomallilla ja maksuhalukkuutta logistisella regressiomallilla. Tulosten mukaan vastaajilla on jokseenkin myönteinen näkemys AV-teknologiasta. Selkeä enemmistö piti AV-autoja turvallisempina ja parempina kuljettajina kuin ihmisisten ohjaamia autoja. 67.7 prosenttia vastaajista ilmaisi halukkuutta ottaa kyydin AV-autossa, kun taas keskimääräinen maksuhalukkuus täyden itseohjautuvuuden mahdollistavasta lisävarusteesta oli 3 592 euroa. Turvallisuus, yhteensopivuus yhteiskunnan tarpeiden kanssa ja suhteelliset edut muihin liikennemuotoihin nähden vaikuttivat vahvimmin käyttöaikomuksiin ja maksuhalukkuuteen, kun taas demografisilla muuttujilla oli vähäisempi merkitys. Koska harvalla vastaajalla oli aiempia kokemuksia AV-teknologiasta, voidaan olettaa, että AV-teknologian hyväksyttävyys muuttuu, kun se tulee laajemmin kuluttajien saataville.

ACKNOWLEDGEMENTS

On one of the first courses I took in LUT, the professor asked, “who here wants to make an ambitious master’s thesis?” I raised my hand and knew already then that may my thesis end up being ambitious or not, I was going to be in for a ride.

That ride has been filled with discovery, joy, accomplishments and friendships, both in and out the class room. There will be so much to miss once I leave the campus for the last time as a student whether it is the sauna evenings in PK5, the 7th building gym or taking a course not for the credit points, but just for the sake of learning something useful. LUT is an excellent university and I am glad I chose to apply there. Unfortunately, my university years were also riddled with hardships everyone goes through as a natural part of life. While I possibly experienced a little more than most people do at one time, I am grateful for the folks who supported me through thick and thin. I want to thank them now.

Starting with my family and relatives, to whom I can rely on. Anna, who always has the right words to say when I need to hear them. Milo, on whose couch I must have written more than half of this thesis paper. My supervisors Kaisu Puumalainen and Maija Hujala, who provided their insightful guidance throughout this process.

Most importantly, I want to give a huge thank you to everyone who participated in my survey by answering and spreading it forward. Without you this thesis would be nothing but an empty husk.

Thank you all dearly,

Frans Hollström
in London February 2019

ABBREVIATIONS

ADAS - Advanced driver assistance system

AV - Autonomous vehicle

CAV - Connected (and) autonomous vehicle

CTAM - Car technology acceptance model

HMI - Human Machine Interface

HV - Human driven vehicle

IDT - Innovation diffusion theory

PEOU - Perceived Ease of Use

PU - Perceived Usefulness

PV - Private vehicle OR personal vehicle

SAE level - The degree of vehicle autonomation expressed by figure 0-5

SAE - Society of automotive engineers

SAV - Shared autonomous vehicle

TAM - Technology acceptance model

TRA - Theory of reasoned action

UTAUT - Unified theory of acceptance and use of technology

VKT - Vehicle kilometers travelled

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1. INTRODUCTION

Modern information, communication and sensing technologies have given automobiles eyes, ears and a brain. As a result, vehicles are learning to drive themselves, and this phenomenon can play a large role in how people commute in the 21st century. At the moment autonomous driving is still in the early stages of its life-cycle, but as the technology matures, autonomous vehicles (AVs) will gradually be able to a cover a wider range of circumstances and gain popularity on the roads.

1.1 Background

Technology acceptance and innovation diffusion of autonomous vehicles have become vibrant fields of research in the recent years (Payre et al 2014; Bansal et al 2016; Daziano et al 2017; Johnsen et al 2017; Kaur & Rampersad 2018; Litman 2018; Modi et al 2018; Nieuwenhuijsen et al 2018; Nordhoff et al 2018). Researchers have estimated that AVs could greatly expand options for mobility, bring considerable value of time, cost and safety improvements to households, and potentially facilitate socio-economic benefits and annual savings in the scale of hundreds of billions of dollars in the USA alone (Meyer & Deix 2014; Fagnant & Kockelman 2015). While there is a clear motivation to adopt this technology, AVs face considerable legislative, technological, and public confidence barriers. The burning question most asked in technology acceptance and diffusion studies across the world is whether our society is ready to hand over controls to automation when it comes to our daily commute.

1.2 Research gap and research questions

Autonomous vehicles are still a relatively novel field of research, and there are no undisputed issues nor consensus in literature over any particular subject matter. Published research appears to be more fixated on technical aspects of AVs, while various social, behavioral and acceptance issues, as well as the potential impacts of autonomous vehicles are relatively under-researched in comparison (Cohen et al 2017). At this early stage it is difficult to evaluate how, and in what frame of time AVs could diffuse into our society (Nieuwenhuijsen et al 2018). Moreover, there seems to be a dilemma between what this technology is supposed to achieve and how people perceive it (Kaur & Rampersad 2018). Prior studies that have measured consumer attitudes and perceptions towards AVs have generated mixed results despite having similar structure and purpose (Payre et al 2014; Bansal et al 2016; Daziano et al 2017; Johnsen et al 2017; Liu et al 2018; Nordhoff et al 2018). The fact that autonomous vehicles have been in the public conscious for a good few years now and there is still no clear knowledge of what the general approvability of this technology is, calls for more research.

This thesis paper aims to map out the acceptance of autonomous vehicles with two primary methods. Firstly, this study conducts a comprehensive literature review of the main concepts of innovation diffusion and technology acceptance theories and prior AV adoption and acceptance studies. The literature review also discusses the key socio-economic impacts of the AV technology to give some background for the factors that can influence adoption and acceptance. Secondly, the study conducts a quantitative survey to measure the current acceptance of AVs among consumers in terms of safety, utility, compatibility, anxiety, social influence, willingness to pay and intentions to use. In addition, this study discusses how, and in what timeframe AV technology could begin to diffuse into the society. Although this discussion is largely based on current AV literature, empirical research may give some supporting evidence that there exists enough interest and acceptance towards AVs for the diffusion process to begin. Moreover, the study attempts to uncover what barriers exist for adoption of AVs, what concerns consumers have about the technology, and how both of these dimensions could be positively influenced.

One main research question has been set to guide the thesis process:

> RQ: How do consumers perceive autonomous vehicles as of 2018 in regard to technology acceptance?

The following sub-questions have been formulated to further support the process:

> RSQ1. What acceptance factors affect the adoption of autonomous vehicles the most?

RSQ2. What advantages and disadvantages AVs can have for individuals and the society?

RSQ3. What are the likely scenarios and outcomes for innovation diffusion of autonomous vehicles?

Table 1 represents the research questions, the intended goals of these questions, and the methods and data utilized to answer them.

Table 1. Compilation of research questions, goals, methods and data

Research question	Research goal	Method and data
Main research question 1: How do consumers perceive autonomous vehicles as of 2018 in regard to technology acceptance?	To examine how consumers perceive autonomous vehicles in terms of safety, utility and behavioral intentions.	Synthesis of academic literature, primary data collected with a quantitative survey and explanatory analysis of the survey results
Research sub-question 1: What acceptance factors affect the adoption of autonomous vehicles the most?	To evaluate how AVs' characteristics comply with existing innovation diffusion literature.	Synthesis of academic literature, primary data collected with a quantitative survey and explanatory analysis of the survey results
Research sub-question 2: What advantages and disadvantages AVs can have for individuals and the society?	To identify the main impacts of autonomous driving for individuals and for the society which recur in autonomous vehicle literature.	Synthesis of academic literature, additional findings based on primary data collected with a quantitative survey.
Research sub-question 3: What are the likely scenarios and outcomes for innovation diffusion of autonomous vehicles?	To evaluate the timeframe in which AVs could proliferate and what barriers exist for their adoption.	Synthesis of academic literature, additional findings based on primary data collected with a quantitative survey.

1.3 Delimitation and exclusions

This section describes the delimitations of the study, and what issues were excluded from it to narrow the focus of the thesis paper. It is important to understand that innovation diffusion is a sum of numerous parts, and transportation is almost like the lifeblood of our modern society. Hence, to get to the truth about this topic, a large variety of issues needed to be discussed and considered. To some degree the scope of this study is wider than what is typical for a master’s thesis, but this decision is justified due to the abundance of factors which affect the acceptance and adoption of autonomous vehicles.

Certain issues which could prove to be even significant bottlenecks for the technology such as ethics, liability, legality and cyber security of autonomous vehicles were left for lesser consideration as they were overshadowed by even more pressing issues (Glancy, 2015; Kalra et al 2016; Sun et al 2016). Industrial uses for AVs were addressed only briefly although solid arguments can be made that these fields will likely adopt the AV technology much sooner than consumers do.

Not much emphasis is given to how autonomous vehicles are developed and designed despite the fact that this is the current stage of the AV technology life-cycle. This study is more focused on pointing out design goals for AVs such as what price point and level of sophistication the AV systems need to achieve in order for consumers to find them a lucrative form of transport. Technological development is highly influential for the entire diffusion process of AVs, but due to its scale, it is a topic for another study.

Automated driver assistance systems are not discussed in great detail although they belong in the canon of autonomous driving. This was a deliberate decision to narrow the focus of this thesis paper. If partial automation systems would have been included, they could have provided more insight on how people perceive the currently available automation systems in their vehicles. They could also have provided patterns of how intelligent vehicle technologies have diffused into the society in the past. While this could potentially be an important topic to consider, its exclusion was justified as fully autonomous vehicles are a much larger technological advancement than systems which only partially assist human drivers.

The sustainability of AVs is a theme which would deserve attention considering its urgency (Gružauskas et al 2018). This thesis work leaves environmental impact of AVs relatively obscure although the environmental issues are briefly addressed as how they relate to changes in vehicle kilometers travelled. Social implications are passed on almost entirely despite the fact that AVs could render some members of the society unemployed as they automate the task of driving. On the other hand, AVs can help make for a more equal transportation system by giving people wheels who currently cannot drive due to either impairment or age. Economic sustainability is not directly addressed, although economics of autonomous driving are discussed to the extent of their potential socio-economic benefits, and how changes in transportation costs could influence mobility decisions of consumers.

Various new business models and mobility options may surface in the era of AVs. Although they are acknowledged, none of them will be discussed in greater detail than how they fit the greater picture of autonomous driving. Most notably MaaS (mobility as a service) can gain a boost from AV technology, and arguably most consumers could first experience autonomous driving by using an autonomous taxi.

1.4 Structure and methods of the study

The structure of the study is described in Figure 1. There are overall seven chapters which are followed by references and appendices.

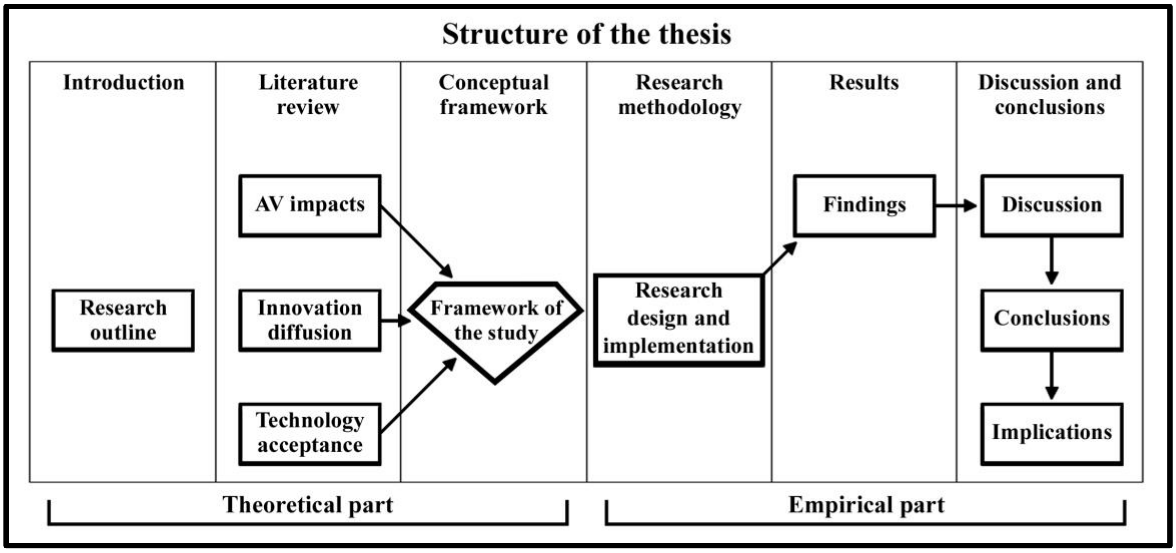

Figure 1. Structure of the study

The study is divided into two parts. The theoretical part consists of the introduction, literature review and conceptual framework while the empirical part contains the research methodology, research results and the discussion and conclusions.

Literature review is split into two chapters, the first of which discusses the origin, taxonomy and potential key impacts of autonomous vehicles based on AV literature. The second chapter of the literature review covers the theories of technology acceptance and innovation diffusion together with prior adoption and acceptance studies of autonomous vehicles. Conceptual framework compiles the main concepts of the study, illustrates their relationship and represents the research framework as basis for the empirical part. Hypotheses are also included in the conceptual framework chapter.

The first chapter of the empirical part of the thesis is research methodology. The purpose of methodology is to detail the implementation of the research, the data collection process and the analysis of the gathered data. A quantitative online survey is utilized to gather data about respondents' acceptance towards autonomous vehicles, and their relationship to new technologies in general. The chosen sampling method is convenience sampling due to time and resource restrictions of the study. Once the data is gathered, it will be analyzed using descriptive analysis, cross tabulation, factor analysis, linear regression analysis and logistic regression analysis. These main findings are discussed in the research results chapter. The last chapter of the thesis paper is called discussion and conclusions. This chapter discusses the main findings of the research and compares the results to observations made by other prior studies on the topic of AV adoption and acceptance. This chapter also contains the answers for the main research question and the research sub-questions. The empirical part closes out the thesis paper by addressing limitations of the study and giving suggestions for the direction of future research.

2. ORIGIN AND KEY IMPACTS OF AUTONOMOUS VEHICLES

This chapter is the first part of the literature review. It provides an overview of the auto industry as well as the principal terminology, brief history and potential key impacts of autonomous vehicles which recur in academia. This is done in order for the reader to understand the origin, the taxonomy and the motivations behind the AV technology.

2.1 The automotive industry today

The auto industry consists of companies associated with designing, developing, manufacturing, marketing and selling motorized vehicles (Rae & Binder 2018). The core of the auto industry is formed primarily by the automakers and original equipment manufacturers (OEMs), but in the recent years also technology companies have begun to play a larger role in auto development (Wong et al 2017). As vehicles are becoming not only carriers of people, but also of big data, Silicon Valley is joining likes of Detroit, Frankfurt and Tokyo as an important development hub for future automobiles (Schreurs & Steuwer 2016).

The size of the global automotive industry is commonly accounted for in the volume of new vehicles sold. In 2017 overall sales were 97,8 million units of which 79,8 million were passenger cars (ACEA 2018). Industry sources imply that annual passenger vehicle sales have effectively double since the 1990s, making the 21st century a golden age of motoring (OICA 2018; Statista 2018). Emerging markets and an increasingly connected world present opportunities for further growth, but they also come with greater risks (Mohr et al 2013; Uchil & Yazdanifard 2014).

Motor vehicles are by nature a risky business as their development is slow and expensive (Jains & Garg 2007). An identified gap in the market may not exist anymore by the time development for a new model is finished due to ever-shifting and extremely competitive market conditions (Blenkhorn & Fleisher 2005; Uchil & Yazdanifard 2014). Alterations to existing production models are time consuming to implement due to the structure of supply chains which can branch across multiple suppliers for only one part of the vehicle (Mohr et al 2013). This complexity is limiting, but it also motivates automakers to innovate as successful new ideas often have a grace period before they can be effectively reproduced by competitors (Uchil & Yazdanifard 2014). Due to automakers' motivations to seek new ideas as well as to keep up with the rest of the industry, massive capital investments are flowing into tiny, but rapidly growing segments such as electric vehicles (Falcão et al 2017).

Electric vehicles (EVs) are one of four megatrends in the auto industry which all supplement one another. The three are communication of cars over the internet, ride sharing services and autonomous vehicles (Greenblatt & Shaheen 2015; Modi et al 2018). The future of the automotive industry based on current large-scale development projects is electric, connected and autonomous (Maurer 2016; Lienert 2018a; Litman 2018; Palmer et al 2018).

2.2 Brief history of autonomous vehicles

As mass motorization began in the first half of the 20th century, lethal traffic accidents grew into a prominent social problem. In the 1920's traffic accidents caused over 200 000 fatalities in USA alone (Norton 2008, p. 21). Driver error was viewed as the prime cause for accidents, and thus, the idea of substituting fallible human drivers with technology practically suggested itself (Kröger 2016). While there have been improvements in road safety by other measures, AVs have been long kept back by not only a technological barrier, but also a cultural one (Wetmore 2003).

The foundation for self-driving cars was initially laid down by two developments in the field of aviation and radio technology (Kröger 2016). The aeroplane stabilizer was introduced in 1914, and it has been regarded as the world's first autopilot (Ceruzzi 1989). This system was primitive by today's standards, but it paved the way for commercial autopilots in aviation. The second influential early breakthrough was guidance of remote-controlled moving mechanisms by utilizing radio waves, as it made remote-controlled vehicles a reality (Green 1925; Time 1925). The age of driver-assistance systems began in the 1950s with the introduction of cruise control, whereas the first assistance system to directly intervene with the driving process was introduced in 1978 in form of anti-lock brakes (Guzzella & Kiencke 1995; Schinkel & Hunt 2002; Wetmore 2003, p. 34).

Attempts at automated driving were made in the 1950s by installing a guide-wire on the road which cars could follow using electronic sensors (Mann 1958). This concept was known as automatic highways, but it had virtually unbridgeable gaps in economic feasibility (Wetmore 2003, p. 10). By the 1970s researchers had realized that AVs are not conceivable unless they are infrastructure independent, but it was not until the 1980s when they became a "serious" topic for academic and industrial research (Tsugawa et al 1979; Thomanek et al 1994; Luettel et al 2012). The most pioneering work was conducted by Ernst Dickmanns from the University of the Federal Armed Forces in Munich. In 1987 Dickmanns' team conducted a test in which a van fitted with cameras and on-board digital processors drove autonomously a 20-kilometer journey on a highway, reaching speeds as high as 96 km/h (Dickmanns 1989). These tests triggered a paradigm shift in AV research, and they convinced the automotive industry to privilege machine vision as the future of autonomous vehicles (Kröger 2016).

2.3 Autonomous vehicles explained

An autonomous vehicle is by definition a vehicle that is capable of driving without human intervention, but it is also commonly used as an umbrella term to incorporate partially automated driving systems (Gasser et al 2012; Maurer 2016; Scharring et al 2017; SAE 2018). AVs monitor the environment with sensors such as radar, LiDAR or cameras, and interpret the sensed data with a driving computer (Koskinen & Halme 1995; Behere & Torngren 2015).

The term connected and autonomous vehicles (CAVs) is not purely the same as simply autonomous vehicles, but as many intended use scenarios for self-driving vehicles require high degrees of connectivity, the term AV is often liberally used instead of CAVs when in fact meaning the latter (Gora & Rüb 2016; SAE 2018; Modi et al 2018). Connected vehicles have their own communication levels; vehicle to infrastructure (V2I), vehicle to vehicle (V2V), vehicle to cloud (V2C), vehicle to pedestrians (V2P) and vehicle to everything (V2X) in the highest level (Bagheri et al 2014). Vehicle connectivity is essentially part of a larger multi-industrial trend called

Internet of Things (IoT), which is enabled by faster cellular networks and new communication technologies (Krasniqi & Hajrizi 2016).

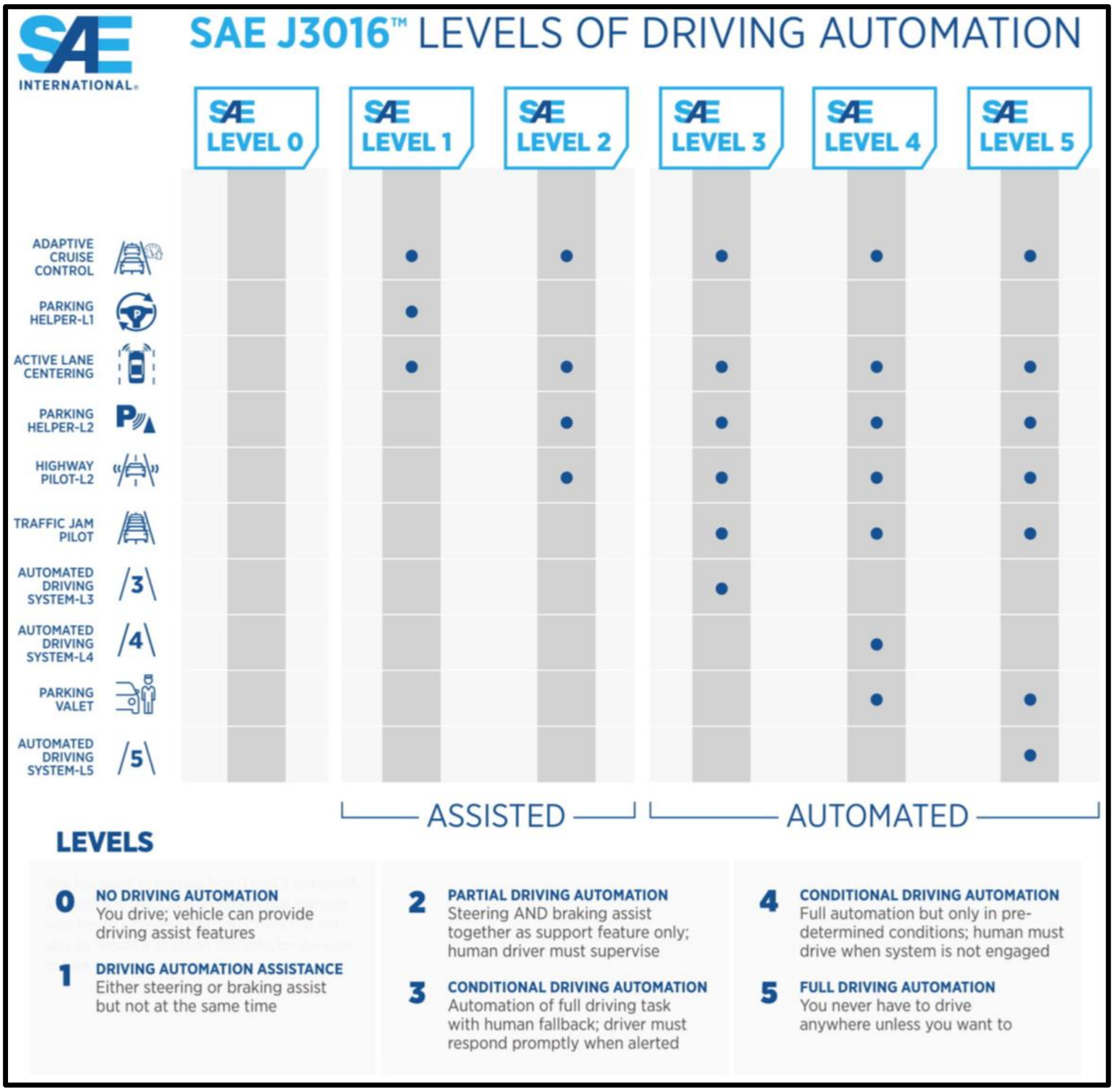

Figure 2. Automated driving level definitions (reconstructed; SAE 2018)

Most commonly automakers and OEMs use the SAE International standard J3016 to distinguish how technologically advanced a vehicle, or rather its automated driving system, is (SAE 2018). The revised 2018 edition is depicted in Figure 2 while the 2014 version is included in Appendix 1.1. As the SAE level increases, the car can perform a wider spectrum of driving tasks and less input overall is required from the driver (Beiker 2016; Puylaert et al 2018). The automation levels are explained more deeply in Table 2 on the next page.

Table 2. Vehicle automation levels (Schreurs & Steuwer 2016; SAE 2018)

Degree of automation	Description
Level 0, no automation	A human driver controls everything with no assistance or automation.
Level 1, driver assistance	The vehicle can automatically do a specific function such as break when another car gets too close to the front bumper on a highway.
Level 2, partial automation	The vehicle has at least one driver assistance system, which can assist in both steering and accelerating/decelerating using information about the driving environment, but human still drives in all circumstances.
Level 3, conditional autom.	Safety-critical functions can be shifted to the car under safe weather and traffic conditions. The vehicle monitors the environment and drives itself, but a human must be always ready to intervene by system's request.
Level 4, high automation	Intervention not needed when requested, but the system can only be used in predetermined conditions. If the conditions change and the driver does not take over eventually, the vehicle stops on the side of the road.
Level 5, full automation	The vehicle does not need a steering wheel or the pedals, but a human is still needed to plug where the vehicle needs to go.

2.4 Key impacts of autonomous vehicles

This sub-chapter examines the potential advantages and disadvantages, which may result from proliferation of autonomous vehicles. No single use-scenario alone for AVs will reap all of the benefits as some of them may even prove to be counter-productive, but together they can bring significant long-term societal improvements (Juliussen & Carlson 2014; Bierstedt et al 2014; Rangarajan & Dunoyer 2014; Underwood 2014; Milakis et al 2017a; Litman 2018).

2.4.1 Passenger productivity and time usage

The general assumption in academia is that AVs could free up time from manual driving, and this could lead to an increase in human productivity (Beiker 2016; Cyganski 2016; Litman 2018). United States Census Bureau (2013) found that US citizens spend on average 26 minutes travelling to work every day, and approximately 80 percent of these strips are taken by car. In Great Britain the daily average for people who drive to work is 52 minutes, implying that the travel times and thus also the proposed productivity impact of AVs, can vary greatly between countries and regions (Pidgeon 2017). It is unquestionable that annually hundreds of hours per driver could be liberated for other causes, but how would the commuters spend their time if they had the chance?

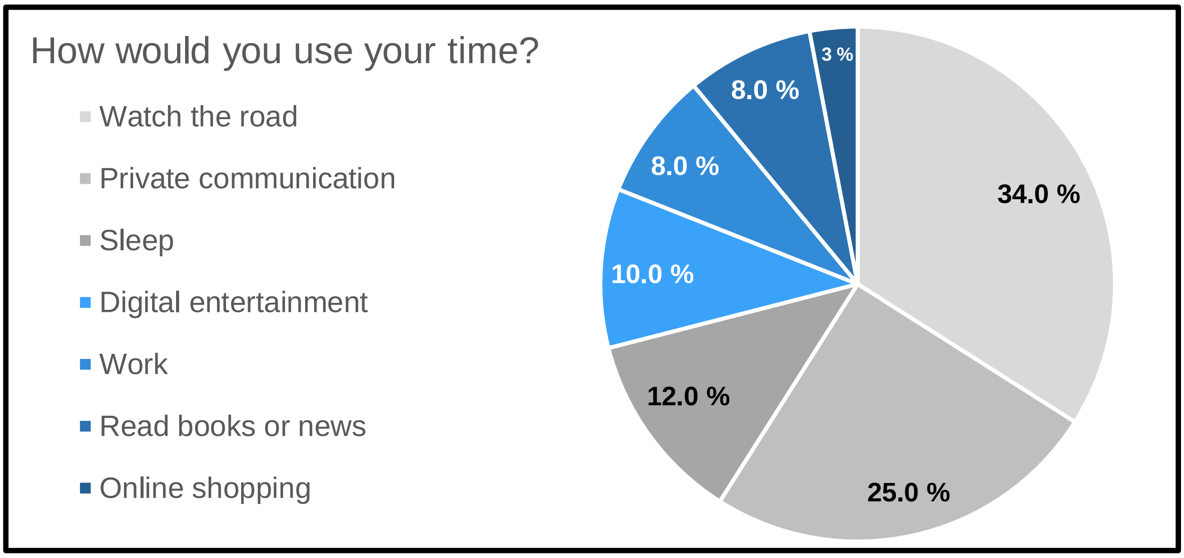

Figure 3. Automated Vehicle Passenger Time Usage (Ipsos/GenPop 2018)

An international survey among 130 000 respondents by Ipsos/GenPop (2018) found that about a third of the time spent riding an AV would still be used paying attention to the road. This suggests that the time freed up by AVs might not directly convert to other activities in full. A synthesis of the survey results is depicted in Figure 3, showing private communication as the second most common activity in popularity followed by relaxation and sleep. What is notable is that only about eight percent of the time, or five minutes an hour, would be spent on work related duties. A smaller study by ERIE Insurance (2018) has made similar observations.

Nevertheless, autonomous vehicles can offer a level flexibility which may prove highly advantageous to individuals who can work from their car or who drive more than average, not to mention the people who cannot drive at all (Beiker 2016). Improved mobility and a more equitable transportation system will open with the use of AVs for people who are injured, vision impaired, seniors or young people below driving age (Anderson et al 2014; Heinrichs & Cyganski 2015; Sivak & Schoettle 2015a). Harper et al (2016) observed however that while AVs can offer more mobility for people with impairments, some of this potential is wasted unless solutions are also provided to how these people manage once they arrive in their destination.

2.4.2 Traffic flow and congestion

Scholars have actively debated in the recent few years whether fully autonomous vehicles can relief the roads from congestion or only worsen the situation (ITF 2015; Kim et al 2015; Malokin et al 2015; Milakis et al 2017b). Congestion is typically caused by rush hours, a lack of parking spaces, an insufficient public transportation network and urbanization as population concentrates into cities faster than infrastructure can cope with them (Barwell 1973; Santos 2004; Grush & Niles 2018). This is a global problem, but it is most prominent in the world's largest cities where commuters can spend on average up to 100 hours a year stuck in traffic jams (INRIX 2018). Successfully reducing congestion could save both time and the environment (Childress et al 2014). Conventional methods such as expanding road infrastructure, issuing road tolls and building more parking spaces all have their limitations (Milakis et al 2017b; Wong et al 2017).

Table 3. Autonomous vehicle adoption and impact on VKT

Study	City/Region Measured	Variables considered	Estimated Increase in VKT
Gucwa 2014	San Francisco Bay	A, B	8 - 24 %
Kim et al 2015	Metro Atlanta	A, B, C, D	4 - 24 %
ITF 2015	Lisbon	E, F, G	6 - 89 %
Childress ea 2015	Puget Region WA	A, B, C D, F	4 - 20 %
Davidson & S. 2015	Brisbane	B, C, F	4 - 41 %
A: road capacity, B: value of time, C: reduced vehicle operating cost, D: reduced parking cost, E: SAV type, F: AV market penetration, G: availability of high capacity public transport			

As there are no AV fleets on the road yet, recent studies are based largely on simulations, which estimate the travel behavior impacts of AVs by alternating assumptions on such variables as the market penetration rates of AVs, increases in road capacity, reductions in operational and parking costs and the improvement of the users' value of time (Truong et al 2017). The results of five studies that measured the impact of AVs on vehicle kilometers travelled (VKT) are synthesized in Table 3.

The three studies conducted in the United States observed VKT increases between 4 - 24 percent and measured largely the same variables (Gucwa 2014; Childress et al 2015; Kim et al 2015). The studies conducted in Portugal and Australia had much different results. In a simulation by International Transport Forum (ITF 2015), a combination of shared autonomous vehicles (SAVs) used by multiple passengers and a lack of high capacity public transport lead to substantially varying increases between 6 and 89 percent in VKT. Davidson and Spinoulas (2015) estimated that that high AV market penetration could increase overall VKT by 4 - 41 percent. Notably there are limitations to these studies. Gucwa (2014) did not consider ride sharing while Kim et al (2015) left out considerations for empty vehicle travel for autonomous parking and AV availability for zero-car households. All of the studies overlooked the increase of travel demand caused by non-drivers such as elderly and the disabled, which Harper et al (2016) estimated could lead to a 14 percent increase in VKT in the US. The significance of small changes cannot be understated because even a one percent increase in VKT leads to approximately 34 billion kilometers of added light-duty vehicle travel in the US (Shladover et al 2012).

New business opportunities for firms and mobility options for consumers will open with Smart transition, but scholars are uncertain whether this can lead to a reduction in congestion. This transition to smarter mobility is typically facilitated by AVs, less car ownership by citizens and a greater use of vehicle sharing through apps (Hensher 2018). Truong et al (2017) estimates that while Smart transition can reduce vehicle demand in form of private ownership, the increased access to mobility will simultaneously satisfy previously unmet demand and generate entirely new demand. In this new rentier model, mobility provider companies have an incentive to create as much mobility as possible in order to maximize profit (Karlsson et al 2016; Docherty et al 2017). Even without Smart transition, there are justified concerns that diffusion of AVs and the subsequent increase in VKT can lead to more congestion. The degrees of freedom provided by AVs can satisfy more trips per household, but this also generates empty kilometers when the vehicle relocates without a passenger (Fagnant & Kockelman 2014; Liang et al 2016; Correia & van Arem 2016).

VKT is however not the only factor to consider what it comes to congestion. Self-driving vehicles can provide solutions for congestion through new approaches in car parking. City planning may become more flexible especially in downtown areas as AVs can relocate a more satellite location after dropping of passengers. This reduces the need for parking spaces in areas such as business districts where space can be freed up and redesigned for a different purpose and infill development (Thigpen 2018). A large proportion of the people driving in the city are only looking for a place to park, and vehicle connectivity and automation can make this process much more efficient (Fagnant & Kockelman 2015; Thigpen 2018). Zhang et al (2015) made an ambitious estimation that parking demand could be reduced by up to 90 percent if regular vehicles were replaced by a smaller fleet of shared autonomous vehicles in which each car was in higher active use.

Autonomous vehicles can contribute to a better flow of traffic in a variety of ways. The safety benefits of AVs can reduce the number of irregularities in traffic such as incidents and accidents, which are attributable to approximately 25 percent of the congestion (FHWA 2005; Puylaert et al 2018). If public officials allocate a lane for AVs, they can be programmed to platoon and drive at high speeds with short headways (Laan & Sadabadi 2017; Morando et al 2018; Litman 2018). Connected AVs can further increase capacity of the roads, intersections and junctions by eliminating specific human related uncertainties in traffic. CAVs are superior to humans both in communicating with other vehicles (V2V) and following the rules of the road (Hoogendoorn et al 2014; Kamal et al 2015; Talebpour & Mahmassani 2016). Once a sufficient number of vehicles has both V2V and infrastructure connectivity, a central computing platform can be used in cities to better control the flow of traffic, and to assist AVs make smarter routing decisions (Hensher 2018).

As a brief summary, AVs will likely cause an increase of some magnitude in overall VKT, but there will potentially also be more solutions to control the flow of traffic and congestion. Regardless of the outcome, the detrimental effects of congestion on passengers' value of time and emissions can be minimized by other means. Electric vehicle technology and renewable energy sources can offset emissions while AV passengers can use their time more freely as they no longer need to drive (Al-Alawi & Bradley 2013; Wadud et al 2016; Cykanski 2016; Palmer et al 2018; Litman 2018).

2.4.3 Costs, savings and vehicle ownership

The proliferation of AVs is projected to change the economics of driving and bring socio-economic cost savings by making transportation more affordable (Fraedrich & Lenz 2016a). Fewer car crashes, less congestion, an option to replace car ownership with alternative mobility solutions and automation of human labor are among the more common projected financial incentives (Kittelson 2010; Litman 2018). The notion that AVs can save fuel through driving efficiency optimization and uniform motion of traffic is frequently raised in literature (Chang & Morlok 2005; Ke et al 2010; Saust et al 2012; Wadud et al 2016). Additionally, the prices for car insurances could go down as traffic becomes safer and liability shifts more from the drivers to OEMS and manufacturers (Wadud et al 2016; Litman 2018).

Not all costs go down as autonomous vehicles are likely to make some aspects of car ownership noticeably more expensive. AV systems add a heavy premium on top of the base price of a car, and their maintenance will also cost more than that of human-driven vehicles (HVs) to ensure reliability (Litman 2018). The model year 2018 Audi A8 cost over 20 000 USD more in the US than its predecessor mainly due to the automated systems which were included as standard features (Smith 2017). The more advanced automated systems in Google's test cars and some military vehicles reportedly costs 100 000 USD, most of which is due to the price of sensors such as LiDAR and cameras (KPMG & CAR 2012).

Fagnant & Kockelman (2015) estimate that there will be no clear economic incentives for most consumers to buy AVs until the price of the technology drops to at least 10 000 USD, which is unlikely to happen for at least another decade. They also estimated that the costs savings from fewer crashes, fuel efficiency, travel time reduction, lower insurance and parking costs could accumulate to 2000 - 4000 USD per year per AV depending on adoption rate, which could justify a higher premium for AVs over HVs if realized. Gradually the learning effects and economies of scale will reduce the price of AV technology. This could be supported by policies such as tax reductions, if the socio-economic benefits of AVs are deemed sufficient enough by policymakers to justify the support (Nieuwenhuijsen et al 2018). In a few decades, prices could fall as low as 1000 to 1500 USD per vehicle, but the unaffordability of the technology may remain a barrier for diffusion for a long time (KPMG and CAR 2012; Fagnant & Kockelman 2015).

From a productivity and cost standpoint, AVs could create significant value in industrial and manufacturing use (Geyer et al 2013; Wachenfeld et al 2016). AV technologies are already used on some industrial sites such as mines and farms, where they can operate in a more controllable setting (ETQ 2012; Flämig 2016). Freight is assumed to be among the first industries to deploy AV systems on public roads, which can play a significant role in supply chain automation and optimization (Geyer et al 2013; Flämig 2016; Wachenfeld et al 2016; Wadud 2017). While the initial investments into autonomous fleets could be expensive, they can potentially provide substantial savings later on (Fagnant & Kockelman 2015). For instance, platooning of autonomous trucks could save fuel by about 10-15 percent from reduced air resistance, automation could lower labor costs and servicing times could improve due to increased flexibility (Kunze et al 2009; Bullis 2011; Fagnant & Kockelman 2015). As early adopters, the freight industry can have a major impact in shaping AV related policies to a more favorable direction, and also increase awareness of the AV technology among the public (Schreurs & Steuwer 2016).

Autonomous taxis and busses will gain popularity as AVs proliferate. Litman (2018) estimates that AVs could cost less per VKT than human driven taxis and ride hailing services, but more than human driven personal vehicles. As depicted in Figure 4, an autonomous taxi could be even twice cheaper than a regular taxi mainly due to reduced labor costs, but also the level of service would be considerably lower (Litman 2018). Autonomous taxis could also be subject to vandalism and malicious littering due to lack of effective human supervision, which is an added cost often overlooked by industry analysts (Keeney 2017; Kok et al 2017).

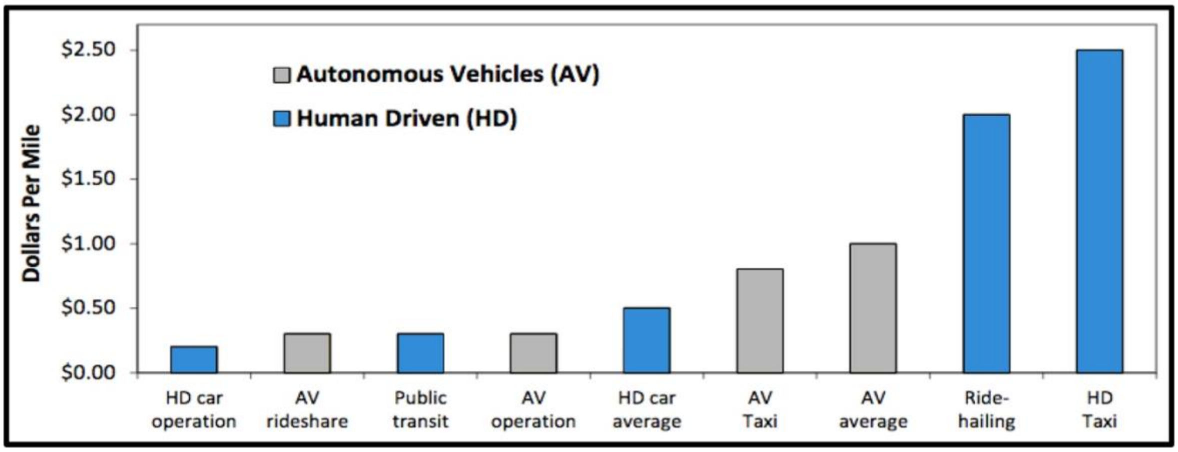

Figure 4. Cost comparison of AV and human driven mobility (Litman 2018)

Any reduction in the number of road accidents has immediate financial benefits as car crashes cost 414 billion USD for the year 2017 in the US alone in form of property damage, medical expenses, and loss of wages and productivity (NSC 2018). There are no studies on how much money could be saved globally, but to highlight the scale of the US estimation, only 27 of the 188 nations measured have a higher nominal GDP than 414 billion USD (World Bank 2018). Fagnant and Kockelman (2015) estimated that the social benefits of AVs driven mainly by reduced number of accidents and congestion could comprehensively accumulate to annual savings of 434 billion USD at 90 percent market penetration. Their estimation also included that the number of vehicles on the road could simultaneously drop by approximately 45 percent, but they did not explicitly specify how they came to this conclusion.

Fagnant and Kockelman also are not the only scholars who have suggested that a proportion of the households could forego car ownership once new AV facilitated mobility services are available, resulting in potentially thousands of dollars of annual savings per household (Shaheen & Cohen 2007; Fraedrich & Lenz 2016a; Pavone 2016; Winner & Wachenfeld 2016; Litman 2018; Nieuwenhuijsen et al 2018). Zhang et al (2018) used travel data provided by Atlanta Regional Commission to examine how AVs could impact vehicle ownership. They found that more than 18 percent of the households could reduce the number of vehicles in the AV era without changing current travel patterns, leading to a 9.5 percent reduction in private vehicle (PV) ownership. It should be noted though that in Atlanta there are approximately two PVs per household, and results could differ in another region with less privately-owned vehicles. Zhang et al (2018) also pointed out that they were among the few who have studied this specific impact, implying that there is not yet much evidence to support the notion that AVs could reduce the number of PVs. There are however other trends that support the notion that AVs could reduce private vehicle ownership.

An argument can be made that a car as an object has less value to its owner than the mobility it provides. As the car stays parked for more than 95 percent of the time on average, it represents a huge waste of resources any time it is not moving (RAC 2012; Bagloee et al 2016). Meanwhile the demand for mobility will keep on increasing due to the Earth's population growth, but the planetary boundaries put a limit on how many people can own a PV (Steffen et al 2015). What this could mean for automakers in the future is that they will have a customer base which is smaller in proportion to entire population, but more frequent in purchases (Bierstedt et al 2014). The cars will see higher active use and thus have shorter lifespans.

Like much of the current AV literature, the economics of autonomous driving are largely based on speculation and scenarios drawn upon existing transportation data (Fraedrich & Lenz 2016a; Wadud 2017; Litman 2018). It is likely that most of the potential cost benefits of AVs on both individual and socio-economic level will not be realized until diffusion has progressed significantly (Fagnant & Kockelman 2015).

2.4.4 Traffic safety and human-machine interactions

As established in the history segment of this literature review, safety is the core issue that conceived the dream of an autonomous vehicle. According to WHO (2015), the total number of traffic deaths globally is 1.25 million per year, while the number of injuries is more than 20 million. Anderson et al (2014) estimate there to be 5.3 million car crashes per year in the USA. For the year 2017, traffic fatalities in the United States were approximately 40 000 with 4,5 million injuries, and these figures have been trending up in the recent few years (NSC 2018).

The research community is relatively unanimous that AV technology and vehicle connectivity can significantly reduce the number of traffic accidents (Simonite 2013; Anderson et al 2014; Fagnant & Kockelman 2015; Kyriakidis et al 2015; Rau et al 2015; Morando et al 2018). Self-driving cars can neutralize characteristics of human behavior on the wheel such as speeding, road rage, egoistic-dives, and unpredictable lane changes (Anderson et al 2014). Machines do not get angry, distracted or intoxicated (Simonite 2013). AVs have faster reaction times than humans do, they don't overcompensate, and they have a more unified level of driving experience (Anderson et al 2014). Fagnant and Kockelman (2015) assumed AV technology could eliminate nearly all human error, which is connected to over 90 percent of crashes in the US.

AV technology requires a great magnitude development and time to match the level of sophistication and safety of human drivers in all driving situations (Koopman & Wagner 2017). Challenges in AV development include teaching the driving systems to sense and recognize dissimilar obstacles on the road such as humans of all shapes and sizes, and various objects with different material compositions (Farhadi et al 2009; Campbell et al 2010; ETQ 2012). If the driving system is placed in a position where there will inevitably be a crash, it needs to be able to make quick decisions to mitigate the damages (Fagnant & Kockelman 2015). Particularly the decisions between life and death are in the center of AV ethics debate, as there often are no clear answers to whose life is more valuable than the other's (Lin 2016). Gerdes and Thornton (2016) state that considerable responsibility is placed "on the programmers of AVs to ensure their control algorithms collectively produce actions that are legally and ethically acceptable to humans."

Examinations into safety benefits of AVs have been carried out with a variety of different approaches. A number of studies have used real-world data from AV testing in California (Sivak & Schoettle 2015b; Dixit et al 2016; Bhavsar et al 2017; Favarò et al 2017). Sivak & Schoettle (2015b) observed that AV was not at fault in any of the occurred crashes and injury levels were lower for the crashes involving AVs than those with only human driven vehicles. However, not enough autonomous kilometers have yet been driven to make the data used by these studies statistically relevant (Morando et al 2018). Pairing autonomous driving with vehicle connectivity can add more layers of safety. The number of chain collisions can be significantly reduced through platoon driving by CAVs, but there are still risks if HVs get mixed with them (Tian et al 2016; Wei et al 2017; (Litman 2018) Morando et al (2018) observed that AV technology can reduce conflicts in signaled intersections and roundabouts by 20 to 65 percent with market penetration rates between 50 and 100 percent. Kockelman et al (2016) assumed that automakers program AVs to be more conservative drivers to avoid conflicts and incidents on the road, as in the era of autonomous driving liability shifts more from human drivers to the manufacturers.

Concerns of privacy and cyber security are in the minds of both the researchers and the consumers (Koopman & Wagner 2017; Kauer & Rampersad 2018). Unless cyber security is addressed properly, it can counteract any safety benefits which AVs could have over human drivers (Morando et al 2018). Rannenberg (2016) argues that a privacy-by-design approach for autonomous driving scenarios is needed, in which the CAV does not collect, process and transmit any other data than what it needs by minimum to improve the driving situation in order to keep additional privacy risks low. AV owners should also be able to choose how much personally identifiable information is collected and shared, who can access it, and for what purpose.

Morando et al (2018) anticipated that most of the AV safety benefits will not be realized until market penetration of SAE level 4 and 5 AVs reaches at least 50 percent. As all cars on the road do not become machine driven overnight, AVs will have to cope with HVs as the latter will remain the majority on the roads possibly for decades (Färber 2016). In the transition period to full vehicle autonomy, many vehicles will have only conditionally automated systems, which have their own set of issues and limitations (Nieuwenhuijsen et al 2018).

Some of the expected automation benefits of these vehicles can be undermined by so-called “ironies of automation” which result from human-machine interactions (Bainbridge 1983). For example, conditional automation is supposed to give the user brief moments to engage in secondary tasks while driving, but shifting attention away from the road jeopardizes safety in general (Naujoks et al 2016). This makes the mixed systems with both human and machine control much more complex and unpredictable than those with solely a single mode, not only in terms of their behavior in traffic, but also in terms of who is liable in case of an accident (Beiker 2012; Grunwald 2016).

The predicted effects of automation and driver assist systems have not always been as large as aimed for (Martens & Jenssen 2012). The indirect behavioral changes of drivers, also known as behavioral adaptation (BA), are partly responsible for this phenomenon (Peng 2014; Sullivan et al 2016). BA refers to unintended behavior of drivers that occurs after a change in vehicle or traffic systems, as these systems alter the drivers' perceived enhancement of safety margins (Martens & Jenssen 2012). This change can encourage drivers to behave in a certain way that diminishes some of the intended safety benefits, such as by driving faster or in more difficult weather conditions, shortening headways to other vehicles, making less experienced drivers overestimate their capabilities or changing their mobility patterns by favoring a car over other forms of transport. The amount of adaptation is influenced by the driver personality and their trust in the technology. Adaptation thus changes over time, and it differs between user groups and even on an individual level (Sullivan et al 2016).

The reduced vigilance caused by monotony of supervising tasks is not only a phenomenon observed among semi-automated vehicles, but other technology appliances as well (Young & Stanton 2002; Saxby et al 2013; Beggiato et al 2015). According Ford product development chief Raj Nair, even the engineers trained to observe the AV system lost "situational awareness" as they overtime began to trust the automated system too much (Naughton 2017). Kelly Funkhouser and Frank Drews in their 2016 study on human reactions to AV system breakdowns observed that the time spent in autonomous mode increased subsequent braking reaction times. Dixit et al (2016) found that exposure to automated disengagements and accidents increased the likelihood of the driver taking control of the vehicle, but a higher number of kilometers travelled in AVs reduced this likelihood and slowed reaction times (Dixit et al 2016). Both of these studies averaged reaction times of about 0,83 seconds, which is similar to those of manual control, but they did not establish what changes occur over an extended period of time (Johansson & Rumar 1971; Dixit et al 2016; Funkhouser & Drews 2016).

Naturally, reaction times further increase in high and full automation when the driver is not required to actively monitor the environment. Shen and Neyens (2017) observed how quickly a human driver can shift attention from a non-driving task back to road in order to intervene with the system in case of a simulated accident. Participants in AVs had much slower and more extreme responses than drivers of regular cars. These findings echo those of Gold et al (2013) that the quality of driving decisions made erodes when a human driver is requested to take over controls quickly from an AV system. Merat et al (2014) found that it takes approximately 15 seconds from the driver to resume control from automation, but it takes on average 40 seconds to stably and adequately regain control of the vehicle, implying that there are limits to how humans could be used as last resort if the AV technology fails.

Many arguments can be made on behalf of the potential safety benefits of AVs once the technology and its adoption advance to a sufficient level. However, the transition period to full autonomy is riddled with uncertainties, which especially policymakers need to respond to by aiming for a balance in AV usage and its restrictions (Levinson 2015; Guerra 2015; Kockelman et al 2016; APA 2016; Grush & Niles 2018).

3. THEORETICAL BACKGROUND AND PRIOR STUDIES

This chapter of the literature review examines the theoretical background of innovation diffusion and technology acceptance. The aim is to understand what factors affect an individual's decisions to adopt a new innovation, and what elements influence a person's acceptance of technology. This chapter also discusses prior AV adoption and acceptance studies. The last segment concludes the literature review with a summary of the main themes and findings of chapters two and three.

3.1 Innovation diffusion theory

Autonomous driving is an emerging technology and thus understanding the theory of innovation diffusion is vital in order to evaluate the market potential of self-driving cars. Innovation can be broadly defined as any novel idea which generates new or additional value when applied and turned into a solution (Drucker 2002; Lee & Olson 2010). Innovation adoption refers to the series of actions made by individuals when they begin to use the innovation (Hall & Rosenberg 2010).

The origin of the innovation diffusion theory (IDT) is varied and spans over many disciplines such as communication, political science, public health, history, education, economics and technology (Dooley 1999; Stuart 2000; Sherry & Gibson 2002; Bennett & Bennett 2003; Sahin 2006). The concept of diffusion was first studied by a French sociologist Gabriel Tarde in the 1890s, and he also plotted the original diffusion S-curve (Toews 2003; Kaminski 2011). Later Ryan and Gross (1950) introduced the adopter categories and Katz (1957) concepts of opinion leaders and followers. Essentially IDT argues that the potential users decide whether to adopt or reject an innovation based on the beliefs they form about the innovation (Surry & Farquhar 1997; Agarwal 2000; Sahin 2006).

The current theory popularized by University of New Mexico professor Everett Rogers expanded greatly on prior literature by arguing that the spread of a new idea is fueled by four main elements which work in conjunction with one another. These four elements are the innovation itself, the communication channels, time and the social system (Rogers 2003, p 11). For any innovation to be adopted, the technology first needs to be communicated through a channel over a period of time, and this process takes place within a social system (Bruce et al 2014). The diffusion process relies heavily on human capital and the innovation cannot become self-sustainable until it is widely adopted within the society. Technological and cultural developments have shaped the elements innovation diffusion over the years since the theory was first introduced. Globalization has extended the close-form boundary of society, which has broadened the effect of external and internal factors of innovation diffusion (Hubert et al 1989; Ganesh & Kumar 1996; Massiani & Gohs 2015).

3.1.1 Innovation-decision process and innovation characteristics

Rogers (2003) identifies main five stages in an individual's decision-making process concerning whether the individual should adopt or reject a new innovation. The process that forms the core of IDT is depicted in Figure 5.

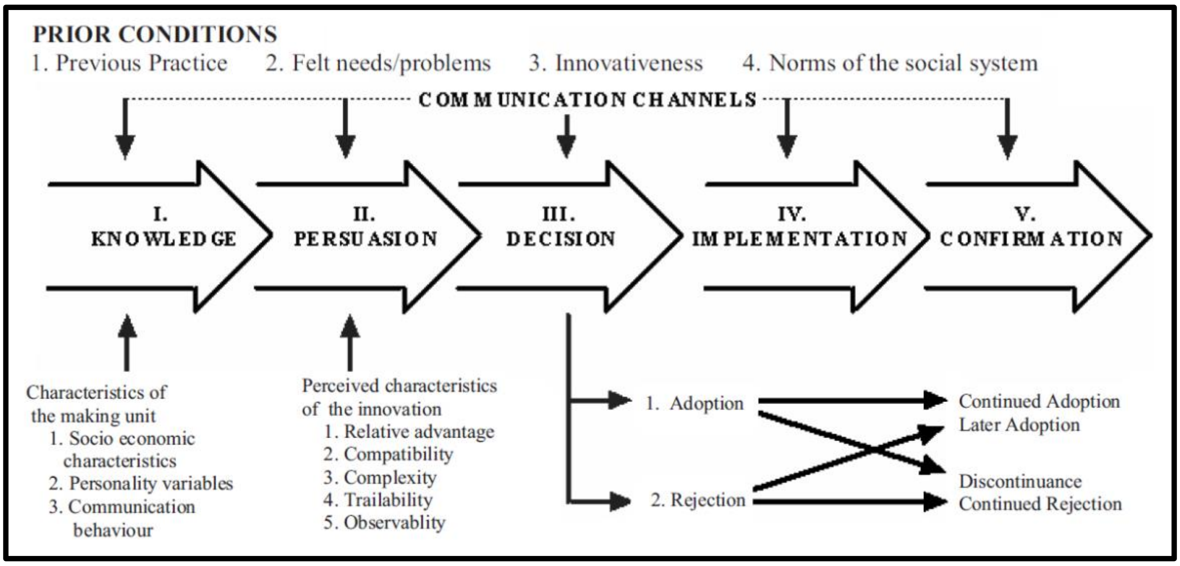

Figure 5. Five stages of innovation-decision process (Rogers 2003, p 170)

The individual first becomes aware of the innovation in the knowledge stage, but it is not until the persuasion stage when that person begins to show interest and actively seek more information about the innovation (Agarwal, 2000). In the decision stage the individual ponders various benefits and risks before adopting or rejecting the innovation (Bruce et al 2014). In the implementation stage the individual adopts the innovation and gets first-hand experiences of its usefulness before confirming the innovation-decision as the right one in the final stage. Notably the innovation can be turned down at any of these five stages, and the process can be resumed at a later point in time. (Rogers 2003, p 168.)

Characteristics of an innovation weigh heavily on the persuasion and subsequent decision of the individual. Thus, they are highly important to determining the speed of the entire diffusion process (Agarwal & Prasad 1997; Lee et al 2011). Rogers (2003, p 15-16) identifies five distinct innovation attributes for innovation adoption rate: relative advantage, compatibility, complexity, trialability, and observability.

Relative advantage is *“the degree to which an innovation is perceived as better than the idea it supersedes”* (Rogers 2003, p 15). Any benefit perceived by the adopter as an upgrade accounts as a relative advantage, but this attribute’s two clarifying subsections are economic profitability and provided social status. These subsections are equally important as potential users are convinced to adopt the innovation based on both its economic feasibility and social prestige provided by ownership.

Compatibility is defined as *“the degree to which the innovation is perceived as consistent with the existing values, past experiences, and needs of potential adopters”* (Rogers, 2003, p 15). Essentially the innovation should not be incompatible with sociocultural values or its adoption rates are compromised. Innovations that satisfy needs of widespread markets are generally adopted faster than innovations that are geared towards solving only marginal issues.

Complexity refers to *“the degree to which an innovation is perceived as relatively difficult to understand and use”* (Rogers, 2003, p 16). While some early users may enjoy added complexity, generally it has a negative effect on the adoption rate of an innovation further down the line. Technically modern innovations are more complex than ever, but simplicity and user friendliness has been the norm in user controls and interfaces for decades (Nielsen 1999; Uflacker & Busse 2007; Lee et al 2013).

Trialability is *“the degree to which the innovation may be experimented with on a limited basis”* (Rogers, 2003, p 16). Having access to a trial or test period in case of new innovation is particularly important for potential adopters. Making a “fool-proof” product before market introduction is vital as defects slow down adoption rates, while innovations which achieve positive results trigger positive diffusion early on.

Observability is *“the degree to which the results of an innovation are visible to others”* (Rogers, 2003, p 16). Innovations with clear physical results have typically higher adoption rates than those where results are less visibly apparent such as in case of software leaning innovations. Knowledge of the benefits can still spread through word-of-mouth between adopters and non-users.

3.1.2 Innovation adopter categories

The interplay by the members of the social system as well as the nature of the social system itself are significant determinants for the rate of adoption of the innovation (Ryan & Gross 1943; Katz 1957). Adopters in the system can be divided into five categories based on their main characteristics, values and the decision period (Rogers 2003). Rogers’ five adopter categories are depicted in Figure 6.

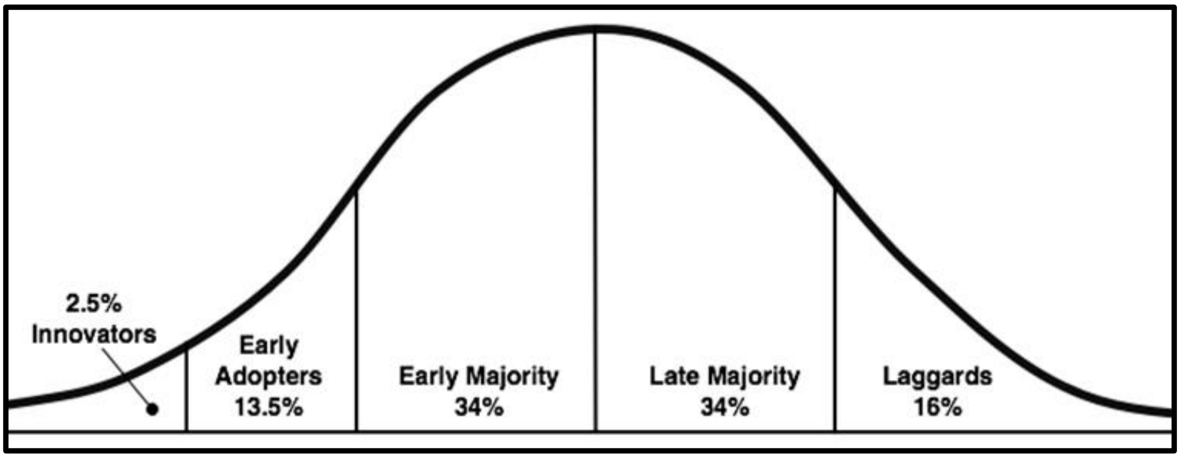

Figure 6. Innovation adopter categorization (Rogers 2003, p 281)

Uncertainties caused by a lack of knowledge and experiences within the society can keep individuals cautious about adopting new technologies (Wozniak 1987; Moore 1999). What sets innovators and early adopters apart from the rest is that they are more willing to absorb a potential risk or failure with an innovation, and they are thus also among the first to adopt a new idea (Rogers 2003, p. 282). Particularly early adopters are influential in triggering the critical mass of adoption as they act as a point of reference for the early majority who will only adopt the innovation once it has shown enough positive benefits. Once most of the uncertainties with the innovation have been cleared, the late majority joins in, followed by laggards once the innovation has proven to be good beyond all doubt (Bruce et al 2014). Some people may never adopt the innovation whether it is because they never become aware of it, they do not have the means to access it or they have significant misgivings about it (Bruce et al 2014). More detailed descriptions of each adopter category are included in Appendix 1.2.

3.1.3 Phases of innovation and the dominant design

A pivotal moment in the technology life-cycle of a new technology or innovation is the emergence of a dominant design. Figure 7 depicts the industrial innovation phases and dynamics.

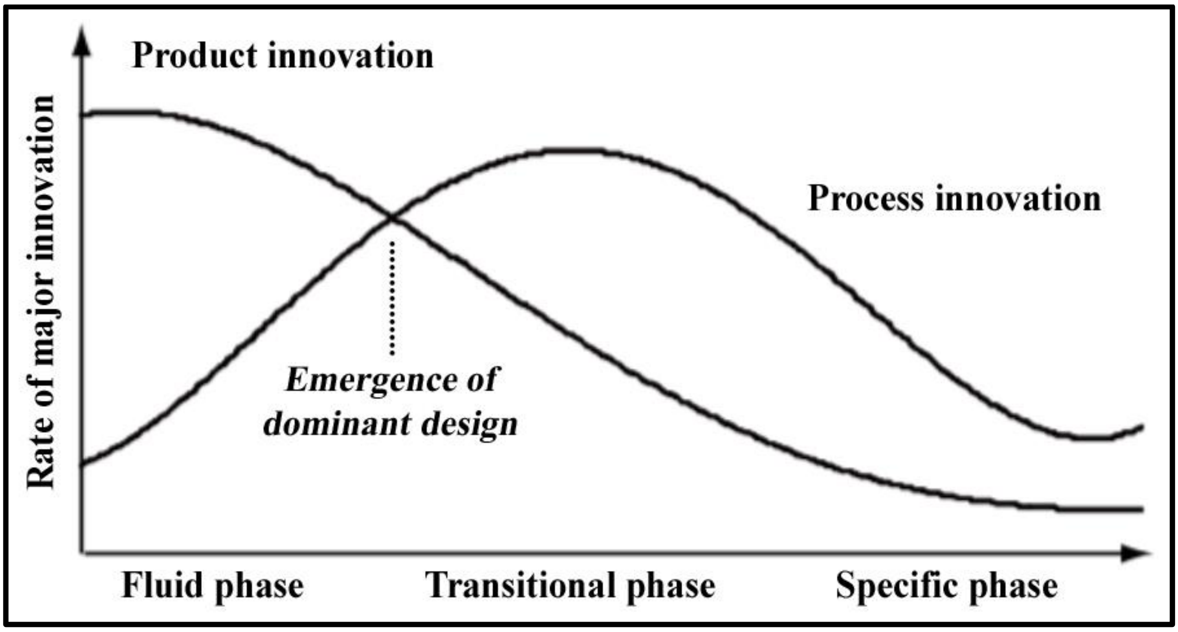

Figure 7. Phases of Innovation (Utterback 1996)

Suarez and Utterback (1995) describe the concept of dominant design as “a specific path, along an industry’s design hierarchy, which establishes dominance among competing design paths”. Abernathy and Utterback (1978) describe the early phase of industrial innovation as the fluid phase. In this phase the rate of product innovation is high, process innovation is yet to build up significantly, and the competitive emphasis is on product functionality. Once dominant design is fully realized, efforts in the transitional and specific phase go towards reduction of costs and improving the efficiency of processes that can also drop the prices for customers (Abernathy & Utterback 1978; Peltoniemi 2009).

3.1.4 The Bass diffusion model and the innovation S-curve

Besides Rogers, widely influential contributions to innovation diffusion theory were made around the same time period by University of Texas professor Frank M. Bass (1963). First introduced in 1969, the Bass Diffusion Model and its variations have enjoyed continued popularity among industry researchers, business managers and analysts for five decades (Srinivasan & Mason 1986; Bemmaor 1995; DeKimpe et al 2000; Goldenberg et al 2002; Mazhari 2017; Blazquez et al 2018; Min et al 2018).

The key assumption of the Bass diffusion model is that the number of prior adopters influences the timing of a consumer's initial purchase. Consumer behavior in the model is a mix of innovative and imitative behavior (Bass 2004). The Bass model combines Rogers adopter categories into only two groups of adopters, innovators that are those who make the adoption decision independently of other individuals in the social system and imitators who represent the other four categories (Bass 1969). Like in the Rogers' diffusion theory, Bass assumes that the diffusion process is binary, implying that the consumer either adopts the innovation, or waits to adopt.

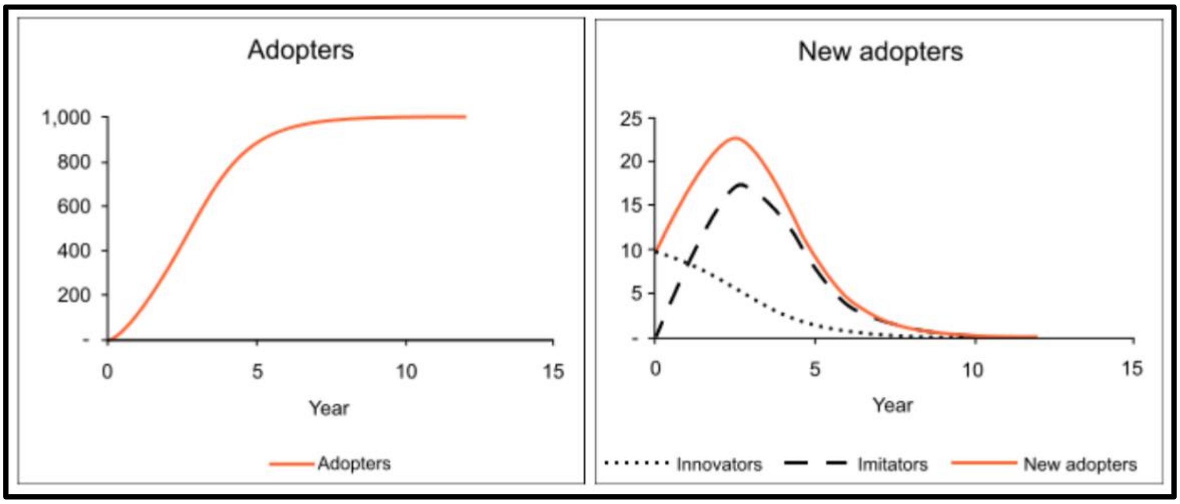

Figure 8. Typical Bass model diffusion patterns (Massiani & Gohs 2015)

Fundamentally the Bass diffusion model was designed to answer how many consumers will eventually adopt the new product and when. For the initial adopters the decision is spontaneous while subsequent adopters are imitators (Bass 2004).

As the diffusion process progresses, more individuals become agents who can be imitated, which in turn leads to an increase in the diffusion rate. The rate of diffusion eventually slows down since there are less people who have not yet adopted the innovation. This process is depicted in Figure 8 on the previous page which has logistic curves for both new adopters and the overall number of adopters.

The Bass diffusion model is effective in predicting a sales peak of a product when it is applied to historical data. The data that is used to calculate an S-shaped curve for the product sales can be based on sales of a prior similar product or the early sales data of the product itself. The model however assumes that the new product is an innovation, and that it has no substitutes or competing products. The longer the range of the forecast, the less accurate the model becomes. The large number of historical precedents that could serve as parameter values is often the pitfall of anticipatory diffusion modelling (Massiani & Hogs 2015). To address this, researchers can explore low, medium and high adoption scenarios, or plot the diffusion by assigning a probability distribution curve (Cooper & Gutowski 2018).

Over the years, extensions have been made to the Bass model. Robinson and Lakhani (1975) incorporated the effect of product price on sales rate, Feichtinger (1982) extended the model to consider repeat purchases, Horsky and Simon (1983) incorporated marketing variables, namely the effect of advertising, and Kalish (1985) considered reductions in product price and functional uncertainty more clearly than the original model. Bass himself has over the years come up with extensions to his original model. In 1987 he extended the model to fit multi-generational innovations and later in 1994 include marketing mix variables of price and advertising, implying that spread of the innovation can be accelerated through promotional efforts (Bass & Norton 1987; Bass et al 1994). Both the Generalized Bass Model and the original are included and explained in Appendix 1.3.

While this thesis paper does not directly use the Bass Diffusion Model to evaluate the potential adoption of autonomous vehicles, it is an essential tool within the context of innovation diffusion theory as either it directly, or the key elements it has helped to make popular, are used by diffusion theorists to predict the life-cycles of new technologies (Srinivasan & Mason 1986; Bemmaor 1995; DeKimpe et al 2000; Goldenberg et al 2002; Mazhari 2017; Blazquez et al 2018; Min et al 2018).

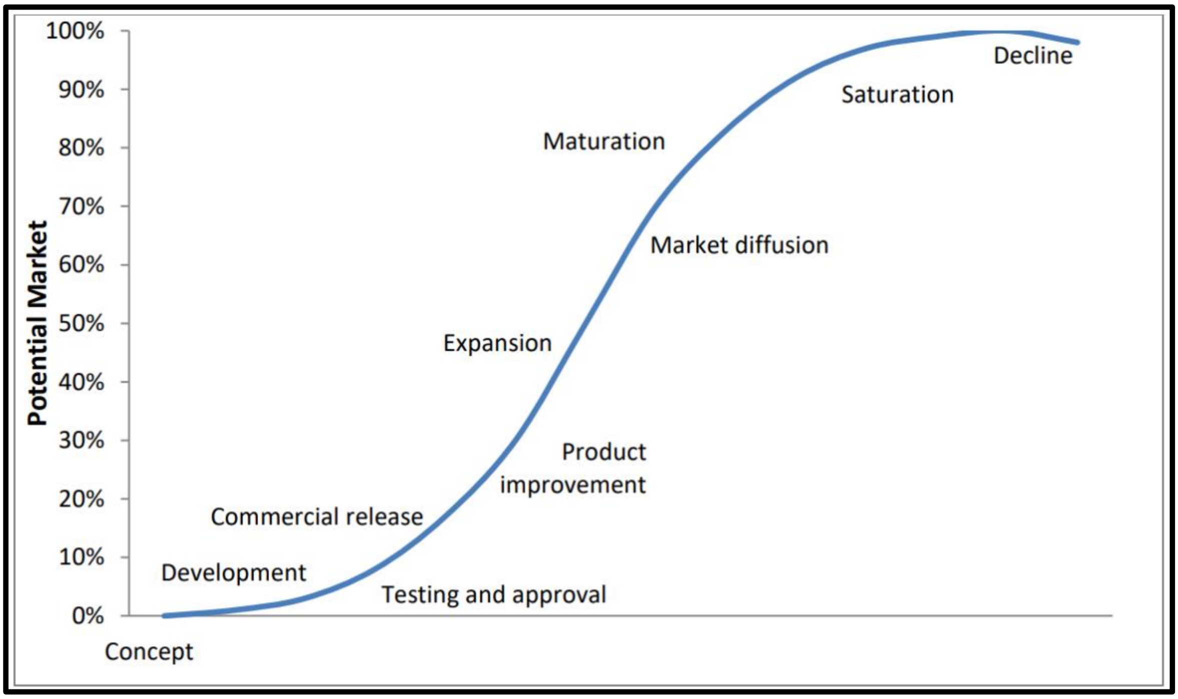

Figure 9. Innovation S-curve (Litman 2018)

Figure 9 illustrates an innovation S-curve. It is a common framework to describe generic innovation deployment patterns and technology life-cycles (Wonglimpiyarat & Yuberk 2005; Bruce et al 2014; Litman 2018). It contains several phases from testing and approval up until the decline of the innovation (Litman 2018). In the S-curve the Y-axis represents the number of adopters while the X-axis represents time. The logistics curve with S shape describes how an innovation may reach a saturation point (Bruce et al 2014).

3.2 Technology acceptance theory

The term of acceptance refers to the process of approving, agreeing or acknowledging something or someone, whilst also incorporating a “willingness for something” (Fraedrich & Lenz 2016b; Johnsen et al 2017). Acceptance could be described as an unstable construct. It is by nature processual and changeable over time, and it depends on the people, their attitudes, actions, expectations, values and the environment (Grunwald 2016). Understanding what factors affect the perception and acceptance of technology is vital in order to improve upon how people appreciate a specific technology (Liu et al 2018). Public acceptance is a precondition for deployment of new technologies as without it, investing effort in development of such technologies is often unproductive (Van der Laan et al 1997).

In the context of everyday technologies, acceptance primarily means purchase and use by individual consumers, but these technologies can also have implications for third parties (Fraedrich & Lenz 2016b). In the case of AVs both their users and non-users on the road are affected. For AVs to be successful, their technical aspects need to comply with user acceptance, behavioral intentions and societal values as well as safety, legal, ethical and economic considerations (Johnsen et al 2017).

There are many approaches to studying technology acceptance as well as an abundance of various acceptance models, which could be due to the argument that there is a lack of universal definition of acceptance (Adell 2009; Johnsen et al 2017). Franken (2007) divides acceptance into behavioral and attitudinal components. Behavioral acceptance describes the form of observable behavior, while attitude acceptance is a combination of experience and emotions.

3.2.1 Technology acceptance model

Models and theories frequently utilized in understanding how new technologies are used and adopted, include the Theory of Reasoned Action (Fishbein & Ajzen 1975), its derivative, the Technology Acceptance Model (Davis et al 1989) and the already reviewed Innovation Diffusion Theory (Rogers 2003).

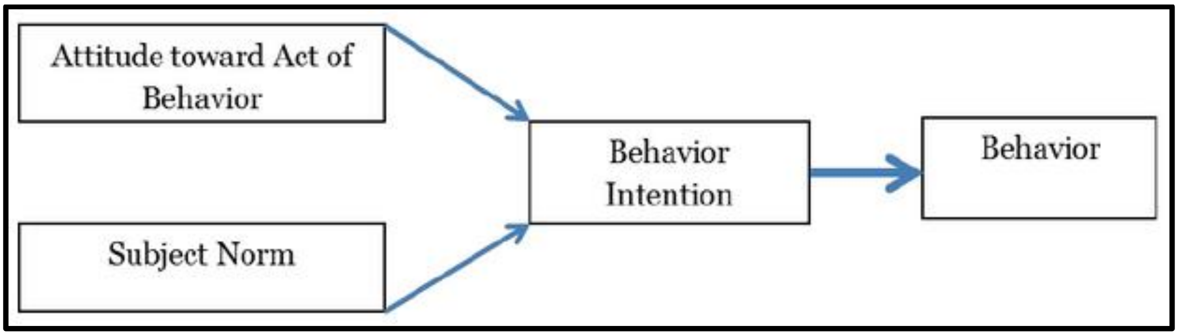

Figure 10. Theory of Reasoned Action (Fishbein & Ajzen 1975)

Theory of reasoned action (TRA) and technology acceptance model (TAM) aim to explain how consumers adopt, perceive and intent to use an innovation, and the actual use of the innovation (Ismail & Che Razak 2011). Figure 10 represents the diagrams of TRA. It is a broad model from social psychology, which has been utilized to explain user behavior in a wide a variety of fields.

Theory of Reasoned Action explains how the individual's actual behavior is determined by behavior intention, which in turn is influenced by subjective norms and attitudes towards the act of behavior (Fishbein & Azjen 1975). Attitude describes the individual's negative or positive evaluation of performing the act of particular behavior, whilst subjective norms refer to the perceptions of other people's opinions whether the individual should perform the action or not. Ajzen (1991) later revised TRA to include perceived behavioral control as a third influence variable in order to account for possible non-voluntary behaviors (Appendix 1.4).

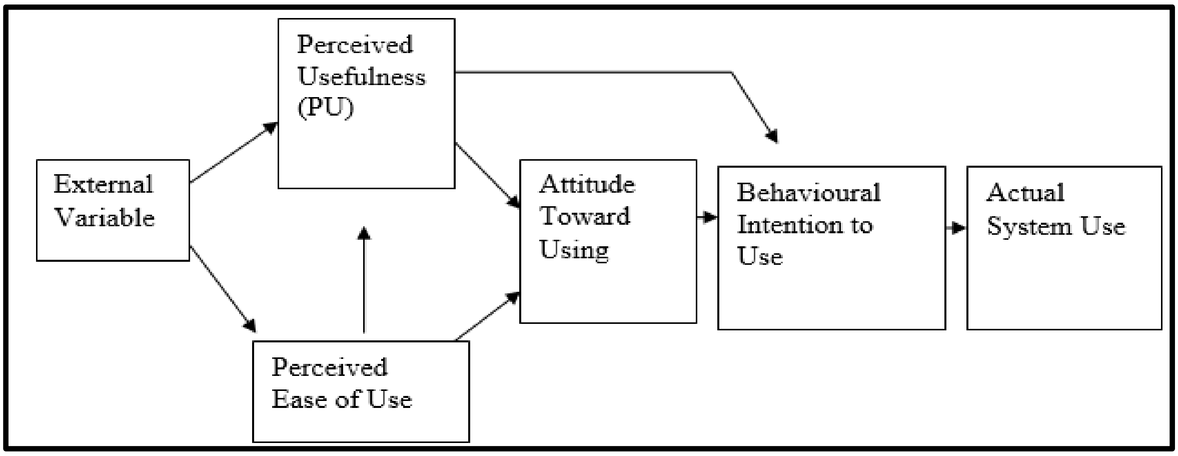

Figure 11. Technology Acceptance Model (Davis 1989; Davis et al 1989)

The Technology Acceptance Model is depicted in Figure 11. It was developed by Davis (1989) as an extension of TRA. It is one of the most common and reliable theoretical models used in empirical studies for technology forecasting (Chen et al 2017; Gkypali et al 2018; Kabbiri et al 2018; Sepasgozar et al 2018; van Oorschot et al 2018; Verma & Sinha 2018). In TAM perceived usefulness (PU) and perceived ease of use (PEOU) are represented as main determinants of attitude towards use. Davis et al (1989) define PU as the user's subjective probability that the use of a specific innovation enhances performance, while PEOU is the user's evaluation that the innovation requires little effort to utilize and it is easy to use. In some later variations of TAM, subjective norms are still included as influence for PU and behavioral intention (Venkatesh & Morris 2000). A great number of studies, particularly in the field of information technology research, have established that attitude has the most significant influence on intention to use, and that it has a direct relationship with behavioral intention (Taylor & Todd 1995; Morris & Dillon 1997; Shih & Fang 2004; Bauer et al 2005; Nysveen et al 2005; Hsu et al 2006; Rohm & Sultan 2006; Hong et al 2008; Nor & Pearson 2008; Ismail & Che Razak 2011).

A more recent variation of TAM is the Unified Theory of Acceptance and Use of Technology (UTAUT) model by Venkatesh et al (2003). In UTAUT the intention to use a system is influenced by effort expectancy, performance expectancy and social influence (Venkatesh et al 2003). The first two of these are practically the same as PU and PEOU were in the TAM model while social influence outlines the individual's perception of how important other people believe one should use the new system. Meanwhile usage behavior is directly influenced by intention to use and facilitating conditions, the latter of which represents the extent to which individuals are aware of the organization and technical infrastructures that support the use of the system (Venkatesh et al, 2003). Illustration of the UTAUT is included in Appendix 1.5.

It is not unordinary for researchers to mix structures between innovation diffusion theory and TAM in acceptance and adoption studies due to similarity of their constructs (Sigala et al 2000; Chen et al 2002; Wu & Wang 2005; Chang & Tung 2008; Lee et al 2011 Al-Ajam & Md Nor 2013; Prieto et al 2015; Mutahar 2017; Septiani et al 2017). Relative advantage in IDT is remarkably similar to perceived usefulness in TAM while same can be argued about complexity and perceived ease of use (Davis et al 1989; Rogers 2003; Lee et al 2011). Compatibility, trialability and observability have likewise shown positive correlation with acceptance when combined with constructs of TAM (Tran & Cheng 2017; Mutahar et al 2017).

3.2.2 Car technology acceptance model

As mentioned earlier, there are numerous variations of TRA and TAM as each specific technology can have many versions of their own of these models. Several acceptance models adopted to measure perceptions towards AVs are based on TAMs formulated earlier to measure advanced driver assistance systems (Johnsen et al 2017). Osswald et al (2012) formulated the Car Technology Acceptance Model

(CTAM) by merging TAM together with UTAUT, and by adding four direct determinants of intention to use the AV technology. CTAM is depicted in Figure 12.

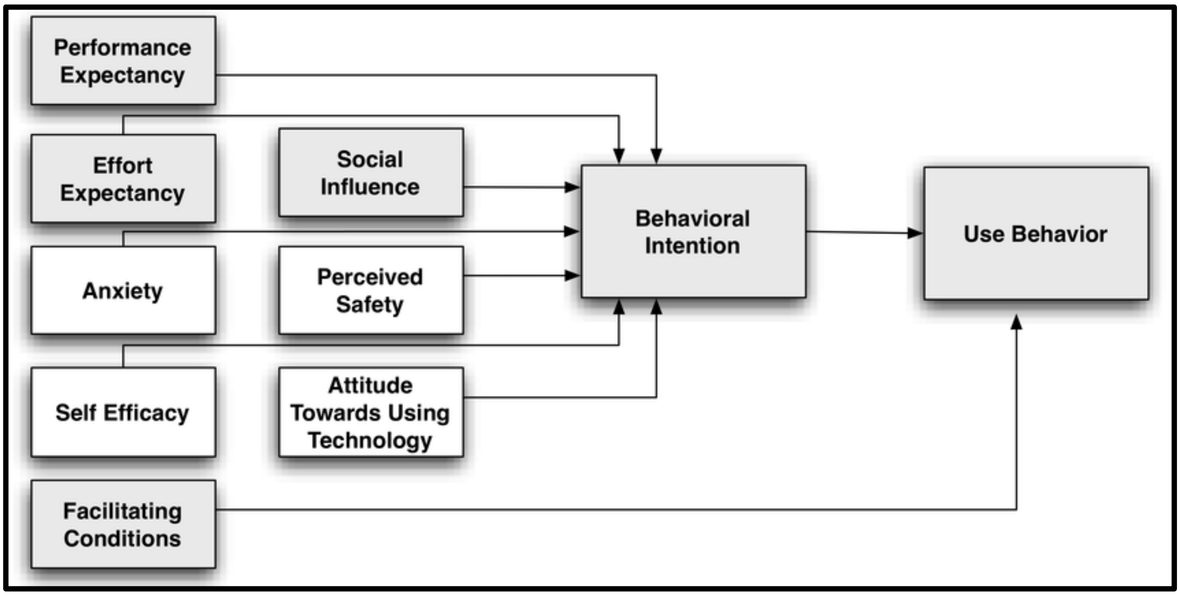

Figure 12. Car Technology Acceptance Research Model (Osswald et al 2012)

Perceived safety refers to user's belief about how the technology can affect safety, anxiety represents the anxious or emotional reactions caused by use of the technology, self-efficacy is the belief in user's competence to use the technology, and attitude towards using technology is the overall affective reaction upon using the technology (Osswald et al 2012). CTAM forms the base of the research framework of this study, which is discussed more in chapter four.

3.3 Automaker strategies and AV diffusion scenarios

In this segment the potential AV diffusion scenarios and automaker strategies are discussed to evaluate when fully autonomous vehicles could become available to the public and at what rate they could gain popularity.

Automakers have adopted different strategies in their development efforts of AVs. Most modern vehicles have driver assistance systems in them as standard features, and SAE level 2 systems are available even in affordable car segments (Horaczek 2018). Audi's flagship model A8 became the world's first production car to achieve true SAE level 3 autonomy in 2017, while the rest of the manufacturers are either still developing systems capable of conditional automation or skipping it altogether

(Taylor 2017). Automakers such as Toyota, Ford and Volvo have deemed SAE level 3 automation unsafe and unfeasible, and have set their aim straight to high automation (Robotics Law Journal 2017). Nissan, Daimler and General Motors have set a goal to rollout their versions of AVs in the year 2020, although little information has been released stating the degree of autonomy of these vehicles (Beiker 2016).

The wide range of automaker strategies can be credited to the fact that the industry is unsettled on what will be the dominant design of driving automation. Referring back to Abernathy and Utterback's phases of industrial innovation, the development of AVs could be described as still being in the fluid phase. Whether conditional and high automation are competing designs is not however a straightforward question. Even though full automation may in the end phase out conditional automation the same way AVs could replace the human driver, SAE level 3 can potentially have several decades of vitality in it before SAE levels 4 and 5 take over (Bierstedt et al 2014; Milakis et al 2017a). Conditional automation can also prove important in molding legislation and public perception of AVs in preparation for further automation levels (Gasser 2016; Winkle 2016).

Table 4. Diffusion estimates of AV levels (Nieuwenhuijsen et al 2018)

	Introduction	Market penetration	Source
Level 1, assisted	2000	0–10% in 2000 10–20% in 2015	Shladover (1995), Kyriakidis et al (2015)
Level 2, partial	2015	0–5% in 2015	Kyriakidis et al (2015)
Level 3, conditional	2017–2020	70% in 2020	Underwood (2014), Rangarajan and Dunoyer (2014), Juliussen and Carlson (2014)
Level 4, high	2018–2024	Highway, some urban streets before 2030	Underwood (2014), Shladover (2015)
Level 5, full	2025- 2045	25% in 2035 50% in 2035–2050 75% in 2045 – 2060 90% in 2055	Bierstedt et al (2014), Juliussen & Carlson (2014), Rangarajan & Dunoyer (2014), Underwood (2014), Litman (2015), Milakis et al (2017a)

The synthesis shown in Table 4 gives an early understanding of the possible diffusion of AVs, and its scale of time. Currently there is no consensus in academia over the prospective innovation diffusion of the various levels of AVs, and even the terminology used across the studies is different (Nieuwenhuijsen et al 2018). Due to the long range of the forecasts, any growth scenarios for AVs at this point are highly speculative.

AV academia estimated the introduction of SAE level 3 automation correctly, but wildly missed the estimations for its market penetration. In the case of full automation, scholars and industry experts estimate that the market introduction could take place any time between 2025 and 2045, while the public polls place introduction around the year 2030 (De Winter et al 2014; Kyriakidis et al 2015; Milakis et al 2017a). In the most favorable scenarios fully autonomous vehicles are introduced in the second half of 2020 and could make up for more than half of the entire vehicle fleet by the 2050s (Bierstedt et al 2014; Litman 2015; Milakis et al 2017a). Talebian and Mishra (2018) estimate using IDT and agent-based modelling that AVs could reach market saturation by 2050, but this would require annual price reductions for AVs to average 15 to 20 percent.

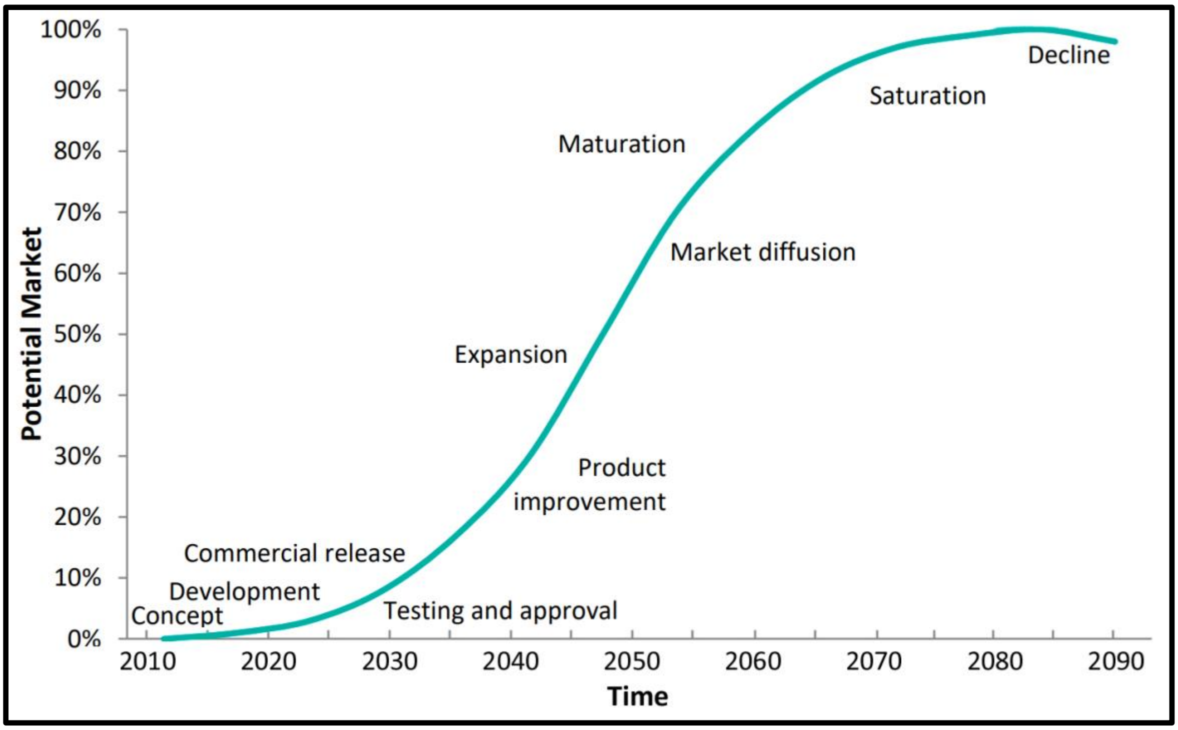

Figure 13. Estimated deployment scenario for SAE level 5 AVs (Litman 2018; Nieuwenhuijsen et al 2018)

Figure 13 shows a hypothetical deployment pattern for fully autonomous vehicles based on innovation diffusion literature synthesis by Nieuwenhuijsen et al (2018), which is drawn upon the innovation S-curve illustration by Litman (2018). In this scenario the most rapid phase of diffusion of SAE level 5 AVs could take place between the early 2040s and late 2050s given that the technology becomes commercially available in the first half of the 2030s. While this could be considered "a middle of the line" estimation when looking at the spectrum of potential outcomes suggested by various AV diffusion studies, there are too many uncertainties at this point to accurately evaluate what is most likely going to happen.

What the research community is more congruent about are the factors which support technological development and market proliferation of AVs. This has become to be known as the "AV in bloom" -scenario, in which the technological development of AVs is strong, AVs are supported by legislators and public perception of consumers is good (Fagnant & Kockelman 2015; Milakis et al 2017a; Nieuwenhuijsen et al 2018). Nieuwenhuijsen et al (2018) found that policy instruments which support knowledge transfer and creation of external research funds are the most effective measures at accelerating market take-up of high levels of automation.

Even in the most optimistic scenarios there are tangible factors which greatly slow down the AV diffusion process. High purchase prices and rapid value depreciation of new cars, long lifespans, and a vibrant secondhand market decelerate the diffusion of new vehicle technologies as they reduce the demand for new vehicles overall (Berkovec 1985; Garsten 2018; Litman 2018). It is therefore unlikely that the most enthusiastic AV diffusion scenarios materialize (Litman 2018) All in all, the accuracy of the diffusion forecasts will greatly improve once high and full automation levels become commercially available and actual early sales data can be utilized (Bass 2004; Massiani & Hogs 2015; Cooper & Gutowski 2018).

3.4 Prior technology acceptance studies on autonomous vehicles

Fundamentally acceptance of AVs boils down to two questions: "To what extent are individuals ready to use fully-automated vehicles, and to what extent are we as a society prepared to accept a transport system with fully automated vehicles on the road?” (Fraedrich & Lenz 2016b). AVs are an unprecedented case for technology acceptance as while there are forms of transport which have very high levels of automation such as aeroplanes, ships and trains, in all of these cases there is a human to supervise them and take over controls if necessary (Fraedrich & Lenz 2016b). The base criteria for acceptance in case of AVs therefore is that they need to be able to drive better than humans and the user still needs to be able to override their controls as a last line of action (Rupp & King 2010; Nordhoff et al 2018).

The great challenge in measuring the public perception towards autonomous vehicles at this point is the very fact that there are hardly any experiences among consumers of this technology (Fraedrich & Lenz 2016b). This implies that respondents will have different levels of understanding of what autonomous driving is, and this in turn affects the context in which their perceptions of challenges, obstacles, benefits and risks are embedded in. This limits the level of validity most surveys of AV acceptance can establish because the object of the survey is not clearly defined as people have not yet encountered it (Fraedrich & Lenz 2016b).

3.4.1 General awareness and acceptance

Hulse et al (2018) observed in their UK based survey that people perceive AVs as a “somewhat low risk” form of transport and they generally do not oppose AV use on public roads (n=925). A multinational survey among 5 000 car owners by IHS Markit (2017) found that only 44 percent of respondents thought full automation would be a desirable feature in their next vehicle. There were regional differences as desirability was highest among the Chinese respondents with 72 percent (IHS Markit 2017). A few other studies have also made the observation that people in low income countries such as China and India are more acceptive of AVs than people from high income countries (WEF & BCG 2015; Nordhoff et al 2018). Residents of low-income nations have also expressed higher than usual interest towards sharing an autonomous taxi ride with strangers if it reduces costs (WEF & BCG 2015).

A poll by Gartner Inc. (2017) echoed the findings of IHS Markit. In their poll 45 percent of the respondents considered riding a fully autonomous vehicle (n=1519). Technology failures caused by unexpected situations and system security were found to be the key reasons for caution among consumers about full automation.

Consumers who already embrace on-demand car services such as Uber were observed to be more likely to ride and purchase SAE level 5 AVs.

Not all studies have deemed general acceptance of AVs lacking. In an Australian survey, Ellis et al (2016) observed a 75 percent probability of use among the respondents and found particularly younger people of ages 18 to 36 to be highly acceptive of AVs (n=265). Nordhoff et al (2018) studied people's acceptance towards driverless vehicles with a comprehensive 20-minute online questionnaire (n=7755). In this survey respondents rated AVs high in perceived usefulness, perceived ease of use and general enjoyment, while they were still concerned whether AVs could drive as well as humans can. What could have significantly influenced the results of this study however, is the fact that in the beginning of the questionnaire the respondents were given a highly detailed description of what the survey owners mean with autonomous vehicles, and what their use purposes are.

Johnsen et al (2017) observed that men clearly have more positive expectations and perceptions towards AVs than women do. Payre et al (2014) and Honenberger et al (2016) evaluated that the difference in approvability of AVs among men and women could be caused by differences between the genders in relation to their level of pleasure and anxiety towards autonomous vehicles. Despite this, both genders share a similar concern about data privacy and liability (Rödel et al 2014; Schoettle & Sivak 2014; Hulse et al 2018).

3.4.2 Trust in AV technology

Several polls and studies have found the general level of trust towards AVs to be limited, with the main concern being the fear that AVs cannot drive as well as humans can (Rödel et al 2014; Johnsen et al 2017; Pew Research Center 2017; Lienert 2018b). Ward et al (2017) observed that trust and knowledge of AV technology can significantly influence the likelihood to purchase an AV. Moreover, Choi and Ji (2015) and Hohenberger et al (2016) found that trust, perceived usefulness and anxiety are strong predictors of intentions to use the AVs.

Körber et al (2018) observed that trust largely determines how comfortable people feel to engage in secondary activities which take their attention off the road while riding highly or fully autonomous vehicles. Remarkably in this study people whose trust was altered through trust promoting methods were significantly more prone to crash in a situation where they were asked to take over controls during the test than those whose trust had been weakened prior to the examination.

Liu et al (2018) tested a psychological model drawn upon the trust heuristic to explain behavioral intention (BI), willingness to pay (WTP) and general acceptance of SAE level 5 AVs among consumers through a survey. They found that social trust affects all three acceptance measures through perceived risks and benefits. Perceived benefit tended to be a stronger influencer on trust than perceived risk, making it a powerful mediator for the trust-acceptance relationship. This implies that the benefits of AVs could overcome even significant risk confidence barriers if communicated sufficiently (Ward et al 2017).

3.4.3 Willingness to pay and intentions to use

A few studies have attempted to grasp people's willingness-to-pay for AV technologies. Daziano et al (2017) found that people could generally pay 4 900 USD on top of standard price for SAE level 5 systems (n=1260). Notable is that the respondents were split evenly into three groups: those who would be willing to pay over 10 000 USD, those who were willing to pay a more modest price, and those who would not pay anything at all (Daziano et al 2017). In a similar study by Bansal et al (2016) conducted among residents of Austin, Texas, an average household would be willing to pay 7 253 USD (n=347), which is significantly higher than what Dazione et al (2017) found. Additionally, they observed that willingness to pay for AV technology among older people is lower than among the rest of the population.

Schoettle and Sivak (2014) surveyed adults in UK, US and Australia (n=1533). In this survey 56.6 percent of respondents answered that they would not pay any extra charge at all for SAE level 4 technologies in their cars, while 25 percent of respondents would pay at least 1 880 USD, and the 10 percent with the highest WTP would pay at least 8 550 USD.

Bansal and Kockelman (2017) assessed WTP for AVs using data obtained from a survey of 2 167 Americans. On average WTP for full automation was 5 857 USD above the standard price of the car, although 59 percent of the respondents were not willing to pay anything for AV technology. Removing zero-WTP-respondents from the sample increased average WTP to 14 196 USD. Importantly, Bansal and Kockelman (2017) point out that WTP is a fluid figure which rather increases over time than decreases, all the while AV technology itself gradually becomes more affordable.

IHS Markit (2017) in their multinational study among 5 000 respondents observed highest WTP among German car owners. On average German respondents were willing to pay 1 016 USD for full automation, while people with lowest WTP were the Chinese with 555 USD, with UK, Canada and US falling in between. Notably the Chinese in this study were the most accepting of AV technology. IHS Markit's findings imply, together with the rest of the WTP studies discussed here, that there are clear differences in WTP based on geographical location.

Kaur and Rampersad (2018) identified that the situations when people are most likely to adopt AVs. These included when AVs could be used in closed environments, when using AV-driven public transportation with human supervision, when finding a carpark and when riding on highways where humans can still take control wherever they want. Their quantitative survey sample was however very narrow as the respondents consisted mainly of students aged 20-30 from the university of Flinders based in Tonsley. This makes the study limited in validity on its own, but its results are in line with other studies into the same topic. An earlier and larger study with 421 respondents by Payre, Cestac and Delholme (2014), found similar situations in which respondents could use AVs as Kaur and Rampersad did, with the added intent of using AVs to navigate in congestion. Payre et al (2014) also found that 68 percent of the respondents were willing to use AVs.

3.4.4 Methods to influence AV acceptance

The public concerns can be appeased foremost by addressing them already in AV system design. The privacy-by-design approach described by Ranenberg (2016) can help to mitigate concerns of privacy and cyber security, while the concern that AVs cannot drive as well as humans can needs to be solved through technological development (Fagnant & Kockelman 2015). Once the technological uncertainties have been solved, innovation diffusion mechanisms will naturally begin to accelerate adoption of AVs. Information and communication of technological benefits overall plays a vital role in technology acceptance of AVs (Kaur & Rampersad 2018; Nieuwenhuijsen et al 2018). Anania et al (2018) and Ward et al (2017) found that particularly informational materials that convey positive feelings about the technology can increase people’s perceptions of benefits and their willingness to use AVs, while negative information lessens these intentions.

Autonomous vehicle systems themselves can promote trust before technology reaches maturity. A 2014 study found that trust towards AVs increases if it is given a name, gender and voice (Waytz et al 2014). The vehicle in question had a female voice which told the user how the car functioned, and it was given the name IRIS.

Studies into the topic of automated driving human-machine interfaces (HMIs) have made encouraging findings on information provided, trust promoted and minimizing added risk from resulting glances at the HMI, but they have not been consistent in how much, or rather how little, information the test-subjects needed in order to trust the driving system (Naujoks et al 2016; Kraft et al 2018). Automated systems need to communicate to the user clearly their on-going functions and what they are capable of doing to ensure trust and acceptance, but this needs to be done concisely in order to avoid risking mental overload with an abundance of information (Lee & See 2004; Verberne et al 2012; Eom & Lee 2015).

Especially in case of partial and conditional automated systems there is an intricate balancing act between designing human-machine interfaces which communicate to the driver appropriately in an informative manner, and without distracting the driver away from safety-critical functions (Naujoks et al 2015; Dikmen & Burns 2016). For instance, it has been suggested that HMIs should display the time the vehicles remain in autonomous mode, and the system’s degree of certainty how well the automated system could handle a specific situation as incorrect perception over the system's capabilities can lead to overconfidence and misuse of the system (Parasuraman & Riley 1997; Beller et al 2013; Beggiato et al 2015; Larsson 2017).

3.5 Summary of the literature review

Autonomous vehicles can potentially provide solutions to some of automotive's greatest challenges by cutting transportation costs and emissions, reducing congestion, saving time for passengers and greatly improving traffic safety (Meyer & Deix 2014; Fagnant & Kockelman 2015; Litman 2018). While AVs could provide immediate perks even at early stages of adoption, prior studies into impacts of AV technology have suggested that most of the socio-economic benefits will unlikely materialize before the majority of the vehicles on the roads are autonomous.

Various AV adoption studies expect that full automation could be available by the early 2030s and AVs could surpass human-driven vehicles in popularity by the 2050s (Bierstedt et al 2014; Kyriakidis et al 2015; Milakis et al 2017a). Innovation diffusion studies have deemed that strong technological development, supportive nature of legislation and good public perception of AV technology could significantly support adoption and proliferation of autonomous vehicles (Fagnant & Kockelman 2015; Milakis et al 2017a; Nieuwenhuijsen et al 2018). This is not however the current state of affairs as AVs face both technological and public confidence barriers.

AV technology is extraordinarily difficult to develop due to the scale of circumstances the vehicles need to be able to reliably operate in (ETQ 2012; Koopman & Wagner 2017). Moreover, prior public perception studies have deemed general acceptance and trust towards AVs very reserved (Payre et al 2014; Bansal et al 2016; Modi et al 2018). Studies have found that majority of the consumers would not neither use AVs or pay any money for AV technologies in their vehicles (Schoettle & Sivak 2014; Bansal & Kockelman 2017; Daziano et al 2017). The most significant concerns among consumers are the ability of AVs to drive safely, and privacy and cyber security issues (Johnsen et al 2017). People prefer to be able to take control over the vehicle at their wish, but these mixed systems have safety concerns of their own due to unexpected outcomes caused by ironies of automation, and erosion of passengers’ situational awareness (Beiker 2012; Peng 2014; Beggiato et al 2015; Grunwald 2016; Sullivan et al 2016).

Acceptance towards AVs can be influenced by addressing public concerns already in the design of AVs, and by better communication the use purposes of the technology (Ranenberg 2016; Ward et al 2017; Kraft et al 2018). Once the fully autonomous vehicles become available, they can provide more concrete data for researchers to evaluate the diffusion process of AVs, and the reliability of acceptance studies is enhanced as people gain firsthand experiences with the technology which they do not currently have (Fraedrich & Lenz 2016b; Nieuwenhuijsen et al 2018).

4. CONCEPTUAL FRAMEWORK

This chapter synthesizes the main concepts of the study, illustrates their relationship with a conceptual framework, describes the research framework of the thesis and presents the hypotheses that were formulated for the empirical research.

Focal literature on how new technologies are adopted consists of innovation diffusion theory by Rogers (2003), theory of reasoned action by Fishbein and Ajzen (1975) and the technology acceptance model by Davis et al (1989). The literature review has provided the necessary concepts to develop a framework for this study. A summary of the research concepts and topics, their definitions, related subtopics and key literature are presented in Table 5.

Table 5. Definitions of central concepts, related subtopics and key authors

Concept/Topic	Definition	Related subtopics	Key literature
Innovation Diffusion	Theory of comprehending the means how, and at what rate innovations spread across cultures and gain popularity.	Innovation adopter categories; Rate of adoption; Technology life-cycle; Characteristics of social systems	(Abernathy & Utterback 1978); (Suarez and Utterback 1995); Rogers (2003); (Bierstedt et al 2014); (Fagnant & Kockelman 2015); (Litman 2018); (Nieuwenhuijsen et al 2018);
Technology Acceptance	Theory of understanding individual's usage behavior towards (new) technologies based on relationships between usefulness, ease of use, attitude, and possible other criteria	Attitudes toward technology; Consumer behavior; Theory of reasoned actions; Trust in technology; Human-machine relationship	(Fishbein & Ajzen 1975), (Davis et al 1989), (Ismail & Che Razak 2011); (Osswald et al 2012); (Fraedrich & Lenz 2016b); (Johnsen et al 2017)
Impact of AV-technology	Various positive and negative impacts how AVs could affect individuals and the society	Behavioral adaptation; Human-machine; interaction, Traffic Safety; Value of time;	(Anderson et al 2014); (Fagnant & Kockelman 2015); (Sivak & Schoettle 2015b); (Beiker 2016); Maurer et al 2016); (Wadud et al 2016); (Litman 2018)

Figure 14 describes the causal relationships between the main theoretical concepts of innovation diffusion and technology acceptance in context of autonomous vehicles. It is based on the Phases of innovation model by Utterback (1996), Innovation diffusion theory by Rogers (2003), the Bass diffusion model (Bass 1969) and the Innovation system dynamics model (ISDM) by Nieuwenhuijsen et al (2018). ISDM is shown in Appendix 1.6 while Utterback (1996) was shown earlier in literature review in Figure 7. Technology acceptance model and its derivatives were merged with 'innovation decision process' and 'perceived innovation characteristics' to reduce the number of constructs in the framework, but these mergers were justified due to their close resemblance and connection.

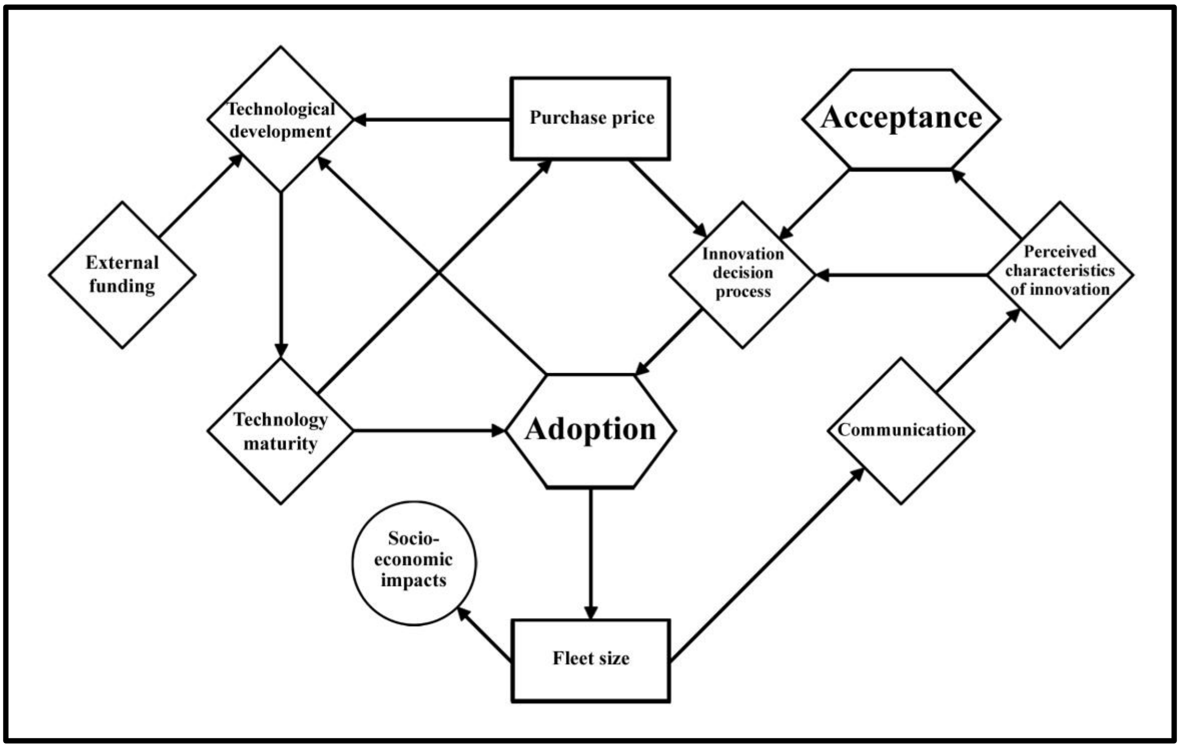

Figure 14. Conceptual framework of the study

Technology development is initially funded with external funds as no money is yet being made from AV sales. Technological development enhances the maturity of technology which translates to reduction in AV prices through learning mechanics. This gradually makes the innovation more affordable and accessible to larger number of consumers. During the innovation decision process, the potential adopters either accept or reject the innovation. If the innovation is adopted, the AV fleet grows which in turn amplifies both the socio-economic impacts and the communication (channels) as the number of adopters who are spreading knowledge about the innovation increases. The added knowledge reinforces the potential adopters' perception of the innovation and with it, their acceptance towards the technology. The perceived characteristics and technology acceptance feed into the innovation decision process and thus a dynamic loop of innovation diffusion is formed. While the relations between the constructs are more intricate and numbered than the conceptual framework leads to believe, the framework's purpose is to only give an overview of the central theories and how they are connected to one another than to exhaustively describe every connection the constructs have with each other.

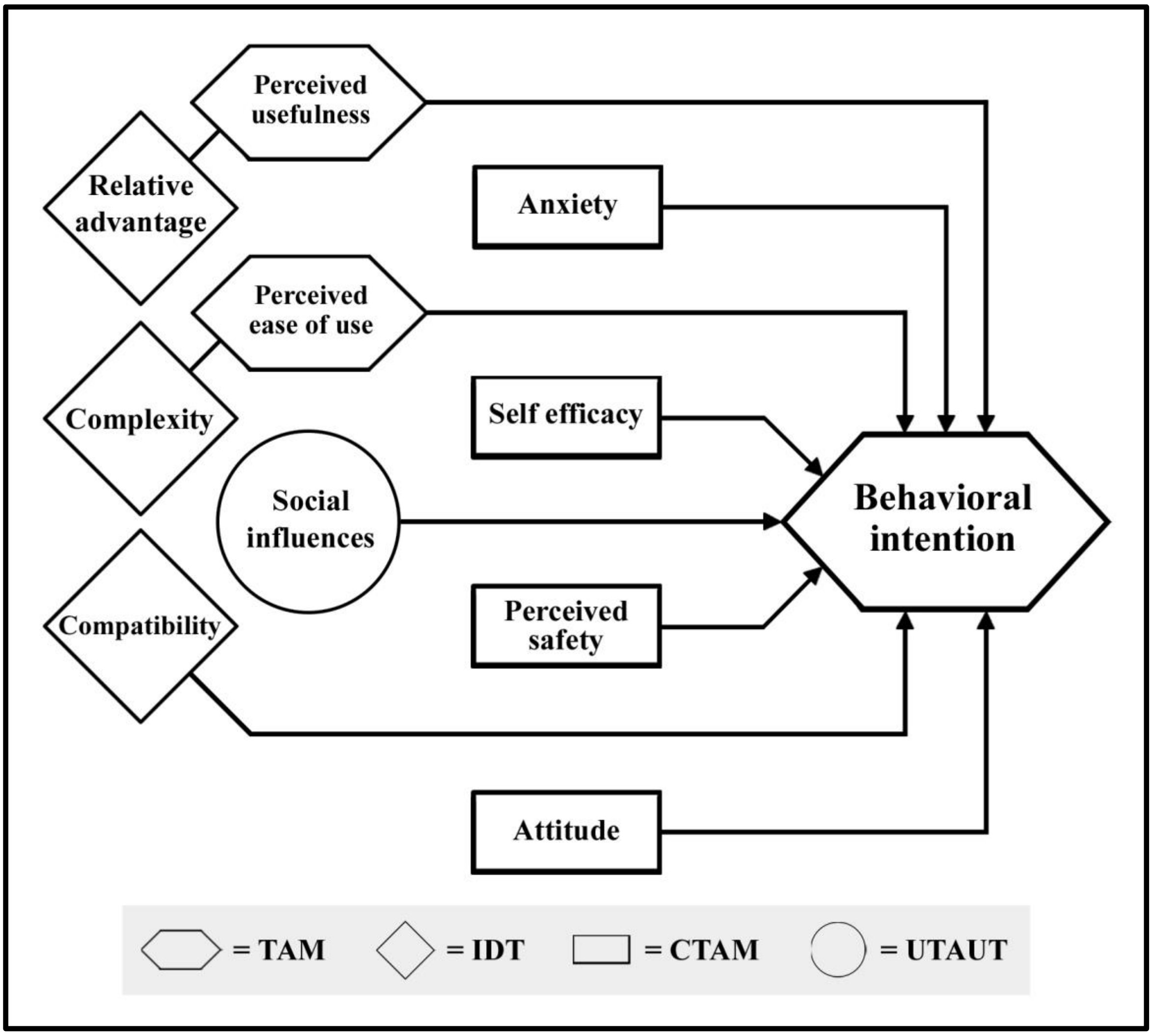

Figure 15. Research framework of the thesis

Figure 15 represents research framework of the thesis. It is largely based on the car technology acceptance model by Osswald et al (2012) with a few innovation characteristic variables added from innovation diffusion theory (Rogers 2003). Performance and effort expectancy were swapped for perceived usefulness (PU) and perceived ease of use (PEOU) for clarity. Relatively advantage and complexity were included as extensions for PU and PEOU while compatibility was included as its own structure. It is not unordinary for technology acceptance and adoption studies to test the relation of compatibility to behavioral intention (Al-Ajam & Md Nor 2013; Prieto et al 2015; Septiani et al 2017). The last two innovation characteristics trialability and observability are not part of this research framework is because it was deemed unlikely that the survey participants would have ever tested AVs or observed their use. For this same reason, the CTAM structures use behavior and facilitating conditions are not included either in the framework. The research framework, and with it, the entire empirical research of this study represents a more behavioral perspective on acceptance of autonomous vehicles.

Table 6. List of hypotheses

H1. Perceived usefulness positively affects intentions to use AV.
H2. Perceived ease of use positively affects intentions to use AV.
H3. Compatibility positively affects intentions to use AV.
H4. Social influence in terms of approvability positively affects intentions to use AV.
H5. Perceived safety positively affects intentions to use AV.
H6. Attitude positively affects intentions to use AV.
H7. Self-efficacy positively affects intentions to use AV.
H8. The lower the level of anxiety, the higher the level of intentions to use AV a person has.
H9. Perceived usefulness positively affects willingness to pay for AV.
H10. Perceived ease of use positively affects willingness to pay for AV.
H11. Compatibility positively affects willingness to pay for AV.
H12. Social influence in terms of approvability positively affects willingness to pay for AV.
H13. Perceived safety positively affects willingness to pay for AV.
H14. Attitude positively affects willingness to pay for AV.
H15. Self-efficacy positively affects willingness to pay for AV.
H16. The lower the level of anxiety, the higher the level of willingness to pay for AV a person has.

Table 6 lists the hypotheses that were formulated for this research. They will be tested as part of the explanatory analysis to determine the relations the explanatory variables of the research framework have with the two dimensions of behavioral intention; intentions to use and willingness to pay.

5. METHODOLOGY

This chapter presents the implementation of the research methodology. The aim is to describe the chosen research methods, the data collection process and the analysis methods of the collected data. An evaluation and measurement of validity and reliability is also included in this chapter.

5.1 Research design

The research design outlines how the study is conducted, how and what information is collected, what methods are used and how the collected data is analyzed in order to answer the research questions (Bryman & Bell 2007, p. 40.) The research design is depicted in Figure 16 and It was based on the research 'onion' by Saunders et al (2009, p. 108).

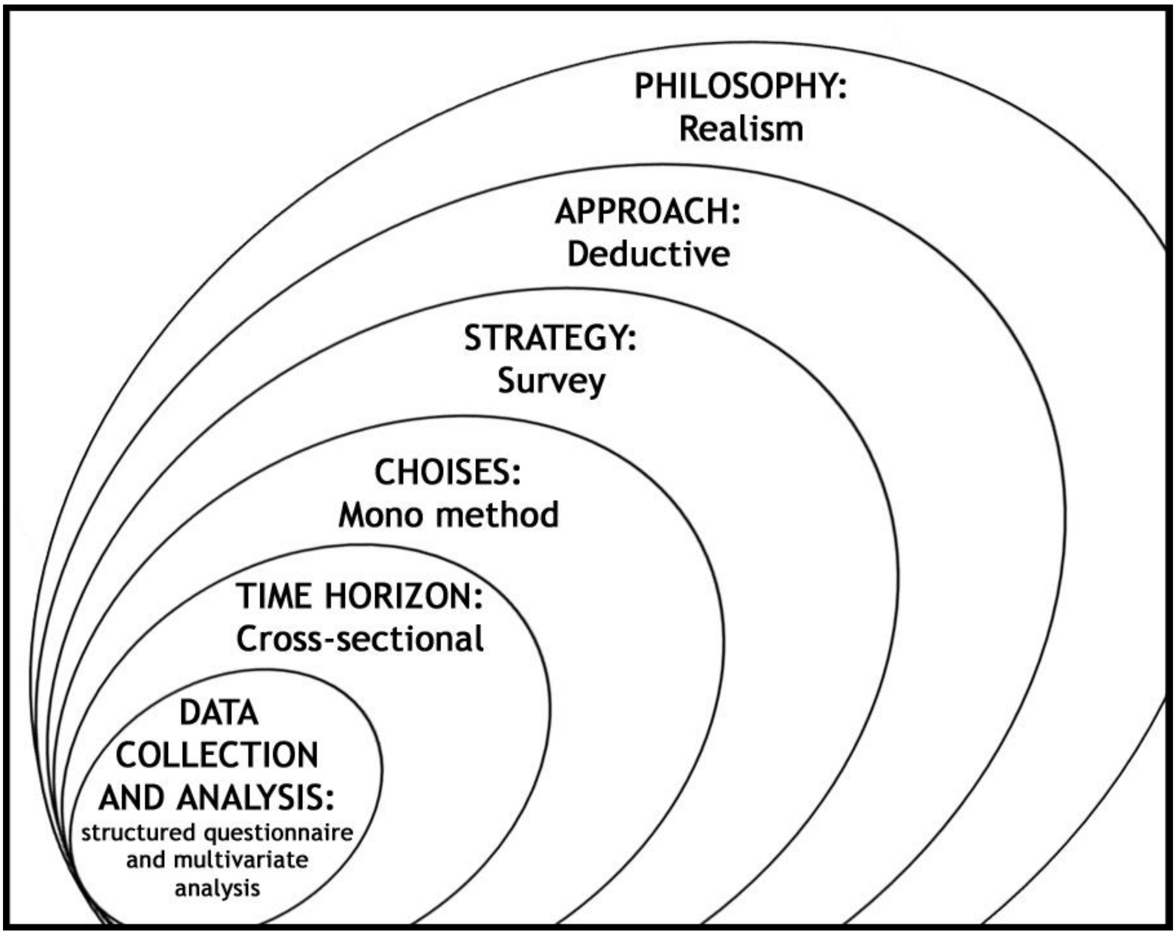

Figure 16. The Research Design

The philosophy of the study is realism which believes the object of the research "exists independently of human thoughts and beliefs or knowledge of their existence, but they are interpreted through social conditioning" (Saunders et al 2009, p. 119). Context is important for this philosophy. Inaccuracies in collected data are due to occur because so few of the respondents have experiences of autonomous vehicles.

The nature of the study is explanatory which includes examining and explaining relationships between variables particularly in terms of cause and effect (Saunders et al 2009, p. 362). Thus, the layers of the research design were chosen accordingly. The approach of the study is deductive as the research is rooted in testing existing theories with empirical data (Saunders et al 2009 p. 590). After all, the research framework of the study is based on the car technology acceptance model by Osswald et al (2012) and innovation diffusion theory by Rogers (2003). Survey was chosen as the research strategy as the study included a structured collection of data from a large group of people (Saunders 2009 p. 144). The time horizon of the study was cross-sectional due to the fact that the questionnaire was open for a relatively short period of time, thus capturing a snapshot of the phenomenon which was researched (Saunders et al 2009, p. 155). In terms of methodological choices, the study represents a mono method study as primary, quantitative data was collected utilizing only one method and the data was analyzed using quantitative data analysis procedures (Saunders et al 2009, p. 151).

5.2 Methods and description of the survey

Quantitative online questionnaire was chosen as the research method to gather primary data. Quantitative research is inclined to standardizes, abstracted and structured modes of collecting and analyzing empirical data (Zikmund et al 2010, p. 134). Research participants are typically given categories for answering from which the respondents pick the most suitable option according to their knowledge. This method is particularly fit for collection of data from large groups of people in a short time frame, as the respondents are able to answer the questions without the need of the researcher to be present (Kozinets 2010, p. 43; Creswell 2013). The downside of quantitative research methods is that the potential output of each respondent is often very low, but quantitative research can nevertheless be accurate in testing specific research questions (Aliaga & Gunderson 2000; Jansen et al 2007).

As the intent was to measure the perception the respondents had about AVs purely based on their current level of experiences and knowledge, the object of the survey was described as little as possible. In the survey, the following definition was given for autonomous vehicles before the first question: “A self-driving car is a car that can fully drive itself without needing help or assistance from a human driver. Human still needs to set a destination. Besides passenger cars, there can also be self-driving busses, taxis and trucks.” Notably other surveys have taken a very different approach as they may have measured opinions on examples of use cases for autonomous vehicles, and even described their possible advantages and disadvantages over human-driven vehicles (Ellis et al 2016; Hulse et al 2018; Nordhoff et al 2018).

5.2.1 Survey structure

The survey consisted of introduction, nine question segments divided by their semantic content and background questions which are asked last. There were thirty questions overall. Twelve of these are various background and control questions while the rest of the questions measure the variables of the research framework. Each segment measured one or two variables of the research framework. Table 7 on the next page describes the structure of the survey.

Notably two versions of the survey were made, one in English and one in Finnish. The Finnish version is a translation of the English version, and the translation process may have caused minor nuance differences between the versions. Nevertheless, both versions aim to ask the same questions as congruently as possible.

Table 7. Structure of the survey

Segment	No. of items	Rationale	Measurement scale
Introduction		This segment welcomes the respondent to the survey, gives a quick overview of the research topic and ensures confidentiality and anonymity.	
Prior experiences	3	Description of AV and ADAS, and measurement of respondent's earlier use of them. Also asks how actively respondent follows AV related news.	Closed multiple choice
Transport habits	4	Asks preferred transportation method, driver's license, car ownership and preference to drive or ride.	Closed multiple choice
Perceived safety	5	Measures how respondents consider safety of self-driving cars in comparison to regular cars. Also asks how comfortable respondent would feel riding alone and with others, and whether there should be an option for manual drive despite automation.	Likert scale 7, FCF2*
Social influence	2	Measures how the respondent perceives acceptance of others concerning AV use, and compatibility in terms of whether there is a need for AVs in the society.	Likert scale 7
Usefulness and ease of use	5	Asks about how easy the respondent thinks AVs would be to use, could AVs reduce costs of transportation and could AVs help them to save time and money.	Likert scale 7
Attitude towards technology	2	Measures the technology orientation in of respondents by asking their general attitude towards new technologies and how quickly they learn to use them.	Likert scale 7
Behavioral intentions	3	Measures intentions to use and willingness to pay for AVs	Likert scale 7 and closed multiple choice
General acceptance	1	Asks about respondent's perception of AVs' overall positive/negative effects to the society.	Likert scale 7
Background	5	Gathers information on the respondent's age, gender, education, monthly household income and nationality.	Closed multiple choice
Total:	30	*FCF# (Forced choice format with # representing the number of alternatives)	

5.2.2 Survey question format

The survey consisted solely of closed questions. A few background questions included an option for respondents to freely write an answer if they felt given response categories did not suit them personally. Most commonly respondents were asked to respond by using a seven-point rating scale, which is also commonly referred to in research as the Likert scale. Wadgave and Khainar (2016) define Likert scale as “a psychometric response scale primarily used in questionnaires to assess subject’s perception.” Typically, Likert scale format refers to questions which specifically measure to which degree respondents agree or disagree with a certain statement (Saunders et al 2009, p. 594). However, Likert type-scale is often interchangeably used to describe any type of rank question which asks respondents to give an answer on a scale of negative, neutral or positive answer categories.

Research has shown that particularly less informed respondents have a tendency to agree more than disagree with statements of which they have no prior knowledge of (Pew Research Center (2018a). This phenomenon is known as acquiescence bias or the “yes”-bias. People may also agree more than disagree out of their tendency for politeness or respect (Lavrakas 2008). To take this into account, most questions were formed using wordings such as “how likely or unlikely” rather than measuring the respondents’ level of agreement to a given statement. The questions which did not use the Likert scale for answering either gave a few response categories or weighted different statements to one another using a forced choice format. In this format the respondent cannot give a non-answer such as “don’t know” which can increase the number of usable responses for analysis (Lavrakas 2008).

Moreover, batteries of ranked questions are susceptible to a phenomenon called straight-lining, which is a habit of the respondents to quickly answer the same response to multiple consecutive questions in order to finish the survey quickly (Leiner 2013; Kim et al 2018). To address this, the questions were spread on several pages of the survey, and the overall number of questions was kept low so the respondents would answer them all reliably (Cole et al 2012; Pew Research Center 2016). The survey forms in both languages are included in appendices 2.1 and 2.2.

5.2.3 Sampling and data collection

For sampling the research used non-probability convenience sampling method. What non-probability sampling means is that with this technique the chance or probability of each case being selected is unknown (Saunders et al 2009, p. 596; Pew Research Center 2018b). Non-probability samples that are unrestricted are called convenience samples (Adams et al 2014, p. 75). This is the least reliable technique in collecting data that would reflect the views of the entire population, but as convenience sampling is the cheapest and easiest to conduct, it is also the most common method (Andres 2012, p. 97). In convenience sampling the researchers collect data from the respondent pools that are most easily accessible. In the case of this research, this was mainly the people who are either undertaking or have completed some form of higher education.

Google Forms was used as a data collection tool for the survey. No pilot version of the survey was made due to the time constraints of the research process, but the survey was inspected by the study's supervisors before data collection began. The questionnaire was open for 10 days from 12th of December to 21st of December 2018. The survey was accessible to anyone who received the link. Since no respondent identification was used to ensure anonymity, it is possible that the same respondent could have answered more than once. However, as no perk was offered for answering the likelihood of multiple responses per person is very low.

Table 8. Survey respondent channels

Channel	Description	Links shared	Activity
LUT Intranet	Communication platform for LUT employees	Finnish and English	Published 12th of December, visible in top announcements for 2 days
LinkedIn Post	Professional network	English	Published 12th of December, post viewed 300 times before deletion
Kauppalehti.fi - keskustelu	Discussion forum for popular Finnish Business magazine	Finnish	Published 14th of December, total number of views 600 by 21st
The Student Room	World's largest education related discussion forum	English	Published 14th of December, view count unknown
Facebook: Dissertation Survey Exchange	Student survey exchange group with 6000 members	English	Published 14th of December, responses on exchange basis
Email and private message campaign	Prior contacts in entrepreneurship	Finnish and English	Approximately 50 sent, most replied back, unknown how many completed the survey
Friends and family and their colleagues	-	Finnish and English	Initial sent to 20, but they also helped to gather responses from their colleagues.

Table 8 on the previous page lists and describes the main channels through which respondents were gathered. While there is no way to accurately measure how many responses originated from each channel, the timestamps and the activity on the channels can be used to make tentative estimations. Approximately a third of the responses were garnered by posts on the LUT Intranet for staff members, Kauppalehti.fi discussion forum and LinkedIn. The second third came through student sources and the email campaign, and the final third of the responses originated from word of mouth activities by survey owner's family members and friends who passed on the survey in social media to their friends, acquaintances and colleagues.

The Finnish and the English survey overall received a combined total of 309 responses, but after inspecting each response one by one, the final sample was narrowed down to 300. Two of the responses were excluded on the basis of being non-European in order to keep the sample more geographically focused while six responses were removed because they showed clear traces of straight-lining and carelessness. The last response excluded from the sample was picked randomly to prone down the sample to a more aesthetically pleasing number. In the end there were 206 accepted Finnish responses, and 94 responses from English speakers.

5.3. Data analysis methods and measurement

The collected data was analyzed using Excel and Stata 15. At first descriptive analysis and cross tabulation was conducted to get a grasp of the data. Factor analysis was used to develop measures and transform the data to reduce the overall number of variables to a more manageable level. These factors were then used as part of explanatory analysis to answer the main research question (RQ1. How do consumers perceive autonomous vehicles as of 2018 in regard to technology acceptance?) and one sub-question (sRQ1. What acceptance factors affect the adoption of autonomous vehicles the most?) of this study. The explanatory analysis consisted of multiple linear regression analysis and binary logistic regression analysis due to their popularity to measure ordinal and categorical data.

5.3.1 Reliability and validity

Quality of a quantitative research is measured by two dimensions, reliability and validity. Reliability describes the consistency of the survey responses while validity can be described as a measurement of the survey's capability to provide information that is needed to meet the purpose of the study (Zikmund et al 2010, p. 305-307). Validity of a quantitative study thus measures how accurately the study is able to measure the concept that is being researched (Heale & Twycross 2015). A basic example of a survey which would not be considered valid would be a survey which has been designed to explore the use of autonomous vehicles, but which actually measures only purchase instead. Reliability on the other hand measures how consistently a research tool such as a survey, can produce the same results if used in the same situation on repeated occasions by the same participant (Heale & Twycross 2015).

Homogeneity, also known as internal consistency, was tested using Cronbach's alpha (Price et al 2015). Cronbach's alpha is the mean of all split-half coefficients that result from different splittings of a test (Psychometrika 2008). It is therefore an estimation of the correlation between two random samples of items from a universe of items like those in the test (Cronbach 1951, Agbo 2010). These tests were done for variables as part of explanatory analysis and they are reported in chapter six.

The survey length had implications for construct validity. Shorter surveys are more capable of gathering a larger sample and respondents answer short surveys more carefully than longer ones which improves both overall reliability and validity. However, to keep the survey short many constructs of the research framework could be measured with only one or few questions. Particularly self-efficacy and attitude were not measured accurately by the survey and this in turn means that any analysis done on the relationship of these constructs with behavioral intention needs to be interpreted carefully, and the results are not by any means generalizable.

5.3.2 Data formulation

The data collected with the survey needed to be recoded before it could be analyzed. The results of the Finnish and English surveys had to be merged together to form a single data set. Once this was done, answer categories which had received a very small amount of responses were identified with descriptive analysis, and some of the smaller categories were merged with others so there would be less outliers. For instance, in case of question B8 (Appendix 3.8) the small group of active followers of AV news were combined with those who follow AV related news only somewhat actively. Finally, all answer categories had to be given nominal values. For example, results of “yes or no” -questions were transformed to binary data by coding yes’s as 1 and no’s as 0. A more detailed description of data transformations is included in Appendix 2.3.

6. RESULTS

This chapter contains the survey results and analysis of the findings. Descriptive analysis, cross tabulation, factor analysis, Pearson's correlation, multiple linear regression analysis and logistic regression analysis were used to interpret the results. Linear regression with a single independent variable were not used because nearly all of these models ended up implying statistically significant relation between the measured variables. In cases where the causal relationship of only two variables needed to be examined, cross tabulation or correlation analysis was used instead.

6.1 Descriptive analysis

This sub-chapter examines the results with descriptive tables and charts. The purpose is to get an initial understanding of the sample. Charts were drawn for each of the variables, but due to their large quantity, not all can be discussed here. Appendix 3 contains all of the descriptive figures and charts for both the background and survey questions.

6.1.1 Language, gender and age

The Finnish speakers made up for 68.7 percent of the respondent group while 31.3 percent of were English speakers. Since non-Europeans were excluded from the sample and no country of origin was measured, it can be assumed that majority of the respondents live in Finland while the rest of them live elsewhere in Europe.

Table 9. Distribution of genders

Language	Female	Male	Other or non-conforming	Total
English	62 66,0 %	32 34,0 %	-	94
Finnish	73 35,4 %	130 63,1 %	3 1,5 %	206
Total	135 45,0 %	162 54,0 %	3 1,0 %	300 100,0 %

Table 9 shows that overall 45.0 percent of the respondents were women, 54.0 percent were men and 1.0 percent other or non-conforming. The vast majority of respondents in the English survey were women while this was the other way around for the Finnish survey. This makes non-Finnish speaking men a minority in this study while Finnish speaking men are somewhat overrepresented.

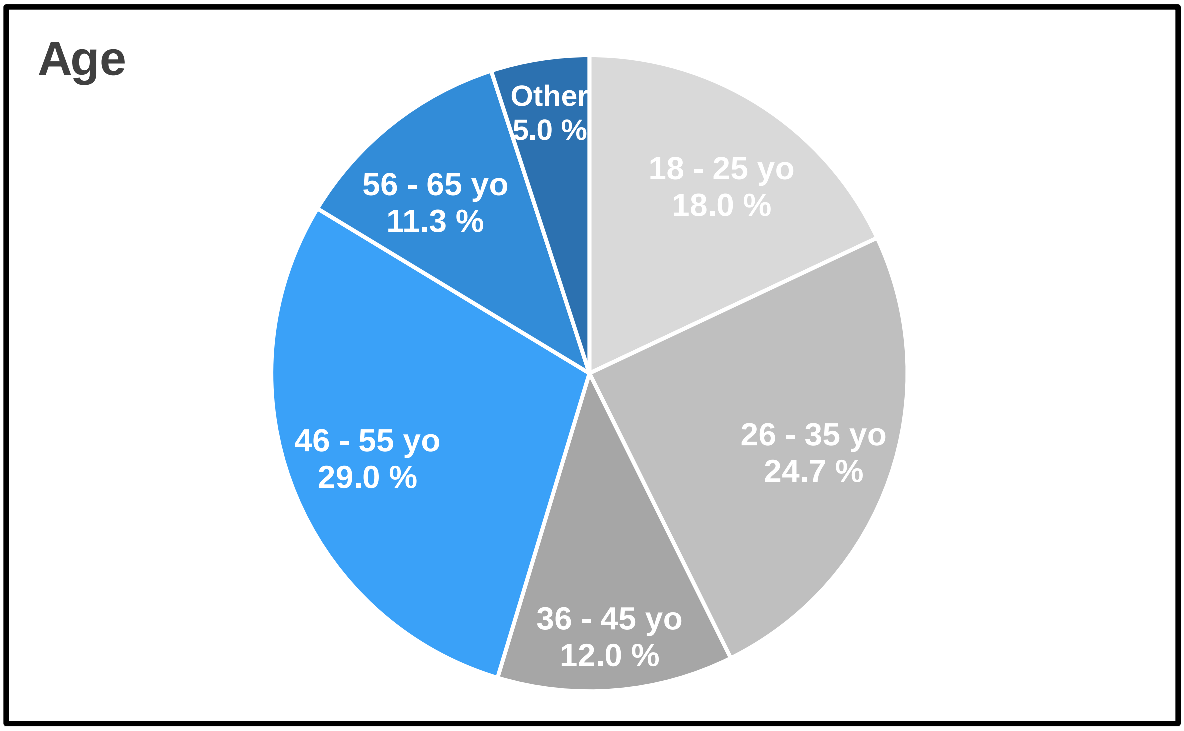

Figure 17. Respondent age groups

The age structure of the respondent group is depicted in Figure 17. The two largest age groups were the 46 - 55 year-olds with 29.0 percent and the 26 - 35 year-olds with 24.7 percent. While the age groups are not even, overall the sample consists of a relatively balanced mix people in different stages of their studies or their professional career. The category “Other” consists of respondents who were under 18 years old (2.7 percent), over 65 (1.0 percent) or did not confirm their age (1.3 percent). The English sample skewed heavily towards young people as over 85 percent of respondents were 18 - 35 years old. In the Finnish survey, only approximately 25 percent of respondents were under 36 years old.

6.1.2 Education

As can be seen from Figure 18, convenience sampling lead into a sample that leans heavily towards highly educated respondents. Nearly half of the respondents had at least a master’s degree. This is an uncommonly high number as among Finnish citizens of ages 25 - 64 this figure is approximately 15 percent (OECD 2018). The number of respondents whose highest completed degree was bachelor was 31.3 percent. In the figure the category of “other” contains both the 2.7 percent of respondents whose highest completed education was elementary school, and the 2.7 percent who had some other form of education that did not fit into the rest of the categories.

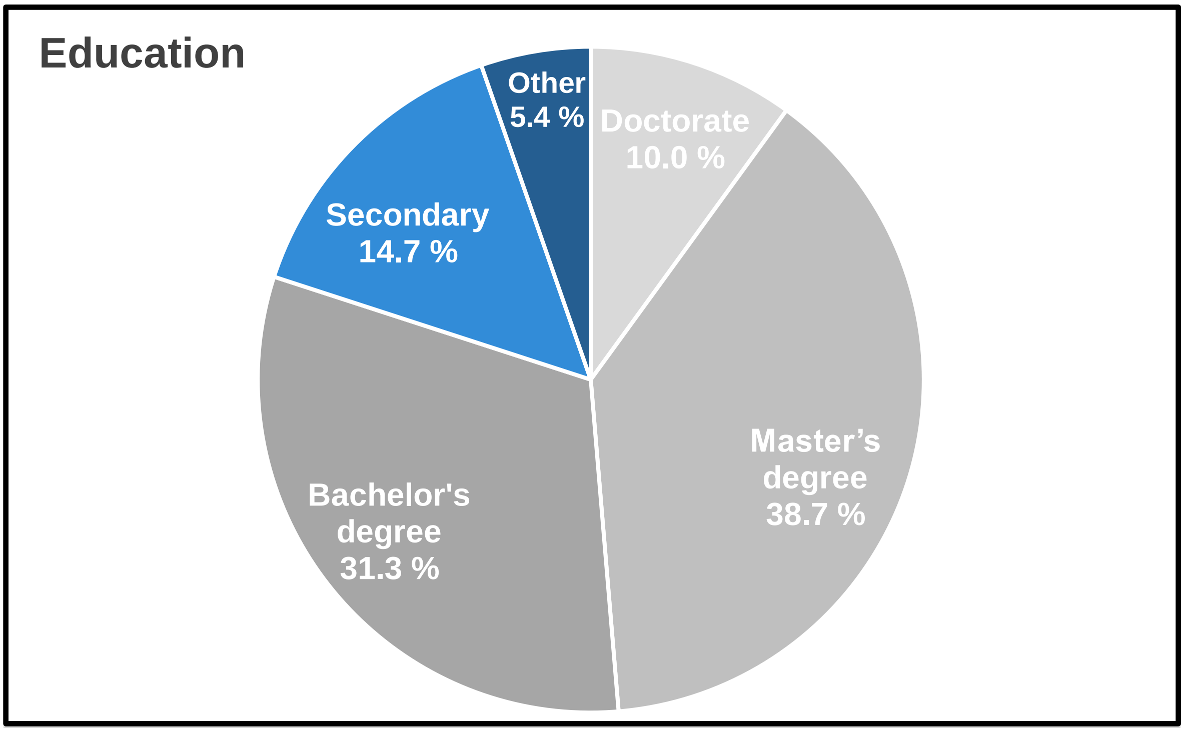

Figure 18. Highest completed degree of education

6.1.3 Monthly household income

Figure 19 represents respondents’ monthly household net income. This is the combined total of disposable income of everyone who lives in the same household with the respondent after taxes and deductibles have been paid. A combined 35.4

percent of the respondents earned less than 3000 euros a month while 34.3 percent of the respondent made between 3000 and 5999 euros. Approximately a fifth of the respondents had an income higher than 6000 euros a month. The “unspecified” category refers to the 10 percent of the respondents who did not give an answer.

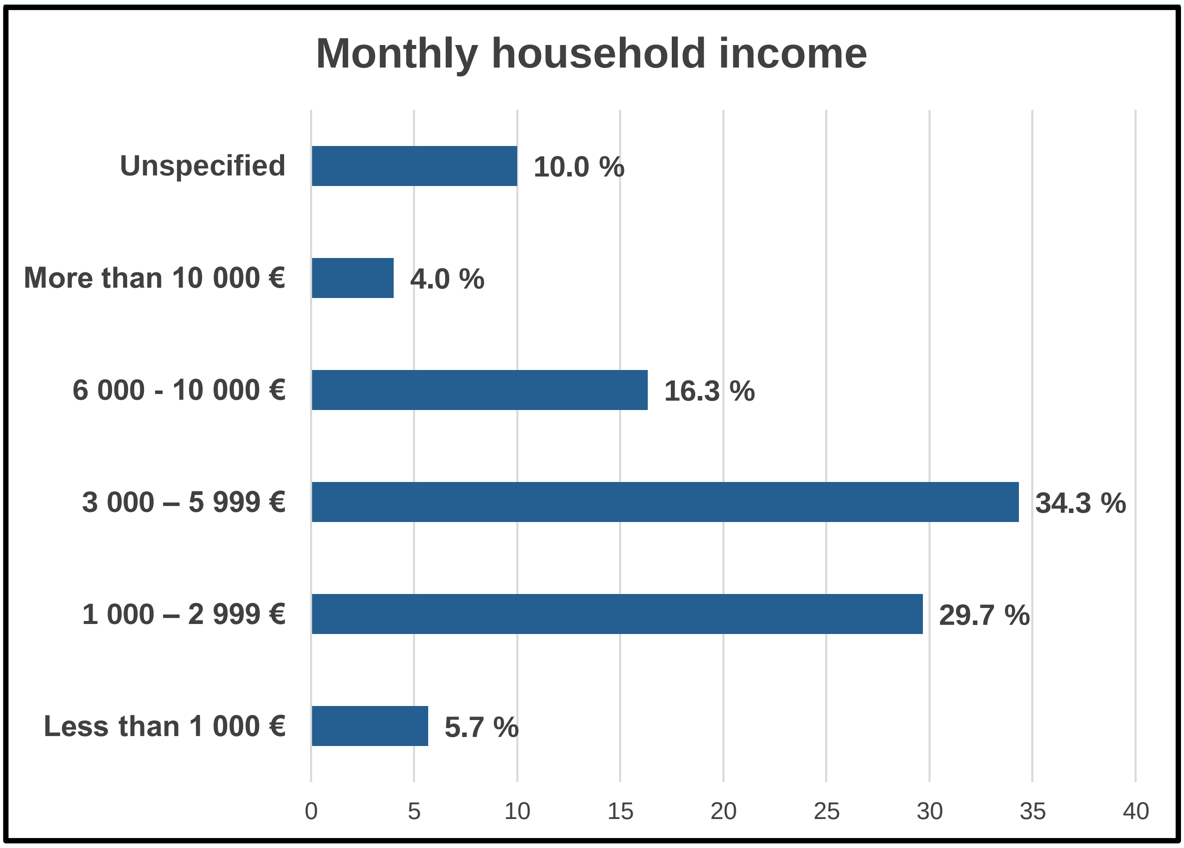

Figure 19. Monthly net household income

6.1.4 Transportation habits and prior AV experience

Personal car was the primary form of transport for 63,7 percent of the respondents while 18.3 percent primarily used public transport and the rest either walked, cycled or used some other form of transport. 91.0 percent of the respondents had a driver’s license and 70.7 percent owned a car either alone or jointly with someone else.

5.3 percent of the respondent (16 people) had prior personal experience of autonomous vehicles. This is a surprisingly high number as full automation AVs are not yet commercially available. It is likely that these people have experience of AVs through some type of public testing, a demo day, work or they in fact have experience only of a lower degree of vehicle autonomy. This factor was controlled however as the description given for AVs on the same page with the question stated that humans are not needed for any driving task in a fully autonomous vehicle.

When asked about prior experiences with driver assistance systems, 43.3 percent of the respondents answered that they had no experience. The given examples of these systems were automatic park assist, lane centering and collision preventer. 32.3 percent had used assistance systems personally and 25.3 percent had been present when someone else used them. Five percent of respondents followed AV related news actively and 29.7 percent somewhat actively. Somewhat inactively and inactively respectively received 36.7 percent and 28.7 percent of the responses.

6.1.5 Mean values and distributions for ranked questions

In case of the ranked scale questions, the mean value represents the overall level of acceptance of the whole respondent group towards the measured object on a scale of 1 to 7. Standard deviations describe the spread of values around the mean value and thus, two variables with equal mean value can still have a large difference in spread of the responses if their standard deviations are dissimilar (Saunders et al 2009, p. 601). Kurtosis and skewness are measures of distribution. Both positive and negative skewness values imply that the distribution is non-symmetric. Negative skewness represents that most of the observations have values the below the mean value while positive skewness implies the opposite (Groeneveld & Meeden 1984). Kurtosis represents the relative sharpness of the distribution relative to the normal distribution (Mardia 1970). High kurtosis indicates that the data is heavy-tailed and it has outliers while low kurtosis is light-tailed and there is typically a lack of outliers (Bryson 1974; DeCarlo 1997).

Table 10 contains the means, standard deviations, skewness and kurtosis values for the all the survey questions which did not measure the background of the respondent. Question 2 had only two response options and therefore its values are different from the rest of the questions, while question 17 was a categorical question in which the respondents were given a choice between different price points.

Table 10. Means, standard deviations and distributions of questionnaire items

Semantic content	Item	M	SD	Skew.	Kurt.
Perceived safety	*Q1. AV better or worse drivers than humans*	4,68	1,44	-0,51	-0,01
Perceived safety	*Q2. Forfeit (1) or keep manual controls (0).*	0,10	0,30	2,74	5,56
Anxiety	*Q3. Comfort while riding AV alone*	3,82	1,62	0,13	-0,74
Anxiety	*Q4. Comfort while riding AV with others*	4,09	1,63	-0,15	-0,71
Perceived safety	*Q5. AV safe or unsafe vs HV*	4,60	1,44	-0,48	-0,18
Social influences	*Q6. Approval of family and friends for AVs*	4,29	1,39	-0,16	-0,32
Compatibility	*Q7. "There is a clear need in our society for self-driving cars."*	4,08	1,66	-0,11	-0,69
Complexity	*Q8. AV easier or harder than HV*	4,93	1,35	-0,40	-0,46
Complexity	*Q9. AV easier or harder than other transport*	4,61	1,27	-0,11	-0,43
Intention to use	*Q10. Could AV replace respondent's current primary transport method*	3,74	1,95	0,05	-1,27
Relative advantage	*Q11. How likely or unlikely self-driving cars could help you save time?*	3,93	1,80	0,08	-1,03
Relative advantage	*Q12. How likely or unlikely self-driving cars could help you save money?*	3,16	1,59	0,37	-0,72
Self-efficacy	*Q13. Ability to learn to use new technologies*	5,43	1,23	-0,71	0,20
Attitude	*Q14. Favorability of views towards new technologies*	5,43	1,20	-0,72	0,123
Intention to use	*Q15. Could you see yourself taking a ride in a self-driving car?*	4,92	1,80	-0,72	-0,50
Intention to use	*Q16. Do you think you will own a self-driving car some day?*	3,86	1,92	-0,153	-1,20
Willingness to pay	*Q17. Largest sum that would pay for AV system in EUR*	3591,67	5484,90	3,42	13,59
General acceptance	*Q18. AV good or a bad thing for society*	4,70	1,60	-0,75	0,128

The quickest indicator of whether respondents were acceptive towards autonomous vehicles was Q18's mean value of 4.70. On a scale of one to seven this figure would imply the respondent group as a whole lean slightly towards expecting AVs to bring positive overall effect on the society rather than negative. A higher score of 5.43 was received by Q14, which seems to imply that the respondents do not view AVs quite as favorably as other new technologies in general. Some other questions which received a higher than average mean value were questions concerning complexity with 4.93 for ease of use of AVs compared to regular cars, and 4.61 when compared to other forms of transport. Perhaps surprisingly respondent group expects AVs to be slightly better drivers than humans are with a mean value of 4.68 for Q1. The lowest mean values were clearly received by questions which measured relative advantage. When asked about the likelihood that AVs could save the respondent time and money, time (Q11) received a mean value of 3.93 while money (Q12) received 3.16. Notably due to the wording of these questions the respondents were not able to explicitly express whether they expected AVs to add additional costs, but it can be assumed that a low ranking for this question would be a tentative indication of this as well.

As for skewness and kurtosis, high mean values received negative skewness while low means had positive skewness. Results for Q2 and Q17 were the most skewed as they had a different question format form the rest, and consequently also the largest number of outliers. A disproportionally small number of respondents in Q2 answered that AVs could forego manual controls while in case of Q17, far fewer respondents expressed interest to pay the highest sums of money for AV systems.

6.1.6 Intentions to use and willingness to pay

A combined total of 67.7 percent of the respondents answered that they would either very likely, likely or somewhat likely see themselves taking a ride in an AV. Each of these three response options received a similar number of responses.

Approximately a fourth of the respondent would not pay anything at all for a full driving automation system on top of the base price of a vehicle. Little more than half would pay at least 3000 euros or more while 11.7 percent would be 10 000 euros or a higher sum of money. The top 3.0 percent of the respondents expressed willingness to pay of 30 000 euros. On average the respondents would pay 3591.67 euros for full automation, and this figure rises to 4853.60 euros if non-payers are excluded. The distribution of responses is shown in Figure 20.

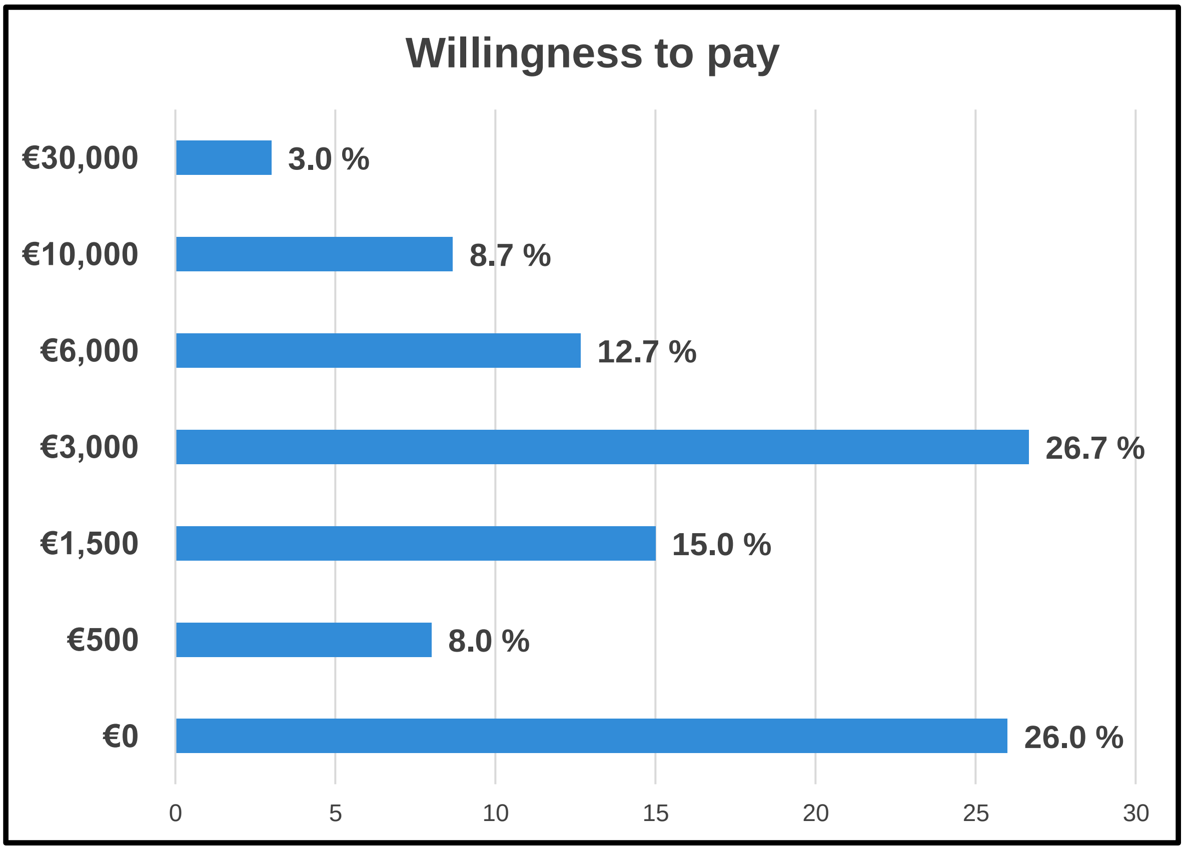

Figure 20. Results for willingness to pay

6.2 Measure development

Principal component factor analysis was performed on variables which were deemed to have an interdependent relationship. As many variables of the research framework were tested using multiple questions, the results which had the same semantic content could be combined into factor variables. This was assumed to make the measurement of causal relationships between research framework variables more convenient. Orthogonal varimax was used as the rotation method for the factor analysis.

Factor 1 was named anxiety and it was formed out of variables Q3 and Q4 which measured the feeling of comfort while riding an AV. This is of course a misleading name for a factor as a high nominal value for this variable represents a lack of anxiety, but this was a fact that needed to be taken into account in later tests. Factor 2 was named technology adaptation. It was formed from Q13 and Q14 which measured the person's overall favorability towards new technologies and how quickly they usually learn to use them. However, factor number two could be described as somewhat of a by-product in attempts to conceive a factor variable that had value in the context of the research framework. Out of the two factor variables, only anxiety was used in subsequent analysis. Results of the factor analysis are compiled in Table 11.

Table 11. Summary of Factor 1, Anxiety and Factor 2, Technology adaptation

Variable	**Label**	**Rotated loadings**		**Uniqueness**
		Factor 1	**Factor 2**	
Q3	*How comfortable or uncomfortable would you feel riding a self-driving car alone?*	0.941		0.087
Q4	*How comfortable or uncomfortable would you feel riding a self-driving car with other people?*	0.956		0.086
Q13	*How much time it usually takes you to learn to use new electronic devices, systems or equipment?*		0.903	0.177
Q14	*How favorable or unfavorable view you usually have towards new technologies in general?*		0.852	0.209
Eigenvalue		2.045	1.396	
Cronbach alpha		0.903	0.716	
KMO (Overall)		0.522		
Rotation method: Orthogonal varimax				
Cumulative percentage of variance explained (two factors): 86.02 %				

Summarized scale	**Number of variables**	**Min**	**Max**	**Mean**	**SD**
Anxiety	2	-2.064	2.260	1.470	1
Technology adaptation	2	-3.678	1.629	-1.270	1

The Kaiser–Meyer–Olkin (KMO) measure was used to measure the sampling adequacy of the variables used in the model and the adequacy of the complete model (Kaiser 1974; Cerny & Kaiser 1977). The overall KMO value exceeded the limit of 0,5 which while not ideal, can still be deemed as acceptable. The internal consistency of summated scales was measured with Cronbach’s alpha separately for both factors. Essentially this measures the level of correlation between the variables used in the factor analysis, and in case of both of the factors the alpha exceeded 0.7 which can be deemed as an acceptable level for explanatory studies. Overall the fit of the factors was deemed suitable, and they could thus be used in further analysis.

Many more factor analysis tests were made than what in the end were used as part of the research. In these tests the factors created were deemed too broad to the point they could no longer accurately measure each intended construct of the research framework (Appendix 4.1). Instead, interdependent variables which measured the same construct were aggregated to create indexes. These new aggregate variables were generated by dividing the sum of the variables used with the number of variables included to calculate the index. Four new (aggregate) variables were created using this method and they were named intentions to use, relative advantage, complexity and perceived safety. Effectively the new variable of relative advantage represents both the likelihood that AVs could save time and money, and it is thus an average of these two separate variables or “advantages”. The reliability of the aggregate variables was measured using Cronbach’s alpha. All of the variables exceeded 0.7 limit while perceived safety was clearly the highest with 0.88. A description of the aggregate variables is contained in Table 12.

Table 12. Summary of aggregate variables

Name of the aggregate variable	Variables used to form the index	Mean	SD	Min	Max	Cronbach alpha
Intention to use	Q10, Q15 and Q16	4.178	1.649	1	7	0.839
Relative advantage	Q11 and Q12	3.545	1.505	1	7	0.721
Complexity	Q8 and Q9	4.775	1.172	2	7	0.745
Perceived safety	Q1 and Q5	4.640	1.363	1	7	0.881

A correlation matrix of all the factors and aggregate variables is included in Appendix 4.2. These will be discussed in greater detail in the regression analysis segment.

6.3 Explanatory analysis

This section discusses the explanatory analyses, details the methods used, ancillary tests conducted and the results of the tests. Each method is detailed in its own respective paragraph.

6.3.1 Multiple linear regression analysis

Multiple linear regression was chosen as the method to examine the relationship between intentions to use autonomous vehicles and the other structures of the research framework which mostly originated from the CTAM model by Osswald et al (2012). Linear regression method has both explanatory and predictive power through regression coefficient and the coefficient of determination (R^2). Regression coefficient is an indicator of the degree of association between two variables whereas R^2 is a measure of the percentage of the variance of the dependent variable that is explained by multiple independent variables (Yin & Fan 2001; Zhang 2017).

Table 13. Summary of the model variables (N 300)

Variable name	Origin	Mean	SD	Min	Max
Intention to use	Q10, Q15, Q16	4.178	1.649	1	7
Relative advantage	Q11, Q12	3.545	1.505	1	7
Complexity	Q8, Q9	4.775	1.172	2	7
Perceived safety	Q1, Q5	4.640	1.363	1	7
Anxiety	Q3, Q4	1.580	1	-2.389	2.228
Social influence	Q6	4.290	1.397	1	7
Compatibility	Q7	4.083	1.658	1	7
Self-efficacy	Q13	5.427	1.237	1	7
Attitude	Q14	5.437	1.199	2	7

Table 13 describes the variables used in the multiple linear regression model. The dependent variable used was intentions to use. This is an aggregate variable of intentions to take a ride in an autonomous vehicle, intentions to own an AV in the future and expectation that AVs could replace current daily travel method. The independent variables used were relative advantage, complexity, perceived safety, anxiety, social influence, compatibility, self-efficacy and attitude. A decision was made to not use any control variables since preliminary tests found no statistically significant connection with any of the main demographic variables and intentions to use. Two of these omitted models are included in appendices 5.1 and 5.2.

As the first step of the analysis process, scatterplots were created of the dependent variable against each independent variable (Appendix 5.3). The linearity between intentions to use AVs and relative advantage, complexity, compatibility and perceived safety is more evident from the scatter plots than in case of rest of the independent variables. Some independent variables could have been potentially excluded from further analysis at this point, but all of them were still included to examine their relations to the dependent variable more closely.

A Pearson's coefficient correlation matrix of the explanatory analysis variables is included in Appendix 4.4. Perceived safety and compatibility had relatively high correlation with intentions to use with coefficient of 0.739 and 0.726, respectively. Self-efficacy and attitude had the lowest levels of correlation with intentions to use, but as explained in section 5.3.1, these variables were not reliably measured by the survey, and thus any findings over their relation to the dependent variable have to be approached with caution. Once correlation between the variables was examined, an ordinary least squares (OLS) regression was ran by using the entry method in which all the variables were added to the model simultaneously.

A Ramsey RESET was run to test the specificity of the model. The output of the test was below a p-value of 0.05, which indicates that the model may have a specificity problem, and some explanatory variables may be missing from the model. While solutions were found to remedy this issue such as altering the dependent variable that was measured or reducing the number of observations, none of these measures were ideal. Despite the apparent nonlinearity of the model, the lesser of two evils was to continue with the original model than fundamentally alter its scope.

Homoscedasticity of the model was tested using the White's original heteroscedasticity test and the Breusch-Pagan test for heteroscedasticity. In order for the variance of error terms to constant in the model, both of these tests would have to receive p-values higher than 0.05. The Breusch-Pagan test found no concern for heteroscedasticity as its p-value was 0.380, but the White's test had a p-value of 0.015, and it thus implies that the model has a heteroscedasticity problem. This could be expected as the Ramsey RESET test reflected specification issues with the model. Heteroscedasticity could be addressed by using hetero robust standard errors method instead of ordinary least squares (OLS) standard errors, but a decision was made to first complete the post evaluation assessment before evaluating whether there was a need to go robust. A residual-versus-fitted plot was created to illustrate the homoscedasticity in the regression model (Appendix 5.4).

As discussed earlier the correlation matrix was able to show high or moderately high correlations between most of the dependent and independent variables (Appendix 4.4). Due to the fact that this multiple linear regression model has eight independent variables and all of them were based on the same ranked scale, it could be expected that certain independent variables would have a high level of correlation also with one another. Particularly the independent variables of relative advantage, perceived safety and compatibility which had high correlation with intentions to use, also showed similar levels of correlation with one another. For instance, perceived safety had a correlation of 0.7542 with compatibility, and 0.6007 with relative advantage. If these were the only independent variables included, there would be a clear concern for multicollinearity in the model.

In order to check for any significant multicollinearity, a test for variance inflation factor (VIF) and tolerance, which is the inverse of VIF, was conducted (Appendix 5.5). According to Hair et al (2010), multicollinearity occurs if the VIF value exceeds 4, or tolerance is less than 0.2. No single variable exceeded the VIF value of 4, and the mean VIF of the model was 2.35 which on the scale of 1 to 10 is on an acceptance level. The tolerance values ranged from 0.2740 in case of anxiety to 0.6705 of self-efficacy. What the tolerance value indicates for example in case of relative advantage is that 54.0 percent of the variation is independent from the other predictor variables. As the model passes the VIF and tolerance tests, it can be concluded that there is no significant multicollinearity in the model. Moreover, component-plus-residual plots were created for each independent variable to ensure linearity in the model (Appendix 5.6).

Lastly, to determine whether the variance in the model is normally distributed, a histogram and a normal probability plot of residuals of the dependent variable were created (Appendix 5.8). Both the histogram and the normal probability plot indicate that the variance is normally distributed, as the histogram does not skew heavily to either direction and the residuals land near the diagonal in the normal probability plot. A Shapiro-Wilk test was conducted, and it obtained a p-value lower than 0.05 which implies a lack of normality. However, this result can be ignored as the Shapiro-Wilk test is never perfectly reliable when the sample size is large.

Table 14. Results of the multiple linear regression model

Dependent variable: Intentions to use an autonomous vehicle					
Independent variables		**Coefficient**	**Std. Error**	**t value**	**P > | t |**
Relative advantage		.2472087	.0490341	5.04	0.000
Complexity		.1447946	.0643778	2.25	0.025
Perceived safety		.2824629	.0696965	4.05	0.000
Anxiety		.2479054	.1036605	2.39	0.017
Social influence		.0826255	.0479611	1.72	0.086
Compatibility		.1948423	.0557262	3.50	0.001
Self-efficacy		-.0470645	.0535775	-0.88	0.380
Attitude		.1282193	.0694665	1.85	0.066
Constant		-.2923507	.5537802	-0.53	0.598
Model fit	**N**	**F (8 291)**	**Prob > F**	**R^2**	**Adj. R^2**
	300	79.09	0.0000	0.6850	0.6763

The results of the multiple regression analysis are shown in Table 14. Overall there were 300 observations for eight independent variables. This ratio greatly exceeds the minimum requirement of 5 observations to 1 independent variable and even the ideal ratio of 20:1. The sample size can thus be deemed ideal, but the generalizability of the results is still limited by other factors such as the sampling method.

The Prob > F value of 0.000 indicates a 0.000 percent chance that the parameters in the regression are zero. This means that the relationships between the variables cannot be random and the model is statistically significant at the significance level of 0.05. The R^2 of 0.685 implies that the 68.5 percent of the variation in the dependent variables is explained by the independent variables in the model. The adjusted R^2, had an explanatory power of 67.6 percent. This measurement is preferred when comparing differences between separate models, but in this explanatory analysis only one linear regression model was tested.

Relative advantage, complexity, perceived safety, anxiety and compatibility all had a p-values lower than 0.05 and thus have a statistically significant influence on intentions to use AVs. The regression coefficients indicate how much the dependent variable can be expected to change when the independent variable changes. The coefficients were overall relatively low across all the independent variables which is partly credit to the fact that there were many predictors included in the model. For instance, an increase of one point in perceived safety would lead to 23.8 percent increase in intentions to use.

In order to check for any influential observations in the regression model, a leverage-versus-squared-residual plot was created (Appendix 5.9). While is it clear that there are observations with a higher than average leverage and squared residuals, there is only a few of them and excluding these observations from the model would not likely influence the overall results significantly due to the large size of the sample.

6.3.2 Binary logistic regression analysis

Respondents' willingness to pay was measured with three logistic regression models. For this analysis three new binary variables were created with 0 representing either low or non-existent WTP while 1 represented a specific minimum price that the respondent would be willing to pay for full automation. In the first model 1 represented a price point of 3000 euros, in the second 500 euros and the third model 6000 euros.

The chosen independent variables were the same as in the multiple linear regression model: relative advantage, complexity, anxiety, self-efficacy, attitude, social influence, compatibility and perceived safety. The categorical variable used was monthly household income with values ranging from 1 to 4. The different income groups based on monthly household income were assigned values as follows: 1 for less than 1000 euros or non-answer; 2 for 1000 - 2999 euros; 3 for 3000 - 5999 euros and 4 for over 6000 euros. The variables were entered to the model simultaneously. All of the logistic regression models had 300 observations for eight independent variables as there were in the case of the linear regression model.

As only the dependent variable in each model is different and the findings are quite similar, only the results of the 3000-euro logistic regression model are discussed in higher detail while the results for the two other models are discussed much more briefly. The 3000-euro model was after all the one which had the largest number of statistically significant independent variables and the observations were more evenly split into occurrences of WTP (1) and non-WTP (0).

The results of the first logistic regression model are shown on the next page in Table 15. In this model only perceived safety and compatibility had a lower P-value than 0.05 and were thus statistically significant. An implication can be made that each point (rank) increase in perceived safety increases the probability of paying at least 3000 euros for full driving automation by 45.3 percent. It is thus the independent variable with the highest influence on WTP, followed by compatibility and its 32.2 percent increase per rank. A higher level of income increases WTP as could be expected, but it is not statistically significant. Likewise models with other categorical variables such as age and education did not lead to any significant findings and were thus left unreported.

Table 15. Results of logistics regression (BLR1)

Dependent variable: Willingness to pay at least 3000 euros for SAE level 5 system				
Independent variables	**Odds ratio**	**Std. error**	**z**	**P > |z|**
Relative advantage	1.254625	.1514712	1.88	0.060
Complexity	.9879477	.1572941	-0.08	0.939
Perceived safety	1.452678	.2620029	2.07	0.038
Anxiety	1.075608	.2714805	0.29	0.773
Social influence	1.070366	.131046	0.56	0.579
Compatibility	1.322621	.1810631	2.04	0.041
Self-efficacy	.8629057	.1131397	-1.12	0.261
Attitude	1.222646	.2154544	1.14	0.254
Monthly household income (Income 1 used as reference category)				
Income 2	.800921	.3384862	-0.53	0.599
Income 3	.9353796	.3885652	-0.16	0.872
Income 4	1.66836	.7894427	1.08	0.279
Model fit	n	chi^2 (11)	Prob > chi^2	Pseudo R^2
	300	86.51	0.0000	0.2081

The Pseudo R^2 measures how well the independent variables explain variation in the dependent variable. The R^2 was 0.2081 which indicates that the model has an explanatory power of approximately 20.8 percent. This is not a particularly high value, but it still implies that the model is better at predicting willingness to pay than a random guess. As the prob > chi^2 is 0.000, it indicates that at least one parameter estimate is statistically significant, and therefore the model also can be deemed statistically significant.

To assess whether the model fits the data, a Hosmer-Lemenshow test was conducted. The p-value obtained value was above 0.05 and thus the model can be concluded to fit the data. To assess the fitness of the model, a classification table was created using a probability cut-off of 0.5. The results are shown in Table 16.

Table 16. Classification table for BLR1

	Actual WTP	Actual non-WTP	Total prediction
Predicted WTP	118	46	**164**
Pred. non-WTP	36	100	**136**
Total actual	**154**	**146**	**300**
	Sensitivity	Specificity	Correct classification rate
	76.62 %	68.49 %	72.67 %

Out of the 154 people who would pay at least 3000 euros for AV system the logistic model was able to predict 118 correctly, and thus the sensitivity of the model was 76.62 percent. In case of the respondents who would pay less than 3000 euros or nothing at all, the model was able to correctly predict 100 out of 146 cases, meaning that the specificity of the model was 68.49 percent. Overall, the model was able to correctly classify 72.67 percent of the cases. While this figure could be higher, what is more important is that model was balanced and it did not classify an alarmingly large number of false positives or negatives.

The sensitivity-specificity graph and ROC-curve are included in Appendix 6.1.2. According to these graphs the ideal probability cut-off value is slightly higher than the 0.5 that was used for the classification test. Adjusting the cut-off probability from 0.5 to 0.55 increases specificity of the model from 68.49 percent to 77.40 percent but also drops the sensitivity from 76.62 percent to 70.78 percent. Nevertheless, this drop in sensitivity is not yet disproportionate to changes in specificity as the total number of correctly classified predictions improves by 1.33 percentage points to 74 percent.

As relative advantage was close to being statistically significant with a P-value of 0.06, this aggregate variable was split back in two for a separate test. This test was made with a smaller number of independent variables to check whether perception of time and money saved could have an influence on WTP (Appendix 6.1.4). In this test expectations of time saved had a statistically significant influence on WTP while money did not. Each rank increase in time caused a 26.5 percent increase in the odds, which was still a smaller influence than perceived safety and compatibility.

The findings of the second (BLR2) and the third (BLR3) logistic regression models are included in appendices 6.2 and 6.3. In the 500-euro model relative advantage was the only statistically significant independent variable that affected WTP while in the 6000-euro model the only independent variable of significance was compatibility. Notably of the explanatory power of BLR2 was the highest of all models with 0.2296 while BLR3 had the lowest value of 0.1697. Hosmer-Lemenshow tests concluded that both models fit the data. Both models had a high correct classification rate, but their sensitivity-specificity is not ideal unless the cut-off probability is adjusted to 0.75 for BLR2 and 0.25 for BLR3.

6.4 Summary of explanatory analysis results

The purpose of this section is to compile the main findings of explanatory analysis and review which hypothesis could be accepted.

Table 17. Hypothesis testing results for intentions to use

Hypothesis	Result
H1. Perceived usefulness positively affects intentions to use AV.	Accepted Coefficient .2472 3rd highest influence
H2. Perceived ease of use positively affects intentions to use AV.	Accepted Coefficient .1448 5th highest influence
H3. Compatibility positively affects intentions to use AV.	Accepted Coefficient .1948 4th highest influence
H4. Social influence in terms of approvability positively affects intentions to use AV.	Rejected
H5. Perceived safety positively affects intentions to use AV.	Accepted Coefficient .2825 Had the highest influence
H6. Attitude positively affects intentions to use AV.	Rejected
H7. Self-efficacy positively affects intentions to use AV.	Rejected
H8. The lower the level of anxiety, the higher the level of intentions to use AV a person has.	Accepted Coefficient .2479 2nd highest influence

Hypothesis testing results for intentions to use are shown in Table 17. Out of the five hypotheses developed for intentions to use, only three ended up been rejected. One must remember though that this survey was limited in its capability to test self-efficacy and attitude and the MLR found both of these to be statistically insignificant.

Table 18. Hypothesis testing results for willingness to pay

Hypothesis	**Result BLR1 (3000 EUR)**	**Result BLR2 (500 EUR)**	**Result BLR3 (6000 EUR)**
H9. Perceived usefulness positively affects willingness to pay for AV.	Rejected	Accepted Odds ratio 1.3460	Rejected
H10. Perceived ease of use positively affects willingness to pay for AV.	Rejected	Rejected	Rejected
H11. Compatibility positively affects willingness to pay for AV.	Accepted. Odds ratio: 1.3226	Rejected (barely)	Accepted Odds ratio: 1.6395
H12. Social influence in terms of approvability positively affects willingness to pay for AV.	Rejected	Rejected	Rejected
H13. Perceived safety positively affects willingness to pay for AV.	Accepted Odds ratio: 1.4526	Rejected	Rejected
H14. Attitude positively affects willingness to pay for AV.	Rejected	Rejected	Rejected
H15. Self-efficacy positively affects willingness to pay for AV.	Rejected	Rejected	Rejected
H16. The lower the level of anxiety, the higher the level of willingness to pay for AV a person has.	Rejected	Rejected	Rejected

Table 18 shows the hypothesis testing result for willingness to pay. The binary logistic regression analysis found much less statistical significance between the predictor variables and willingness to pay for autonomous vehicles, that what was the case for intentions to use in linear regression analysis. Two of the models found compatibility to have a significant influence on WTP, which implies that people who believe that there is a need in the society are also more likely to purchase them. These results are discussed more closely in the next chapter.

7. DISCUSSION AND CONCLUSIONS

The main results of the empirical research are interpreted and discussed in this chapter. Research questions are answered, and reflections are made to see how the findings compare to prior studies. This chapter also discusses the theoretical and practical contributions of the research and gives suggestions for future research on the topic of autonomous vehicle diffusion and acceptance.

7.1 Conclusions

This section answers the main research question and the research sub-questions. The main research question operated more on the general level of acceptance while the research sub-questions examine acceptance from more specific points of view. The answers therefore reflect the nature of the research questions.

RQ: How do consumers perceive autonomous vehicles as of 2018 in regard to technology acceptance?

The survey results imply that the respondents generally view autonomous vehicles as a technology which could do more good than harm for the society. Majority of the respondents expects the potential benefits of the AV technology to outweigh the drawbacks. The respondents also thought that there is a need in the society for AVs, and that they are both safer and to some extent easier to use than human driven vehicles. One aspect which was noticeably at a lower level than other aspects of AVs was cost savings. Vast majority of the respondents did not keep it likely that autonomous vehicles could help them save money. Most respondents would gladly take a ride in an AV, but they are more reserved in their expectations of owning one someday. Overall, the level of acceptance among the respondents could be described as slightly favorable. This can be considered to be an encouraging result for an upcoming technology, especially when arguably the biggest AV related news story of 2018 was the first lethal traffic accident that involved an autonomous vehicle (The Economist 2018).

Even if the general opinion towards AVs would have been lower than neutral, what at this point is important is identifying whether there exists a group of people who have both the initial interest and the financial means to adopt this technology once it becomes available. This is something that the survey results do imply, and it will be discussed in greater detail as part of the answer for research sub-question number three.

As only a small portion of the respondents claimed to have experiences of fully autonomous vehicles, it is likely that each respondent has a very different idea of what these cars are, and what they could be used for. It is therefore likely that also the perceptions people have of AVs will change rapidly once this technology is available to consumers. This research examined technology acceptance towards fully autonomous vehicles in 2018, but in the upcoming years, this acceptance will continue to evolve. The direction of this evolution will likely depend on how smoothly the public testing for AV technology proceeds, and how the potential impact of this technology makes its way to the awareness of the people.

RSQ1: What acceptance factors affect the adoption of autonomous vehicles the most?

In this research the acceptance factors were taken directly from the car technology acceptance model and its antecedents, as well as the innovation diffusion theory. Table 19 represents that the linear regression and the logistic regression analyses had distinctively different outcomes.

Table 19. Most influential factors on behavioral intention by rank

Intentions to use	Willingness to pay
1. Perceived safety	1. Compatibility
2. Anxiety	2. Perceived safety
3. Relative advantage	3. Relative advantage
4. Compatibility	
5. Complexity	

The three most influential constructs for willingness to pay were compatibility, perceived safety and relative advantage, although not all of these were statistically significant in each of the three different regression models tested. The five significant predictors of intentions to use from highest to lowest were perceived safety, anxiety, relative advantage, compatibility and complexity.

Perceived safety was found to be a significant factor for both dimensions of behavioral intention. What the results do not explicitly reveal is whether superior safety of AVs is a factor that truly makes them desirable for consumers or is it rather only a prerequisite for adopting them. Either way, an autonomous vehicle has to be perceived a safe form of transportation or its acceptance will be affected negatively.

Compatibility was the second factor that had an effect on intentions to use and willingness to pay**.** The respondents who would use and buy AVs also seems to have a sense that there is a need in the society for AVs. This is a different parameter than if they would only have a personal need for AVs, as the person feels the technology fits into the social system and other people have use for it too.

Relative advantage was the last factor which had a statistically significant influence on both dimensions of behavioral intention. In this study relative advantage was determined as a combination of how AVs could save the respondents time and money. Truthfully this is a rather narrow way to interpret this variable as relative advantage is commonly described as any kind of superior attribute that an innovation has over its predecessor. When time and money savings were considered individually opposed to being combined together, cost savings clearly had no influence on WTP. A possible explanation for this could be that a high purchase price by itself is a diminishing factor for cost savings. One of the reasons why a proportion of the respondents were ready to pay a higher sum of money for AVs could be that they expected this technology to be expensive, and thus have a smaller likelihood of saving them money over regular vehicles. Expectations of time saved had an influence on WTP, but it is likely that there were other even more significant advantages outside of the scope of this survey that affected the respondents’ interest to purchase AV technology.

Anxiety was another influential factor on intentions to use. The more comfortable the respondent expected to feel when riding an autonomous vehicle, the more prone they were also to taking that ride. Comfort is however a concept which can be interpreted in many more ways than as something that reduces the feeling of anxiety. Comfort can mean relaxation, peace of mind, certainty or even empowerment. In the survey anxiety was measured as part of the safety segment. Because of this, some respondents may have interpreted the questions in a way that comfort was related to the feeling of not having an accident, despite the survey item's intention to measure a much more comprehensive feeling than only the feeling of safety. It is obscure whether being comfortable is a prerequisite for using AVs, or a result of their use. This factor also comprises the dimension of social anxiety. Overall people expected to feel slightly more comfortable when using AVs together with other people than they would alone, but there was also clearly those to whom the presence of other people was a cause of discomfort (Appendix 7.1). This implies that the causes as well as the interpretations for anxiety can be varied.

Complexity was the last variable that was found to have an influence on intentions to use. In the survey the respondents perceived AVs as easier to use than both regular passenger vehicles and other forms of transport, with regular vehicles clearly been the hardest alternative. It however seemed that this ease of use did not fully translate to higher behavioral intentions towards AVs, particularly what it came to WTP. The explanations for this are not as clear as what might seem at first glance.

In the innovation diffusion theory, a point was raised that some of the first and early adopters in fact embrace challenges. To them a high degree of complexity can rather be an incentive for adoption than a deterrent. A greatly reduced complexity is one of the core design goals of AVs, but it is also one of the features which can potentially turn customers off. For decades, automakers have focused efforts on making vehicles fun and enjoyable to drive, and these traits have been highlighted in advertising. Rather than implying that driving is a chore, certain brands like Audi, BMW and Ford have positioned themselves as automakers that produce drivers' cars. An autonomous vehicle is essentially a complete mirror image of this notion. In the survey however, a person's preference for driving rather than being a passenger did not seemingly have any effect on their behavioral intentions towards AVs. The cause for this might be the fact that over 90 percent of the respondents wished that AVs would offer an option for manual driving, and thus it would not be a feature that is taken away completely.

Since this research was testing an established theory, a realistic outcome could also have been that all of the constructs of the research framework could have had a statistically significant influence on behavioral intention. The question therefore is, why was this not the case? One the reasons for this was that attitude and self-efficacy towards AVs were not measured directly, but rather how they relate to a person's attitudes and abilities to use new technologies in general. The fact that social influence was not a determinant for behavioral intention could be that the respondents were not completely certain whether the people who are close to them would approve or disapprove of them using autonomous vehicles. Attitude, self-efficacy and social influence can justifiably still be considered variables that affect acceptance in the context of car technologies, they just did not appear to do so in this research.

Finally, there is also the question why demographic and background variables did not seem to have an effect on behavioral intention. First explanation for this might simply be the regression models themselves and the way the categorical variables were formed. In case of income levels, the reference category used in the logistic regression analysis contained both those respondents who earned less than 1000 euros a month and those who did not specify their income level. The true income level of this category is thus obscure. Possibly a better decision would have been to simply leave the unspecified observations out and combine the two smallest income groups together to make a new reference category. However, this new reference category would have represented both the respondents who have an average level of income, and those who might live in outright poverty. It is thus likely that data transformations would not have provided more insight on how the income level would affect behavioral intention as the sample itself is limited in this regard. Common sense implies that a sufficient level of income is usually a prerequisite for making expensive purchases.

A different possible explanation why demographic variables did not affect behavioral intentions could be that the respondents in the lower end of the spectrum of age, education or income, did not answer the survey questions based on their current life-situation, but based on future expectations. This explanation is highly speculative, but it could make sense given the current stage of the technology life-cycle of autonomous vehicles and the fact that they are not available yet.

RSQ2: What advantages and disadvantages AVs can have for individuals and the society?

This research sub-question attempted to identify the main impacts of autonomous driving for individuals and the society. The main reason why AVs are in development is to improve traffic safety by replacing fallible human drivers with automated and highly connected driving systems. In the United States, 90 percent of the crashes are caused by human error, and thus eliminating this error could likewise reduce the number of accidents by a similar amount (Fagnant & Kockelman 2015). Most of the safety benefits for the society would however require that the vast majority of the vehicles on the road are AVs. Safety was an advantage that was anticipated also by the research participants. In case of overall safety, only 17.3 percent of the respondents expected AVs to be less safe than human driven vehicles while 79.4 percent expected them to be either as good as, or better drivers than humans. While perceived safety was deemed to be at a high level in both the theoretical and the empirical part of this thesis paper, it should be noted that it can potentially take a long time before true SAE level 5 vehicles that function reliably in all conditions, are available.

When evaluating the safety benefits of AVs, the dimension of behavioral adaptation should not be overlooked. The adopters will not always use technology in the way it was intended. The 90 percent drop in accidents cannot be achieved unless fully autonomous vehicles are kept in autonomous mode for all of the time. Since such a large portion of the consumers wants manual controls to remain in AVs, it is likely that AVs will keep having accidents, they will just have most of those accidents when the vehicles are engaged in manual drive. In AV literature there were signs that autonomous mode can erode a person’s ability to drive a vehicle. At his point there exists no long-term evidence that AVs could overall reduce the population's driving skills, but such a scenario can be suspected. If a person is not actively keeping up their ability to perform a certain task, their skill at performing that task decreases. This can possibly make the driving errors performed by human drivers more extreme if they are no longer driving vehicles as often as they used to. How AVs affect the driving skills of the people is however highly speculative, and more research is needed on the topic.

From a cost perspective, most survey respondents did not view AVs as a technology which could save them money. This finding makes sense as in the literature review it was discussed how cost savings can be highly case specific. Single car households are likely not to see much cost benefits at least in the earlier stages of the AV technology life-cycle as AVs are more expensive to buy than human driven vehicles. However, multiple car households may see cost benefits earlier if they can make the switch from owning many regular passenger vehicles to owning just one AV that satisfies all of the trips in the household. AV owners could save money in parking costs as the AV does not need to park where it drops off the passengers. There is also the phenomenon of Smart transition, and how new autonomous mobility services could enable consumers in urban areas to omit car ownership while still retaining a similar level of mobility. In the long term, large scale diffusion of AVs can lead to reduces costs in labor, insurances, and it can reduce occurrences of expensive traffic accidents. There are seemingly many cost benefits which could help to offset the added expenditures. Whether these were better communicated to consumers, they could further improve the acceptance of autonomous vehicles.

In AV literature it was deemed that while AVs can make for a more programmable and controllable traffic system with less irregularities, they will likely also significantly increase the amount of vehicle kilometers travelled. This win-some-lose-some situation makes it difficult to evaluate the final effects on congestion, and with it, the time saving potential of AVs for the society. Individuals can see more immediate benefits when they are freed from the task of driving, and if they travel long trips on highways where AVs can platoon to move faster. Nevertheless, both theoretical and empirical findings imply that these benefits can be very case specific.

In the survey, respondents overall had a neutral perception of whether AVs could save them time. This perception however was slightly more optimistic among the respondents who primarily use some other transportation method than a personal car (Appendix 7.2). What this tentatively implies is that some of the people who are currently mostly commuting on foot, by bicycle or by public transport are open-minded that AVs could satisfy some of their trips in the future. In this regard the survey results verify that vehicle kilometers could increase as AVs proliferate. The fact that the personal car users expect less of a change in time is something that goes against one of the key expectations in AV academia that AVs could cause a large-scale increase in human productivity. These visions might not be perfectly aligned at the moment, but perhaps this will gradually change as people become more familiar with autonomous vehicles.

RSQ3: What are the likely scenarios and outcomes for innovation diffusion of autonomous vehicles?

This question was closely discussed in section 3.3. As a recap, AV adoption studies are projecting full automation to be available by the early 2030s and AVs could surpass human-driven vehicles in popularity by the 2050s. Academia is not however unanimous as some studies place market introduction of full automation as late as 2045, implying that there still exists a great deal of uncertainty in AV development (Nieuwenhuijsen et al 2018). Conditional automation will likely pave the way for the high automation both in building public confidence and molding the legislation. There are also currently large differences between which countries have a more encouraging legislative environment both for the development of AVs and their use (KPMG 2019).

Once full automation is available to the public and legislative issues have been solved, it can be argued that price reductions become the most important driver for AV diffusion. Talebian and Mishra (2018) estimated that in order for AVs to reach market saturation by 2050, AV prices would have to drop annually by 15 to 20 percent. For AVs to be within reach for most consumers, what in particular needs to become more affordable is the price of sensors that enable autonomous driving. The sensors in various test cars have reportedly cost between 50 000 to 100 000

USD (KPMG & CAR 2012; Fagnant & Kockelman 2015). Meanwhile currently available conditional automation systems can add more than 10 000 USD to the base price of the vehicle (Smith 2017).

51.1 percent of the respondents would pay at least 3000 euros for AV technology, while 11.7 percent would pay at least 10 000 euros. While these figures give an initial impression that there would be a small group of people who have both the financial means and the interest to act as early adopters, AV technology has a long bridge to cap before it comes within reach for most consumers to purchase. This point according empirical findings made by this study is between 3000 and 6000 euros. Whether the AV technology can achieve this price level is uncertain because affordability is not the only criteria which needs to be taken into account. AV technology needs to be durable, reliable and frequently maintained, and all of these requirements increase its costs (Litman 2018).

This observation is not based on any finding made by the survey or AV academia, but one might assume that price reductions could end up having a somewhat paradoxical effect on diffusion of AVs. If the prices hypothetically dropped by 20 percent every year, certain consumers might delay their initial AV purchase as they begin to expect that the prices will drop even lower. It is also likely that the automakers will not reduce the AV prices by as much as would be required for rapid market saturation unless they are forced to do so by some other circumstance.

Considering the price cap, the legislation, the technological uncertainties and possible changes which might be required in infrastructure, a completely reasonable argument can be made that the diffusion process of autonomous vehicles may never fully run its course. It is also possible that AVs will not reach the point of market saturation during the lifetime of the current generations, or that there will be vast regional differences in the market penetration of AVs. Anyhow, uncertainties and inaccuracies are common hurdles in any research that aims to predict the future.

7.2 Discussion of the findings

This section’s primary focus is on comparing the findings of the empirical research to those made by prior studies on the topic. Not all of these reflections can be considered fully accurate because there can be differences in the data gathering instruments, the survey and the question formats and the interpretation of the results by different authors.

In the literature review it was established that the public has safety concerns over AVs, and much of these are caused by the fear that the system cannot drive as well as humans can (Rödel et al 2014; Johnsen et al 2017; Pew Research Center 2017; Deloitte 2018; Lienert 2018b). Fluctuation has been a trend in perception of AV safety as 2018 was the year of highly publicized AV road accidents. It is therefore surprising that in the survey conducted as part of this thesis work, confidence in AV safety was deemed very high. Only 17.3 of the respondents thought that AVs will be worse drivers than humans, and 20.7 percent thought AVs will be less safe than regular vehicles. Explaining the reason behind these results is much more difficult. It is possible that since the accidents in 2018 were not domestic, they had less of an effect on Finnish and European respondents than they did on the Americans. It could also be that since the respondent group had highly favorable views towards new technologies in general, they may trust that technological development of autonomous vehicles will eventually sort out most safety related concerns.

Neither explanatory or descriptive analysis found notable differences between the genders in acceptance of autonomous vehicles (Appendix 7.3). This is somewhat surprising as prior studies had made clearer observations that men approved of AVs better than women do (Payre et al 2014; Honenberger et al 2016; Johnsen et al 2017). There is no clear indicator in the survey results which could explain this deviation from the findings made by other studies. It can simply be a coincidence.

Preference to keep manual controls in AVs seems to have remained relatively consistent over the years. In the survey 90.3 percent of the respondents wanted AVs to keep the controls for manual drive while in an earlier study by Schoettle and Sivak (2015) this preference was at 96.2 percent. A Cox automotive (2018) poll found this percentage to be at 84 percent, despite the fact that it was conducted right in the heels of the first lethal car accident involving an AV.

Ward et al (2017) knowledge of AV technology can significantly influence the likelihood to purchase an AV. Statistical significance of news for WTP could not be verified in the logistic regression analysis, but a cross tabulation reveals clearer results (Appendix 7.4). 13.5 percent of the respondents who follow AV related news at least somewhat actively answered that they will “highly likely” own an AV one day while none of the non-followers answered the same. This information is aligned with Rogers’ (2003) theory on innovation decision process, and how individuals who are considering adoption are also actively seeking information about it.

Choi and Ji (2015) and Hohenberger et al (2016) found that perceived usefulness and anxiety are strong predictors of intentions to use AVs. In the multiple linear regression analysis perceived usefulness was the 3rd highest indicator of intentions to use while anxiety was the 2nd. Therefore, the causal relationship that these two variables have with intentions to use is beginning to seem solid, while other variables of the car technology acceptance model need further testing.

Table 20. Comparison of intentions to use

Source	Probability to use AV
Nordhoff et al 2018	90.8 %
Ellis et al 2016	75.0 %
Payre et al 2014	68.0 %
This study 2019	**67.7 %**
Gartner Inc 2017	45.0 %

When asked whether the respondents would see themselves taking a ride in an AV, 67.7 percent answered “somewhat likely” or higher. Table 20 shows that in prior research probability to use has varied between 45.0 to 90.8 percent. There are more notable polls that have measured low intentions to use AVs, but their results are not explicitly comparable to other studies listed in Table 20 due to different format of the questions (Schoettle & Sivak 2014; Bansal & Kockelman 2017; Daziano et al 2017).

While certain repeated polls have witnessed a downward trend in intentions to use AVs partly due to traffic accidents involving AVs in 2018, overall it seems that intentions to use AVs have remained at a high level (Cox Automotive 2018).

Table 21. Comparison of mean WTP

Source	Inflation adjusted mean WTP in EUR
Bansal et al 2016	6 656 EUR
Bansal and Kockelman 2017	5 265 EUR
Daziano et al 2017	4 400 EUR
This study 2019	**3592 EUR**
Schoettle and Sivak 2014	1000 - 1500 EUR*
IHS Markit 2017	915 EUR**
*Estimation, clear mean WTP not reported, **Mean WTP for highest region, Germany	

Table 21 shows that willingness to pay for AVs was among the respondents was at a moderate level when compared to prior research. The variation in the results is quite extreme and it is therefore difficult to establish a common average or a rule-of-thumb for WTP. If only the region of the studies is considered, the American studies (Bansal et al 2016; Bansal & Kockelman 2017) have observed a higher level of WTP than the studies conducted in Europe and Australia. Most of the studies that are listed in Table 21 also observed that more than half of the respondents would not pay anything at all for AV technology. This study however made a different conclusion as only about a fourth of the respondents were non-payers.

It could be expected that measuring willingness to pay with a quantitative survey would be inaccurate unless it was supplemented by a much wider range of supportive questions. These could include such variables as how much the respondents usually pay for car technologies; do they purchase their vehicles new or second-hand and how many people use the same vehicle. This could have helped to profile the respondents better in order to evaluate more clearly what factors affect their responses on WTP. The reason why WTP was not measured this exhaustively in this study was because it would have taken too much space from other important questions. It seems likely however that if AV academia wishes to establish some level of consensus on willingness to pay, the research needs to begin using a more varied line of questioning, and more background variables need to be controlled for than just the bare minimum.

7.3 Theoretical and practical contributions

The research gap which spawned the motivation for this study was the inconsistency of the results made by prior research papers on acceptance and adoption of autonomous vehicles. After synthesizing the key findings made by prior notable studies and conducting an empirical enquiry to examine which findings could be validated, it is unclear whether the identified research gap has been bridged. This is because acceptance is an unstable construct, and studies that measure it will see relatively inconsistent results even if they were conducted with the same respondent group at different points in time. This is true especially for an upcoming technology which people do not yet have much experience of.

While this study's original intentions was to seek whether some level of consistency could be established concerning the technology acceptance towards autonomous vehicles, this study concludes by arguing that such consistency cannot be established at this stage of the AV technology's life-cycle. Measuring acceptance of AVs will remain to be valuable, but the results will be heavily tied to the sample which was collected and the point in time the data collection took place.

In the end, this study's theoretical contributions do not reflect what they were expected to be in the beginning of the research process. This does not mean that this study would be void of theoretical contributions altogether. In fact, in the line of AV literature, this thesis paper was rather unique. There are numerous studies that have measured consumer acceptance of autonomous vehicles, but not many of them have included a regression analysis of the survey findings to examine what factors affect AV acceptance. The fact that this study's research framework was heavily rooted in technology acceptance theory makes this an explanatory study, but the context in which this framework was used adds an exploratory component as well. It seems that only one study has used the car technology acceptance model to measure how consumers perceive autonomous vehicles and analyzed how the CTAM predictor items affect AV acceptance (Böhm et al 2017). However, this earlier study was a limited enquiry with only 70 participants, and it was more focused on measuring attitudes towards AVs rather than each of the other predictor items of CTAM. This thesis work used a wider selection of predictor variables and could thus rank and compare their effect.

One theoretical contribution which this study makes originates from the format of the survey. The online questionnaire was deliberately constructed to influence the responses as little as possible because it was deemed important that the existing acceptance of the respondents would not be altered as a result of taking the survey. As explained in methodology segment of this thesis paper, this kind of minimalistic approach is far less common than how views towards AV technology are usually measured. Testing hypothetical usage scenarios and their effect on AV acceptance as so many other studies have done is not a flawed approach by any means, but it is important that some studies aim to keep the responses intact and uninfluenced. This way the research participants answer only based on the level of knowledge they accumulated of autonomous vehicles through natural communication channels prior to taking the survey. This study therefore makes a contribution to AV literature of how the participants of this research perceived autonomous vehicles in late 2018 simply on the basis of public conversation about this innovation so far.

Besides theoretical contributions, this study makes a few practical contributions as well. The raw data provided by this study can be used to see which aspects of AV acceptance need to be paid attention to the most. The survey respondents already had high expectations for safety of autonomous vehicles, but expectations for cost reductions and value of time benefits were at a much a lower level. Organizations that have it in their interest to grow the popularity of the AV technology should therefore diligently communicate these benefits to the public. The literature review revealed that the AV technology has no shortage of potential, but there are uncertainties in how the diffusion of autonomous vehicles can get to a point where this potential can be fully harnessed.

A second practical contribution that this thesis paper makes was studying the acceptance of a respondent group that consist mainly of Finnish citizens. This is a relatively understudied demographic compared to residents of larger European nations. As the resistance towards AVs was deemed to be at a low level among the participants of this research, the survey results can be useful for companies that consider testing autonomous vehicles and related projects in Finland. Interest towards this type of activity has been on the rise in the recent years because Finland has a relatively favorable legislative environment for autonomous vehicles. Implications of a supportive public opinion can further support these efforts.

7.4 Limitations

Several limitations to the study appeared during the research process. Some of these could be anticipated while others occurred unexpectedly. The respondent group leaned heavily towards highly educated people which meant that the empirical results do not reflect the views of the entire consumer base. The size of the sample was also relatively small compared to what is commonly preferred in consumer perception research. What this means is that the results are not generalizable beyond the demographics of the survey participants.

The compact length of the survey had its own limitations that were addressed in section 5.3.1. In hindsight, there were a few questions concerning attitude and self-efficacy which should have been worded differently as these questions measured the respondents’ views towards new technologies in general rather than their views towards autonomous vehicles. This was not deemed to a problem before the survey was conducted as the goal was to measure attitude and self-efficacy with factor variables, but as described in the measure development chapter, these factor variables could not be reliably formed. What this meant was that attitude and self-efficacy were not accurately measured in this study.

The variables of social influence and compatibility were each also measured only by one question in the survey which limits the validity of the results for these research framework constructs. These are however trade-offs rather than unambiguous drawbacks, and the fact they were made meant that the research was able to attain a higher number of participants.

The multiple linear regression model suffered from some fit, specificity and heteroscedasticity issues. Because of this, the model may have had limitations to how accurately it could measure the relationships between the constructs of the research framework. While improvements could have been made by changing some of the variables included in the model, there was a theoretical justification for each variable that was used.

One of the major limitations of the study was the fact that cyber security, ethics and liability issues were left for close to no consideration in this thesis work. These themes were also not included in the survey, although they could potentially have a significant effect on acceptance of autonomous vehicles. Not everything could be fitted into this study, but these neglected issues can be a subject for future research.

7.5 Suggestions for future research

Since acceptance is an unstable construct, studies like these are worth replicating at regular intervals. While it might be difficult to establish a level of continuity and reliability in terms of AV acceptance at this point in time, future studies may begin to see a clearer level of continuity once the AV technology proliferates.

Future studies could also focus more on testing behavioral intentions towards public transport, taxis or other forms of transport that utilize AV technology. In this report the focus was more on personal vehicles. Willingness to pay was measured rather narrowly in this research and therefore future studies could benchmark WTP for AVs to WTP for other forms of transport. Reliable measurement of WTP also requires a more extensive range of background and control questions.

What could not be touched upon more than briefly in the context of this research was how people’s preferences for driving a car themselves affects acceptance and adaptation of autonomous vehicles. For example, could there be a causal relationship between driving enjoyment and AV acceptance? What could also be examined more closely is how respondents perceive the benefits of autonomous vehicles and how each of these affects behavioral intentions.

One final suggestion for future research would be to radically change the research methods and do a qualitative study instead. A higher input from each research participant might uncover details about people’s perception towards autonomous vehicles which quantitative research is not able to identify.

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APPENDICES

Appendix 1. Appendices for literature review and conceptual framework

Appendix 1.1. Overview of levels of automation by SAE Standard J3016

SAE level	Name	Narrative Definition	Execution of Steering and Acceleration/ Deceleration	*Monitoring* of Driving Environment	Fallback Performance of *Dynamic Driving Task*	System Capability *(Driving Modes)*
***Human driver* monitors the driving environment**						
0	No Automation	the full-time performance by the *human driver* of all aspects of the *dynamic driving task*, even when enhanced by warning or intervention systems	Human driver	Human driver	Human driver	n/a
1	Driver Assistance	the *driving mode*-specific execution by a driver assistance system of either steering or acceleration/deceleration using information about the driving environment and with the expectation that the *human driver* perform all remaining aspects of the *dynamic driving task*	Human driver and system	Human driver	Human driver	Some driving modes
2	Partial Automation	the *driving mode*-specific execution by one or more driver assistance systems of both steering and acceleration/ deceleration using information about the driving environment and with the expectation that the *human driver* perform all remaining aspects of the *dynamic driving task*	**System**	Human driver	Human driver	Some driving modes
***Automated driving system* ("system") monitors the driving environment**						
3	Conditional Automation	the *driving mode*-specific performance by an *automated driving system* of all aspects of the dynamic driving task with the expectation that the *human driver* will respond appropriately to a *request to intervene*	System	**System**	Human driver	Some driving modes
4	High Automation	the *driving mode*-specific performance by an automated driving system of all aspects of the *dynamic driving task*, even if a *human driver* does not respond appropriately to a *request to intervene*	System	System	**System**	Some driving modes
5	Full Automation	the full-time performance by an *automated driving system* of all aspects of the *dynamic driving task* under all roadway and environmental conditions that can be managed by a *human driver*	System	System	System	**All driving modes**

Appendix 1.2. Innovation adopter categories (Rogers 2003, p 282)

Innovators	The innovators are most venturesome of all adopter categories. They typically have "the ability to understand and apply complex technical knowledge". They also possess substantial financial resources, which makes them more willing to risk failure when adopting new innovations. Innovators often form networks with one another. They are vital for triggering innovation diffusion as they bring new ideas into social systems, but they are rarely opinion leaders.
Early adopters	Early adopters are more integrated locally than innovators, and thus they have more influence within their social system. As early adopters are not far ahead average individuals in innovativeness, they serve as relatable and respected role models for others contemplating adoption of the innovation. Change agents typically seek after this category to act as local missionaries in order to trigger the critical mass and speed up the diffusion process.
Early majority	The early majority adopts new ideas just before average system members do, which makes them an important link between the first movers and the relatively late adopters. They seldom hold opinion leadership positions, but they interact frequently with their peers, which increases interconnectedness in the social system. Their innovation decision period is longer in comparison to first movers, because they deliberate for some time before adopting new innovations.
Late majority	The late majority are best characterized by their skepticism. Together with the early majority they represent the largest adopter categories. For the late majority, adoption of the innovation can be a product of economic necessity or peer pressure. They adopt after most of the other members in the social system have already done so, and when most of the innovation's uncertainties have been cleared.
Laggards	Laggards are keen on following patterns how things have always been done in the past. Laggards communicate mainly with one another and are thus somewhat isolate from the rest of the social system. They lack awareness and possess almost no opinion leadership. Laggards may be in a precarious economic position which forces them to extreme caution what it comes to adopting new innovations.

Appendix 1.3. Bass diffusion models (Bass 1969; Bass et al 1994)

Original Bass Model (with constant market potential):

$$\frac{f(t)}{1-F(t)} = p + \frac{q}{M}\left[A(t)\right]$$

F(t) is the installed base fraction

f(t) is the rate of change of *F(t)*

p is the coefficient of innovation (external influence); the likelihood that someone who has not yet adopted the innovation will start using it because of advertizing or other external factors

q is the coefficient of imitation (internal influence); the likelihood that ssomeone who has not yet adopted the innovation will start using it because of "word-of-mouth" or other influence from those already using the product

M *is the* constant potential market; the total number of individuals who will eventually adopt the innovation

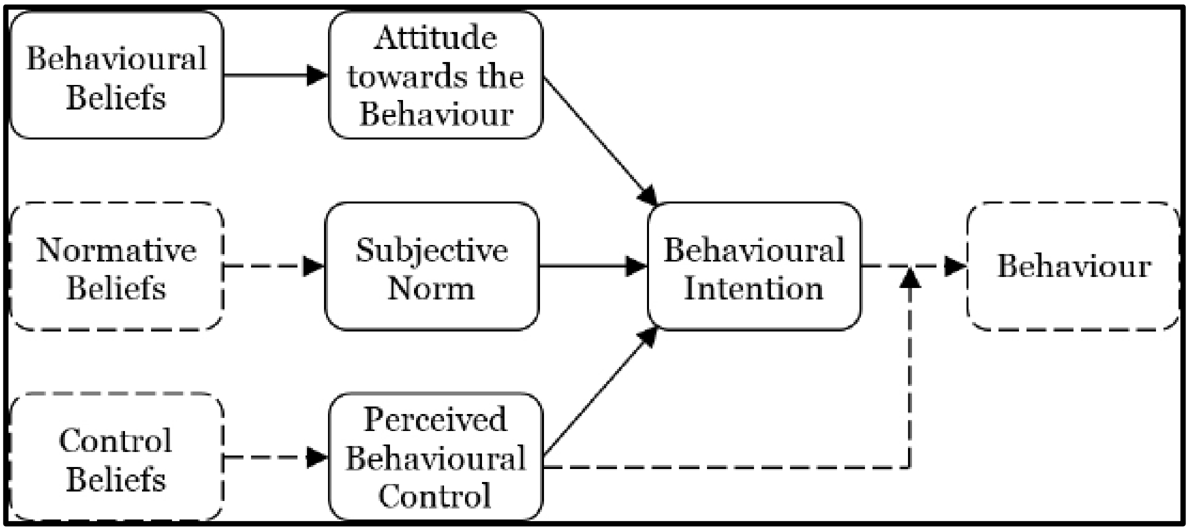
A(t) is the cumulative adopter function

Generalized Bass Model (with pricing):

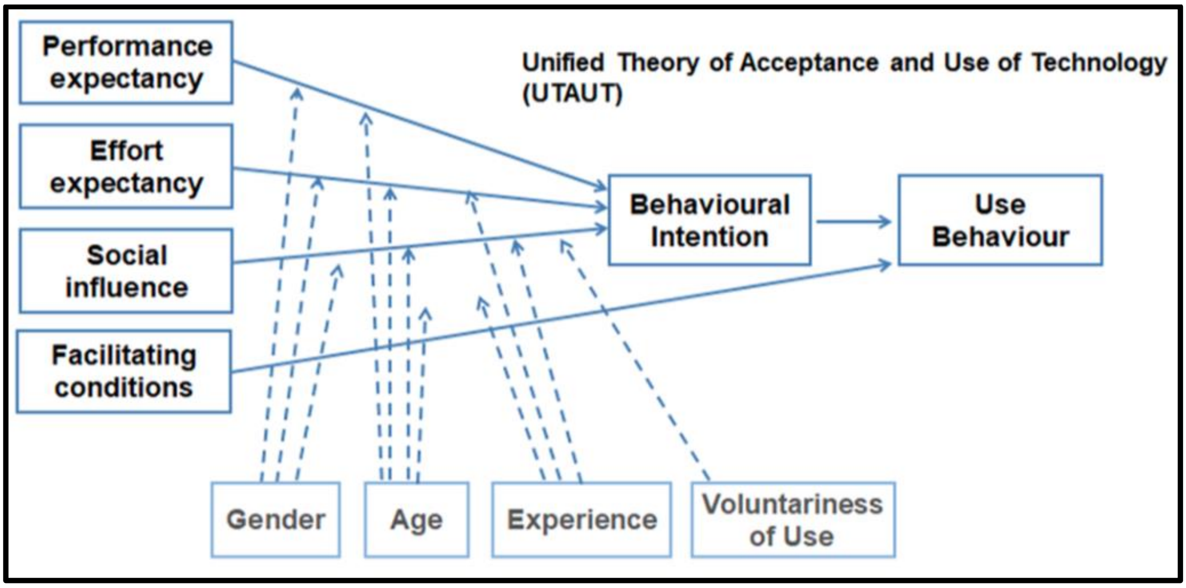
$$\frac{f(t)}{1-F(t)} = (p + qF(t))x(t)$$

x***(t)*** a function of percentage change in price and other variables

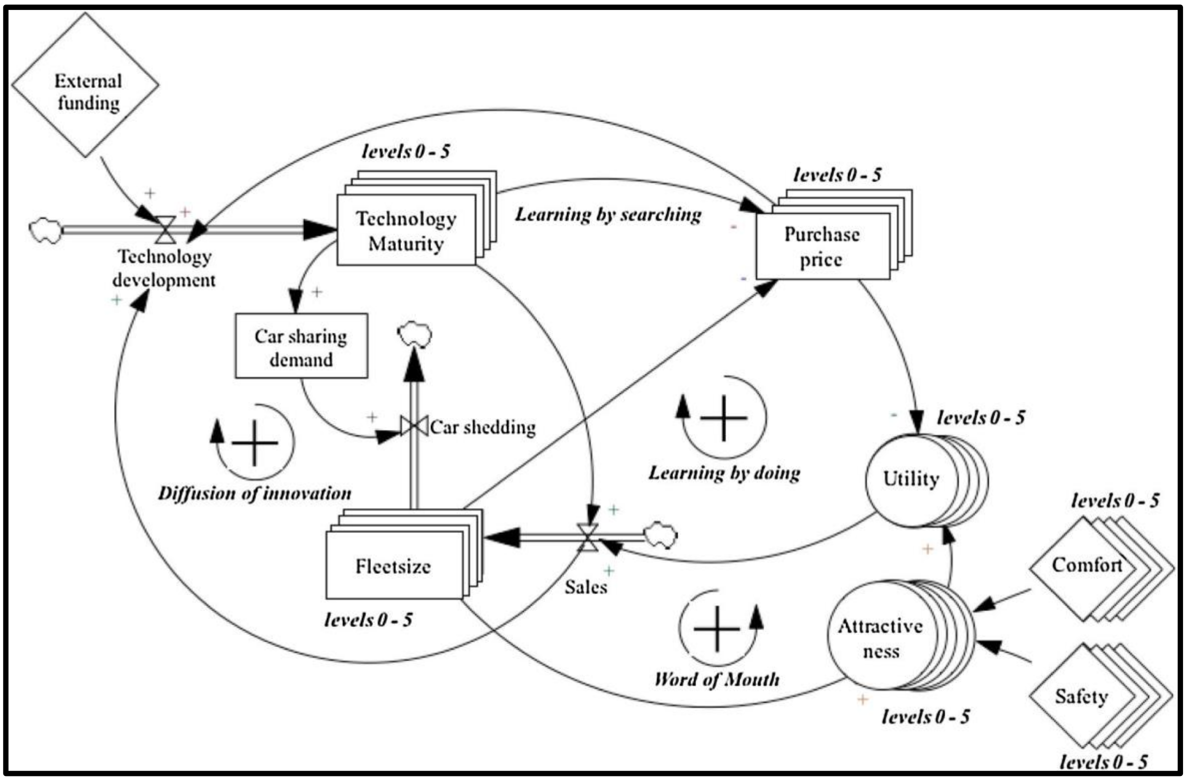
Appendix 1.4. Theory of planned behavior (Ajzen 1991)



Appendix 1.5. UTAUT model (Venkatesh et al 2003)



Appendix 1.6. Dynamic AV diffusion model (Nieuwenhuijsen et al 2018)



Appendix 2. Appendices for methodology

Appendix 2.1 English online survey form

Survey: Acceptance of Self-driving Cars

Welcome! My name is Frans Hollström and this survey is part of my master's thesis about public acceptance of self-driving cars.

I greatly appreciate the time and the effort all the respondents give me by taking this survey. Your help is invaluable, and without it, I could not do this study and complete my degree.

You don't need to be an expert on this topic to answer this survey. The survey consists of 30 multiple choice questions, half of which are dedicated to your background and your preferences as a transportation and technology user.

Since I want you to answer based on your current knowledge, I give only a short description of what self-driving cars are. I won't describe how they could be used, or what advantages and disadvantages they may have.

Expected duration: 5 minutes

Survey closes: 21st of December 2018

Anonymity:

This survey is completely anonymous. Responses cannot be traced back to respondents, and responses will be combined and summarized to further ensure anonymity. I will also not ask you to give any personally identifiable information.

(continues)

(Appendix 2.1 continuation)

Prior experiences 1/3

A self-driving car is a car that can fully drive itself without needing help or assistance from a human driver. Besides passenger cars, there can also be self-driving busses, taxis and trucks.

Have you ever used a self-driving vehicle? *

- ◯ Yes, at least once
- ◯ No

Prior Experiences 2/3

Have you ever used any driver assistance system?* *

- ◯ Yes, personally
- ◯ No, but I was present when someone else used it
- ◯ I have no experience

*For example a system which can:
- automatically park the car in a parking space
- keep the car centered on a lane
- brake in an emergency to prevent collision

Prior Experiences 3/3

How actively or inactively do you follow self-driving car related news? *

- ◯ Inactively
- ◯ Somewhat inactively
- ◯ Somewhat actively
- ◯ Actively

(continues)

(Appendix 2.1 continuation)

Transportation habits 1/2

Do you have a driver's license? *

- ◯ Yes
- ◯ No

Do you currently own a car (personally or jointly)? *

- ◯ Yes
- ◯ No

Transportation habits 2/2

Which option describes you best when you use a car? *

- ◯ Most of the time I prefer to be the passenger.
- ◯ Most of the time I prefer to be the driver.
- ◯ Either way is as fine.

What form of transport you most commonly use (time spent)? *

- ◯ Public transportation
- ◯ Personal car
- ◯ Motorcycle
- ◯ Walking and cycling
- ◯ Aeroplane
- ◯ Other form of transport

(continues)

(Appendix 2.1 continuation)

Ability to drive

Do you think that self-driving systems will be better or worse drivers than humans? *

	1	2	3	4	5	6	7	
Much worse	○	○	○	○	○	○	○	Much better

Please select what you prefer. *

- ○ Self-driving cars need to offer humans also manual controls besides automation.
- ○ Self-driving cars can forego controls for manual driving completely.

Safety 1/2

How comfortable or uncomfortable would you feel riding a self-driving car alone? *

	1	2	3	4	5	6	7	
Very uncomfortable	○	○	○	○	○	○	○	Very comfortable

How comfortable or uncomfortable would you feel riding a self-driving car with other people? *

	1	2	3	4	5	6	7	
Very uncomfortable	○	○	○	○	○	○	○	Very comfortable

(continues)

(Appendix 2.1 continuation)

Safety 2/2

How safe or unsafe do you think self-driving cars will be in comparison to human-driven cars? *

	1	2	3	4	5	6	7	
Significantly less safe	○	○	○	○	○	○	○	Significantly safer

Social influence

Would the people that are close to you approve or disapprove if you used self-driving cars? *

	1	2	3	4	5	6	7	
Strongly disapprove	○	○	○	○	○	○	○	Strongly approve

Do you agree or disagree with the following statement:

"There is a clear need in our society for self-driving cars." *

	1	2	3	4	5	6	7	
Strongly disagree	○	○	○	○	○	○	○	Strongly agree

(continues)

(Appendix 2.1 continuation)

Ease of use

How much easier or harder do you think self-driving cars will be to use than regular cars? *

	1	2	3	4	5	6	7	
Much harder	○	○	○	○	○	○	○	Much easier

How much easier or harder do you think self-driving cars will be to use than other existing transport? *

	1	2	3	4	5	6	7	
Much harder	○	○	○	○	○	○	○	Much easier

Usefulness 1/2

Do you think self-driving cars could replace your usual method of travel? *

	1	2	3	4	5	6	7	
Highly unlikely	○	○	○	○	○	○	○	Highly likely

(continues)

(Appendix 2.1 continuation)

Usefulness 2/2

How likely or unlikely self-driving cars could help you save time? *

	1	2	3	4	5	6	7	
Highly unlikely	○	○	○	○	○	○	○	Highly likely

How likely or unlikely self-driving cars could help you save money? *

	1	2	3	4	5	6	7	
Highly unlikely	○	○	○	○	○	○	○	Highly likely

Adaptation

How much time it usually takes you to learn to use new electronic devices, systems or equipment? *

	1	2	3	4	5	6	7	
I learn very slowly	○	○	○	○	○	○	○	I learn very quickly

How favorable or unfavorable view you usually have towards new technologies in general? *

	1	2	3	4	5	6	7	
Very unfavorable	○	○	○	○	○	○	○	Very favorable

(continues)

(Appendix 2.1 continuation)

Use and ownership

Could you see yourself taking a ride in a self-driving car? *

	1	2	3	4	5	6	7	
Very unlikely	○	○	○	○	○	○	○	Very likely

Do you think you will own a self-driving car some day? *

	1	2	3	4	5	6	7	
Very unlikely	○	○	○	○	○	○	○	Very likely

Willingness to pay

Pick the largest sum that you would be willling to pay for a full self-driving system on top of the standard price of a car. *

- ○ Zero
- ○ 500 € (about 570 $)
- ○ 1 500 € (~ 1700 $)
- ○ 3 000 € (~ 3 400 $)
- ○ 6 000 € (~ 6 800 $)
- ○ 10 000 € (~ 11 400 $)
- ○ 30 000 € (~ 34 200 $)

(continues)

(Appendix 2.1 continuation)

General acceptance

Do you think self-driving cars will overall be a good or a bad thing for our society? *

	1	2	3	4	5	6	7	
Very bad	○	○	○	○	○	○	○	Very good

Background

Great! Just a few questions left.

To which gender you most identify with? *

- ○ Male
- ○ Female
- ○ Other or non-conforming

Where do you live? *

- ○ Asia/Pacific
- ○ Europe
- ○ Latin America
- ○ Middle East/North Africa
- ○ North America (US, Canada or Mexico)
- ○ Sub-Saharan Africa

(continues)

(Appendix 2.1 continuation)

Please specify your highest completed education degree *

- ◯ Elementary school
- ◯ High school or occupational school
- ◯ Bachelor degree (university or uas)
- ◯ Master's degree
- ◯ Doctorate
- ◯ Muu: ____________

Please select your age *

- ◯ Under 18
- ◯ 18 - 25
- ◯ 26 - 35
- ◯ 36 - 45
- ◯ 46 - 55
- ◯ 56 - 65
- ◯ Over 65
- ◯ Prefer not to answer

What is approximately your monthly household net income? *

- ◯ Less than 1 000 e
- ◯ 1 000 – 2 999 e
- ◯ 3 000 – 5 999 e
- ◯ 6 000 - 10 000 e
- ◯ More than 10 000 e
- ◯ Prefer not to answer / I don't know

(continues)

(Appendix 2.1 continuation)

Survey: Acceptance of Self-driving Cars

Thank you very much for finishing the survey! Please support also other students with their research if you get a chance.

The finished thesis paper together with survey results will be published in http://lutpub.lut.fi/ in early 2019. I will also do my best to inform the respondents about the availability of the results by posting about it in the same places where I first unveiled the survey.

Appendix 2.2 Finnish online survey form

Kysely: Suhtautuminen itseohjautuviin autoihin

Tervetuloa! Nimeni on Frans Hollström ja tämä kysely on osa opinnäytetyötäni kuluttajien suhtautumisesta itseohjautuviin autoihin.

Tämä on pitkän opintotaipaleeni viimeinen suoritus. Arvostan suuresti kaikkia vastaajia jotka voivat tukea tutkimustani antamalla aikaansa tähän kyselyyn vastaamiseen.

Sinulla ei tarvitse olla aiempaa tietämystä aiheesta osallistuaksesi kyselyyn. Kyselyssä on 30 monivalintakysymystä joista noin puolet käsittelevät vastaajien taustaa ja mieltymyksiä liikenteen ja teknologian suhteen.

Koska toivon sinun vastaavan nykytietämyksesi pohjalta, annan kyselyssä ainoastaan lyhyen kuvauksen siitä mitä tarkoitan itseohjautuvilla autoilla. En kerro siitä mihin niitä tarkalleen voisi käyttää, tai kuvaile mitä mahdollisia hyviä tai huonoja puolia niillä voisi olla.

Keskimääräinen kesto: 5 minuuttia

Sulkeutuu: 21.12.2018

Anonymiteetti:

Kysely on kokonaan anonyymi eli vastauksia ei voida jäljittää takaisin vastaajille. Lopullisessa työssä vastaukset esitetään ryppäissä mikä edelleen vahvistaa nimettömyyttä. Vastaajilta ei myöskään missään vaiheessa kysytä tai kerätä tunnistetietoja.

(continues)

(Appendix 2.2 continuation)

Aiemmat kokemukset 1/3

Autonominen / itseohjautuva auto on auto joka pystyy ajamaan itsekseen ilman, että ihmisen tarvitsee auttaa ajamisessa. Henkilöautojen lisäksi myös bussit, taksit ja rekat voivat olla itseohjautuvia.

Oletko koskaan käyttänyt itseohjautuvaa autoa? *

- ◯ Kyllä, ainakin kerran
- ◯ En

Aiemmat kokemukset 2/3

Oletko koskaan käyttänyt mitään kuljettajan avustusjärjestelmää?* *

- ◯ Kyllä, henkilökohtaisesti
- ◯ En, mutta olen ollut läsnä, kun joku muu on käyttänyt sellaista
- ◯ Minulla ei ole kokemuksia sellaisista järjestelmistä

*Esim:
- Automaattista pysäköintiavustinta
- kaistalla pysymisen tukijärjestelmää
- automaattista hätäjarrutusjärjestelmää

Aiemmat kokemukset 3/3

Kuinka aktiivisesti tai epäaktiivisesti seuraat itseohjautuvia autoja koskevaa uutisointia? *

- ◯ Epäaktiivisesti
- ◯ Jokseenkin epäaktiivisesti
- ◯ Jokseenkin aktiivisesti
- ◯ Aktiivisesti

(continues)

(Appendix 2.2 continuation)

Liikennetottumukset 1/2

Onko sinulla ajokorttia? *

- ◯ Kyllä
- ◯ Ei

Omistatko auton (yksin tai yhteisesti)? *

- ◯ Kyllä
- ◯ En

Liikennetottumukset 2/2

Valitse mikä vaihtoehto kuvaa sinua parhaiten, kun käytät autoa: *

- ◯ Haluan useammin olla matkustaja kuin kuljettaja.
- ◯ Haluan useammin olla kuljettaja kuin matkustaja.
- ◯ Molemmat vaihtoehdot kelpaavat minulle yhtä hyvin.

Mikä on yleisin käyttämäsi liikennemuoto (käytetyssä ajassa mitattuna)? *

- ◯ Julkinen liikenne
- ◯ Henkilöauto
- ◯ Moottoripyörä
- ◯ Kävely ja pyöräily
- ◯ Lentokone
- ◯ Jokin muu keino

(continues)

(Appendix 2.2 continuation)

Kyvykkyys itseajamiseen

Arveletko itseohjautuvien autojen tulevan olemaan parempia vai huonompia kuljettajia kuin ihmiset? *

	1	2	3	4	5	6	7	
Paljon huonompia	○	○	○	○	○	○	○	Paljon parempia

Valitse kumpaa vaihtoehtoa kannatat *

- ○ Itseohjautuvissa autoissa pitää olla automaation lisäksi mahdollisuus myös manuaaliseen ajamiseen.
- ○ Itseohjautuvat autot voivat luopua manuaalisista (käsikäyttöisistä) ohjauslaitteista kokonaan.

Turvallisuus 1/2

Kuinka mukavalta tai epämukavalta sinusta tuntuisi olla itseohjautuvan auton kyydissä yksin? *

	1	2	3	4	5	6	7	
Erittäin epämukavalta	○	○	○	○	○	○	○	Erittäin mukavalta

Kuinka mukavalta tai epämukavalta sinusta tuntuisi olla itseohjautuvan auton kyydissä muiden ihmisten kanssa? *

	1	2	3	4	5	6	7	
Erittäin epämukavalta	○	○	○	○	○	○	○	Erittäin mukavalta

(continues)

(Appendix 2.2 continuation)

Turvallisuus 2/2

Kuinka turvallisia tai epäturvallisia itseohjaututuvat autot tulevat mielestäsi olemaan tavallisiin autoihin verrattuna? *

	1	2	3	4	5	6	7	
Merkittävästi epäturvallisempia	○	○	○	○	○	○	○	Merkittävästi turvallisempia

Sosiaaliset vaikutteet

Suhtautuisivatko lähimmäisesi hyväksyvästi vai kielteisesti, jos käyttäisit itseohjaututuvaa autoa? *

	1	2	3	4	5	6	7	
Todella kielteisesti	○	○	○	○	○	○	○	Todella hyväksyvästi

Oletko samaa vai erimieltä seuraavan väittämän kanssa:

"Yhdyskunnassamme on selvä tarve itseohjautuville autoille." *

	1	2	3	4	5	6	7	
Vahvasti eri mieltä	○	○	○	○	○	○	○	Vahvasti samaa mieltä

(continues)

(Appendix 2.2 continuation)

Helppokäyttöisyys

Kuvittelisitko itseohjautuvat autot helppokäyttöisemmiksi vai vaikeakäyttöisemmiksi kuin tavalliset autot? *

	1	2	3	4	5	6	7	
Paljon vaikeammiksi	○	○	○	○	○	○	○	Paljon helpommiksi

Kuvittelisitko itseohjautuvat autot helppokäyttöisemmiksi vai vaikeakäyttöisemmiksi kuin muut liikennemuodot? *

	1	2	3	4	5	6	7	
Paljon vaikeammiksi	○	○	○	○	○	○	○	Paljon helpommiksi

Hyödyllisyys 1/2

Voisivatko itseohjautuvat autot mielestäsi korvata pääsääntöisen liikkumismuotosi? *

	1	2	3	4	5	6	7	
Erittäin epätodennäköisesti	○	○	○	○	○	○	○	Erittäin todennäköisesti

(continues)

(Appendix 2.2 continuation)

Hyödyllisyys 2/2

Kuinka todennäköisesti tai epätodennäköisesti itseohjautuvat autot voisivat auttaa sinua säästämään aikaa? *

	1	2	3	4	5	6	7	
Erittäin epätodennäköisesti	○	○	○	○	○	○	○	Erittäin todennäköisesti

Kuinka todennäköisesti tai epätodennäköisesti itseohjautuvat autot voisivat auttaa sinua säästämään rahaa? *

	1	2	3	4	5	6	7	
Erittäin epätodennäköisesti	○	○	○	○	○	○	○	Erittäin todennäköisesti

Mukautuminen

Kuinka kauan sinulla normaalisti kestää oppia käyttämään uusia elektronisia laitteita tai ohjelmia? *

	1	2	3	4	5	6	7	
Opin erittäin hitaasti	○	○	○	○	○	○	○	Opin erittäin nopeasti

Kuinka myönteinen tai kielteinen näkemys sinulla yleensä on uusista teknologioista? *

	1	2	3	4	5	6	7	
Erittäin kielteinen	○	○	○	○	○	○	○	Erittäin myönteinen

(continues)

(Appendix 2.2 continuation)

Käyttö ja omistus

Näkisitkö itsesi ottamassa kyydin itseohjautuvalla autolla? *

	1	2	3	4	5	6	7	
Erittäin epätodennäköisesti	○	○	○	○	○	○	○	Erittäin todennäköisesti

Luulisitko omistavasi itseohjautuvan auton jonain päivänä? *

	1	2	3	4	5	6	7	
Erittäin epätodennäköisesti	○	○	○	○	○	○	○	Erittäin todennäköisesti

Halukkuus maksaa

Valitse suurin mahdollinen summa seuraavista vaihtoehdoista jonka olisit halukas maksamaan itseohjautuvuudesta auton perushinnan päälle. *

- ○ Nolla
- ○ 500 €
- ○ 1 500 €
- ○ 3 000 €
- ○ 6 000 €
- ○ 10 000 €
- ○ 30 000 €

(continues)

(Appendix 2.2 continuation)

Yleinen hyväksyttävyys

Tulevatko itseohjautuvat autot mielestäsi olemaan yleensä ottaen hyvä vai huono asia yhteiskunnallemme? *

	1	2	3	4	5	6	7	
Todella huono	○	○	○	○	○	○	○	Todella hyvä

Taustatiedot

Hienoa! Vielä muutama kysymys jäljellä.

Mikä on sukupuolesi? *

- ○ Mies
- ○ Nainen
- ○ Muu

Missä asut tällä hetkellä? *

- ○ Aasia/Australia
- ○ Eurooppa
- ○ Latinalainen Amerikka
- ○ Lähi-itä / Pohjois-Afrikka
- ○ Pohjois-Amerikka
- ○ Saharan eteläpuolinen Afrikka

(continues)

(Appendix 2.2 continuation)

Mikä on korkein suorittamasi koulutus tai tutkinto? *

- ◯ Peruskoulu
- ◯ Lukio tai ammattikoulu
- ◯ Kandidaatin tutkinto
- ◯ Maisterin tutkinto
- ◯ Tohtorin tutkinto
- ◯ Muu: __________

Mikä on ikäsi? *

- ◯ Alle 18
- ◯ 18 - 25
- ◯ 26 - 35
- ◯ 36 - 45
- ◯ 46 - 55
- ◯ 56 - 65
- ◯ Yli 65
- ◯ En halua vastata

Mitkä ovat keskimäärin kotitaloutesi käytettävissä olevat kuukausitulot? *

- ◯ Alle 1 000 e
- ◯ 1 000 – 2 999 e
- ◯ 3 000 – 5 999 e
- ◯ 6 000 - 10 000 e
- ◯ Yli 10 000 e
- ◯ En osaa / halua vastata

(continues)

(Appendix 2.2 continuation)

Kysely: Suhtautuminen itseohjautuviin autoihin

Kiitos erittäin paljon vastaamisesta! Toivottavasti tuet myös muiden opiskelijoiden tutkimuksia, jotta he menestyvät opinnoissaan.

Valmis gradu yhdessä kyselytulosten kanssa julkaistaan osoitteessa http://lutpub.lut.fi/ alkuvuodesta 2019. Teen myös parhaani ilmoittaakseni vastaajille tuloksista kertomalla niistä samoissa paikoissa missä keräsin vastaajia kyselylle.

Appendix 2.3 Data transformations

Question	**Variable changes**
Q1. Q3. Q4. Q5. Q6. Q7. Q8. Q9. Q10. Q11. Q12. Q13. Q14. Q15. Q16. Q18.	*No changes, all still 1-7 scale ordinal data*
Q2. Please select what you prefer.	*Transformed to binary data* Self-driving cars need to offer humans also manual controls besides automation. -> 0 Self-driving cars can forego controls for manual driving completely. -> 1
Q17. Pick the largest sum that you would be willing to pay for a full self-driving system on top of the standard price of a car.	*Three transformations from categorical to binary data* One: 0 = respondent would not pay anything at all (78) 1 = respondent would pay at least 500 e (222) Two: 0 = respondent would pay less than 3000 e or nothing at all (147) 1 = respondent would pay at least 3000 e (153) Three: 0 = respondent would pay less than 6000 e or nothing at all (147) 1 = respondent would pay at least 6000 e (153)

(continues)

(Appendix 2.3 continuation)

B1. To which gender you most identify with?	*Recode* Female -> 0 Male -> 1 Other or non-confirming -> 2
B2. Language of survey taken	English -> 0 Finnish -> 1
B3. Please specify your highest completed education degree	*Given nominal values* Other -> 0 Elementary school -> 0 Secondary, other or lower -> 0 Bachelor's degree (univ. or uas) -> 1 Master's degree -> 2 Doctorate -> 3
B4. Please select your age	Under 18 -> 0 18 - 25 -> 1 26 – 35 -> 2 36 – 45 -> 3 46 – 55 -> 4 56 – 65 -> 5 Over 65 -> 6 Prefer not to answer -> 6
B5. What is approximately your monthly household net income?	Prefer not to answer / I don't know -> 1 Less than 1 000 -> 1 1 000 – 2 999 -> 2 3 000 – 5 999 -> 3 6 000 - 10 000 -> 4 More than 10 000 -> 4
B6. Have you ever used a self-driving vehicle?	No -> 0 Yes, at least once -> 1
B7. Have you ever used any driver assistance system?	I have no experience -> 0 No, but I was present when someone else used it -> 1 Yes, personally -> 2

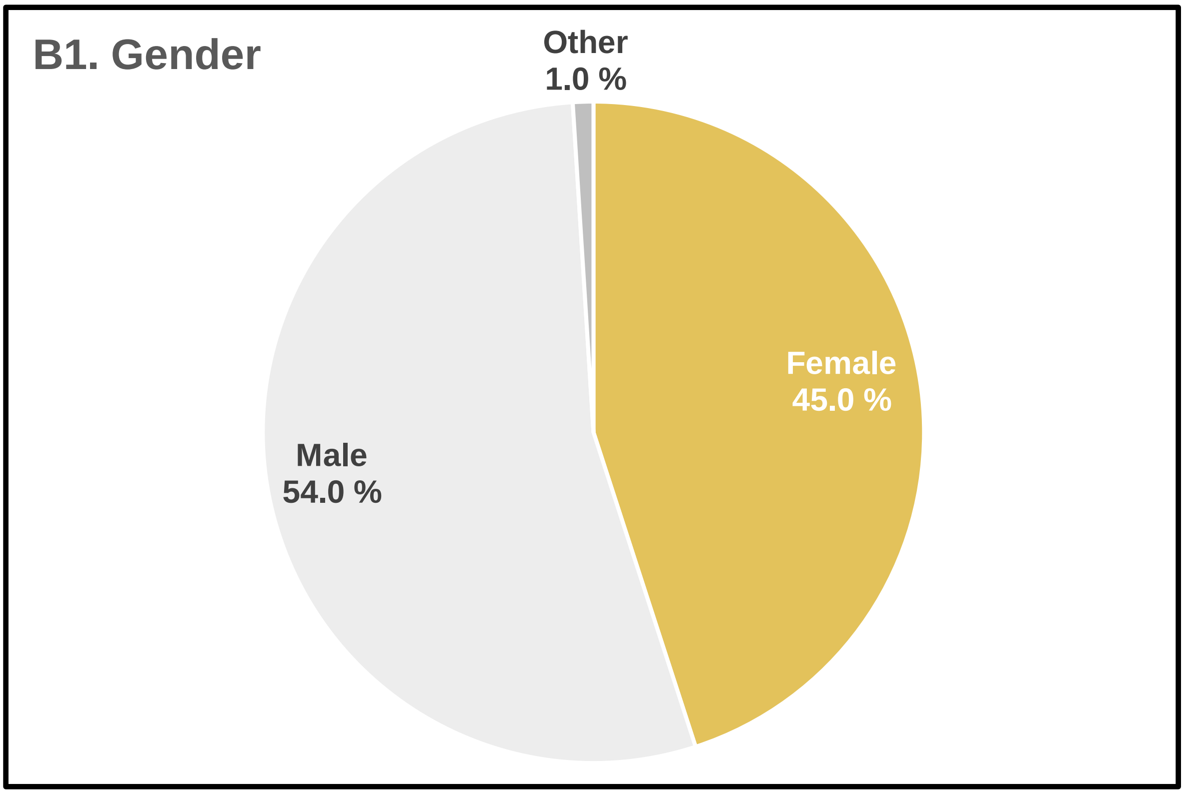
(continues)

(Appendix 2.3 continuation)

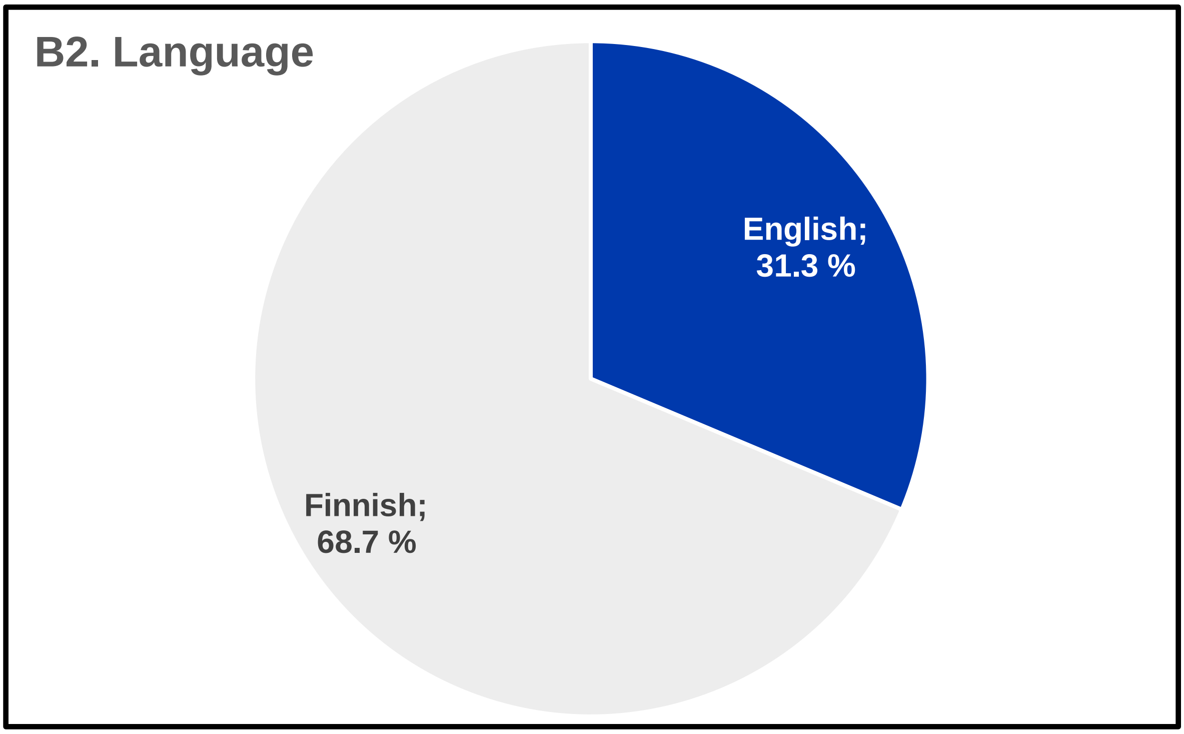
B8. How actively or inactively do you follow self-driving car related news?	Inactively -> 0 Somewhat inactively -> 1 Somewhat actively -> 2 Actively -> 2
B9. Do you have a driver's license?	No -> 0 Yes -> 1
B10. Do you currently own a car (personally or jointly)?	No -> 0 Yes -> 1
B11. Which option describes you best when you use a car?	Most of the time I prefer to be the driver. -> 0 Either way is as fine. -> 1 Most of the time I prefer to be the passenger. -> 2
B12. What form of transport you most commonly use (time spent)?	Other form of transport -> 1 Walking and cycling -> 1 Public transportation -> 2 Personal car -> 3

Appendix 3. Appendices for descriptive analysis

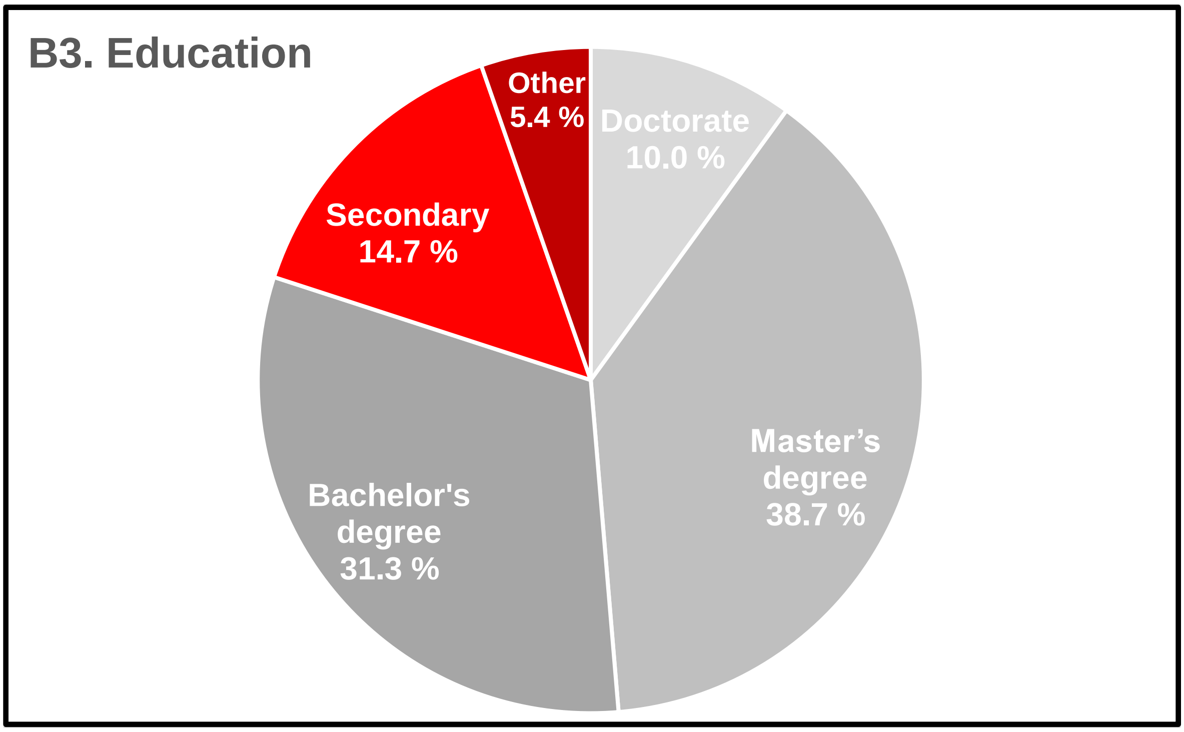
Appendix 3.1 Chart for B1 results, gender



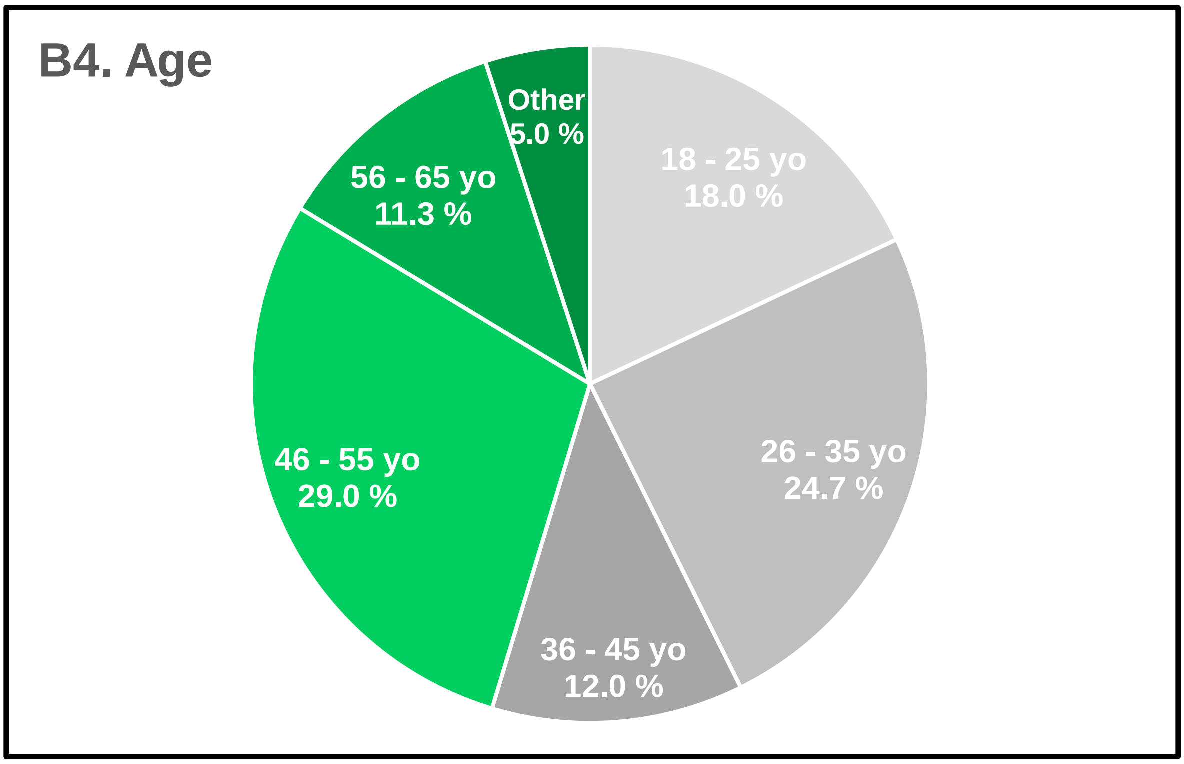
Appendix 3.2 Chart for B2 results, language



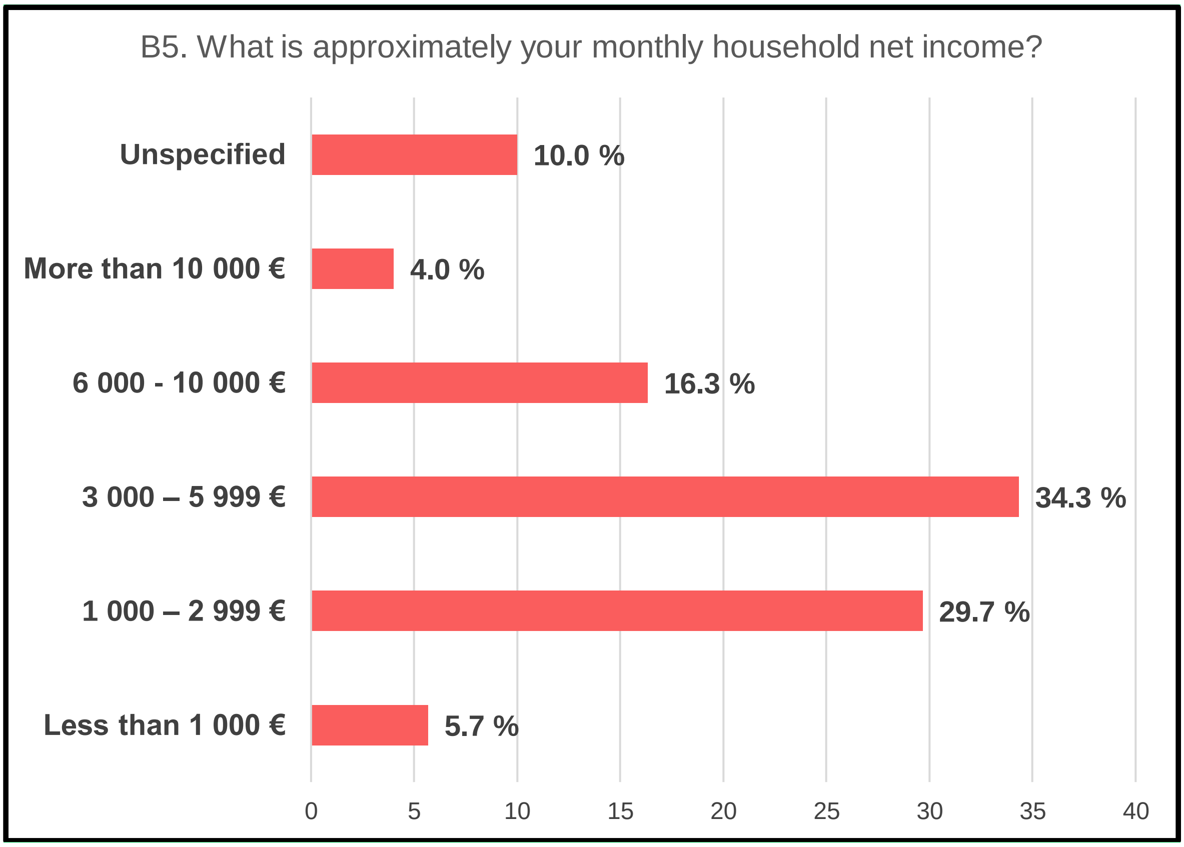
Appendix 3.3 Chart for B3 results, education



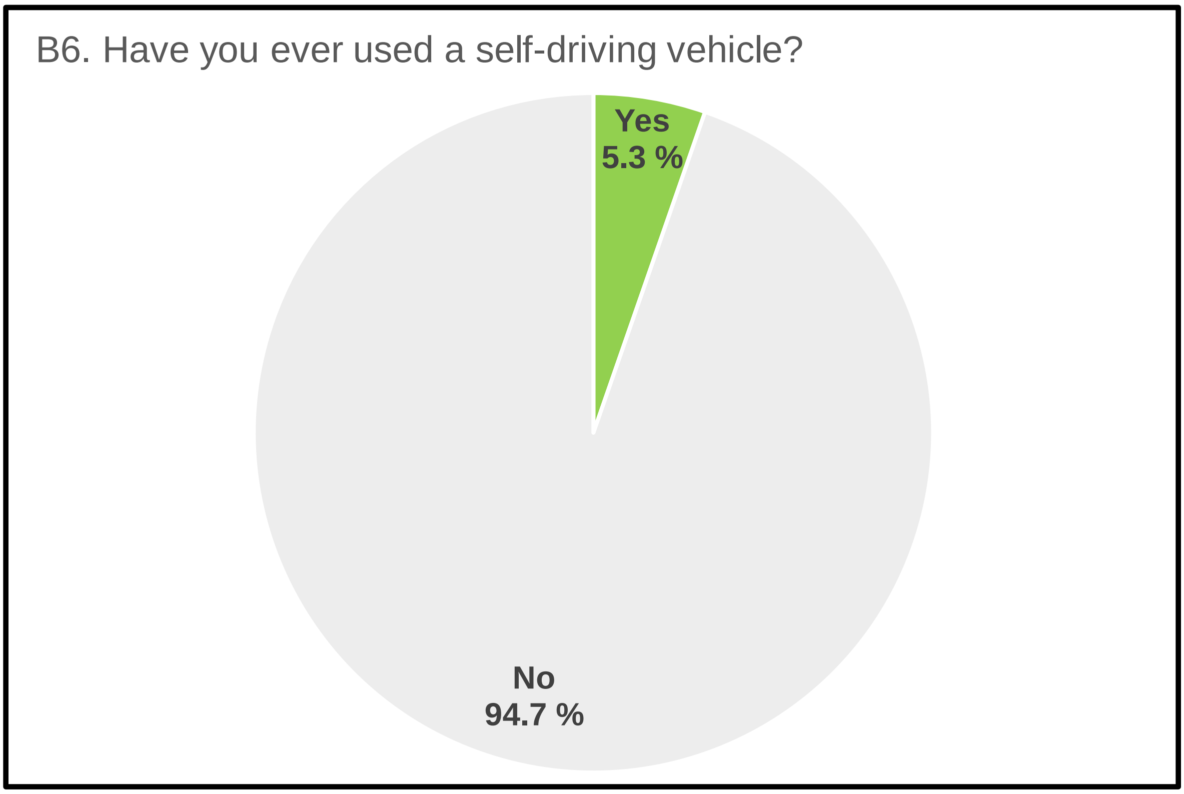
Appendix 3.4 Chart for B4 results, age



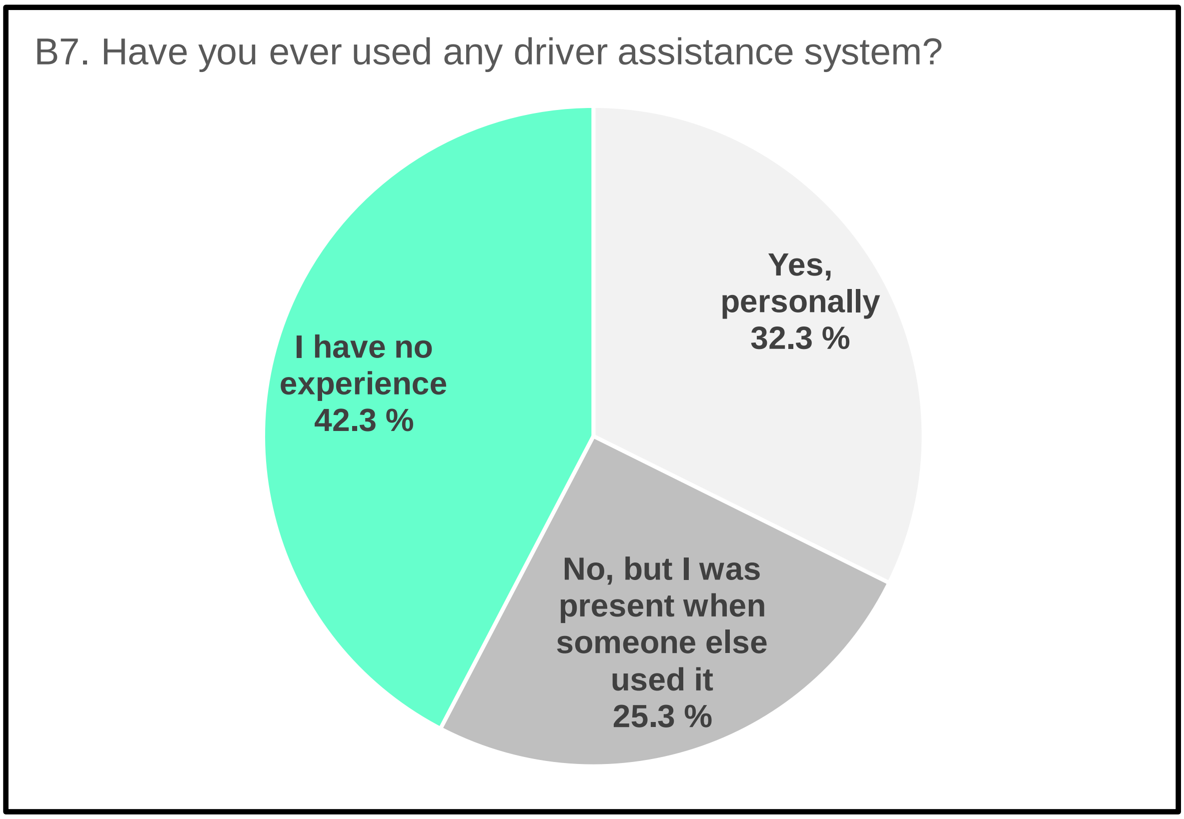
Appendix 3.5 Chart for B5 results, monthly household income



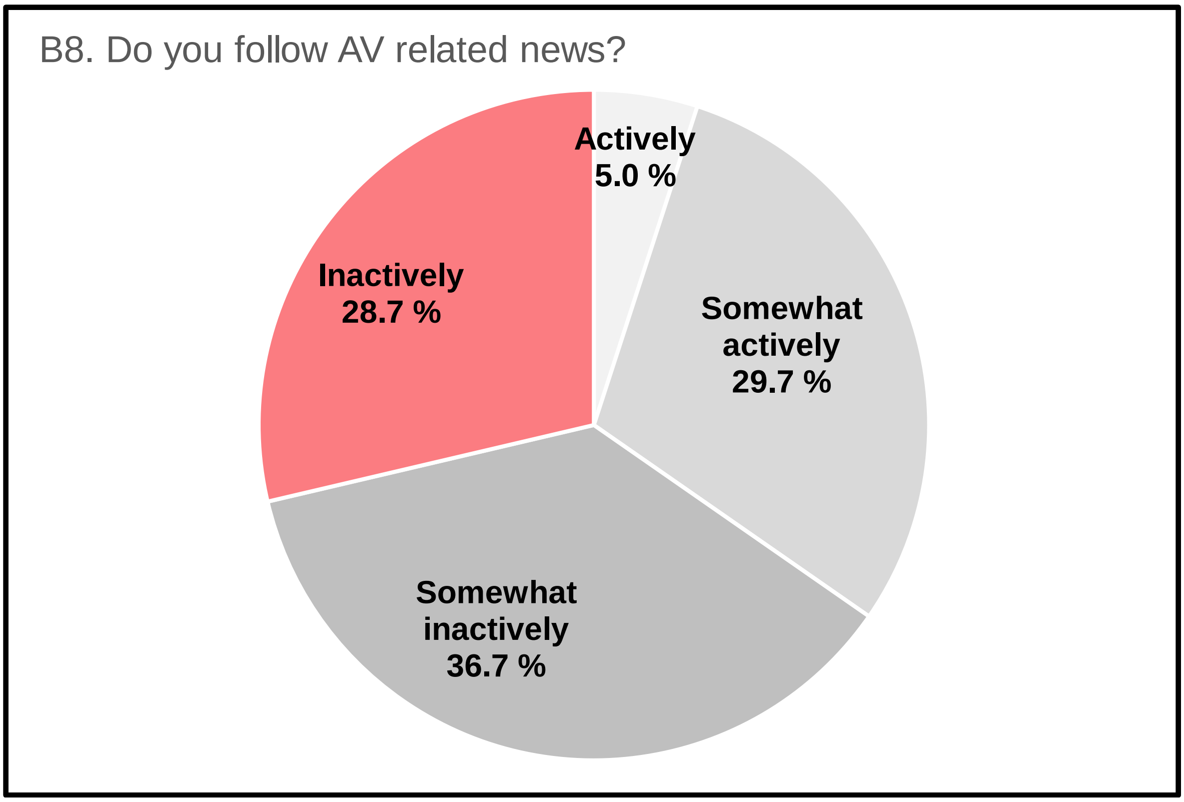
Appendix 3.6 Chart for B6 results, prior AV experience



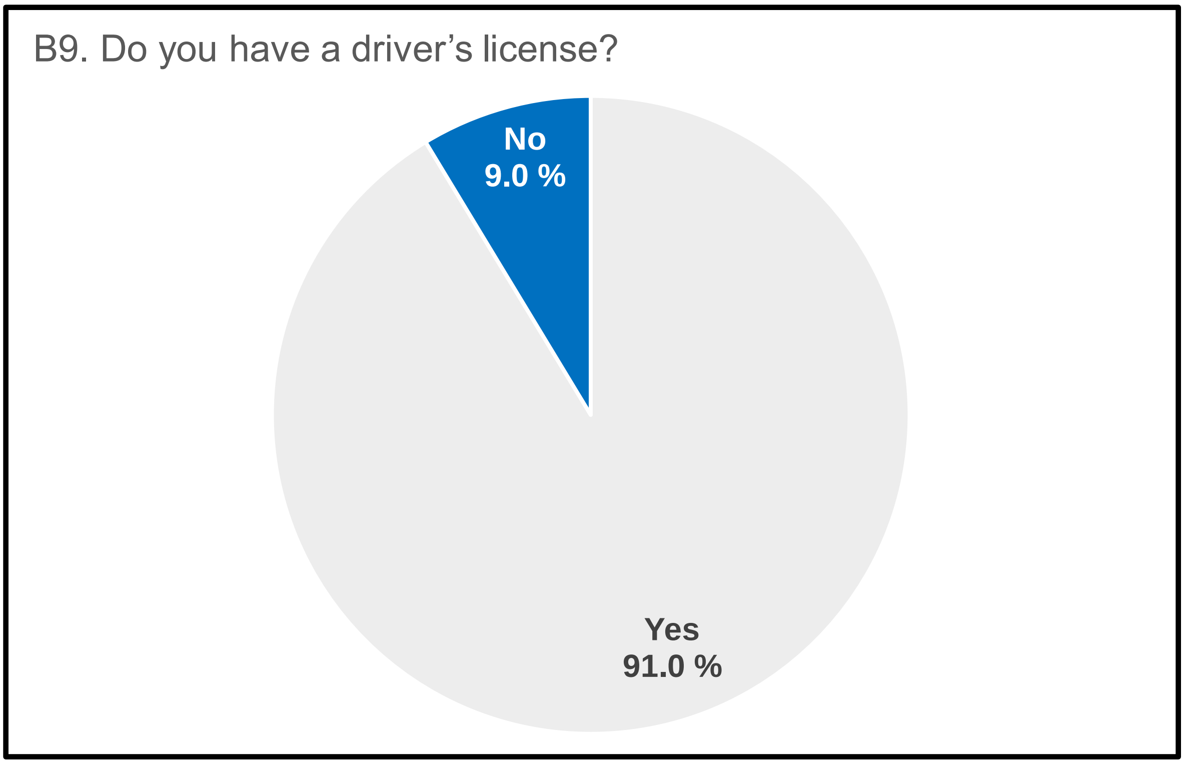
Appendix 3.7 Chart for B7 results, prior ADAS experience



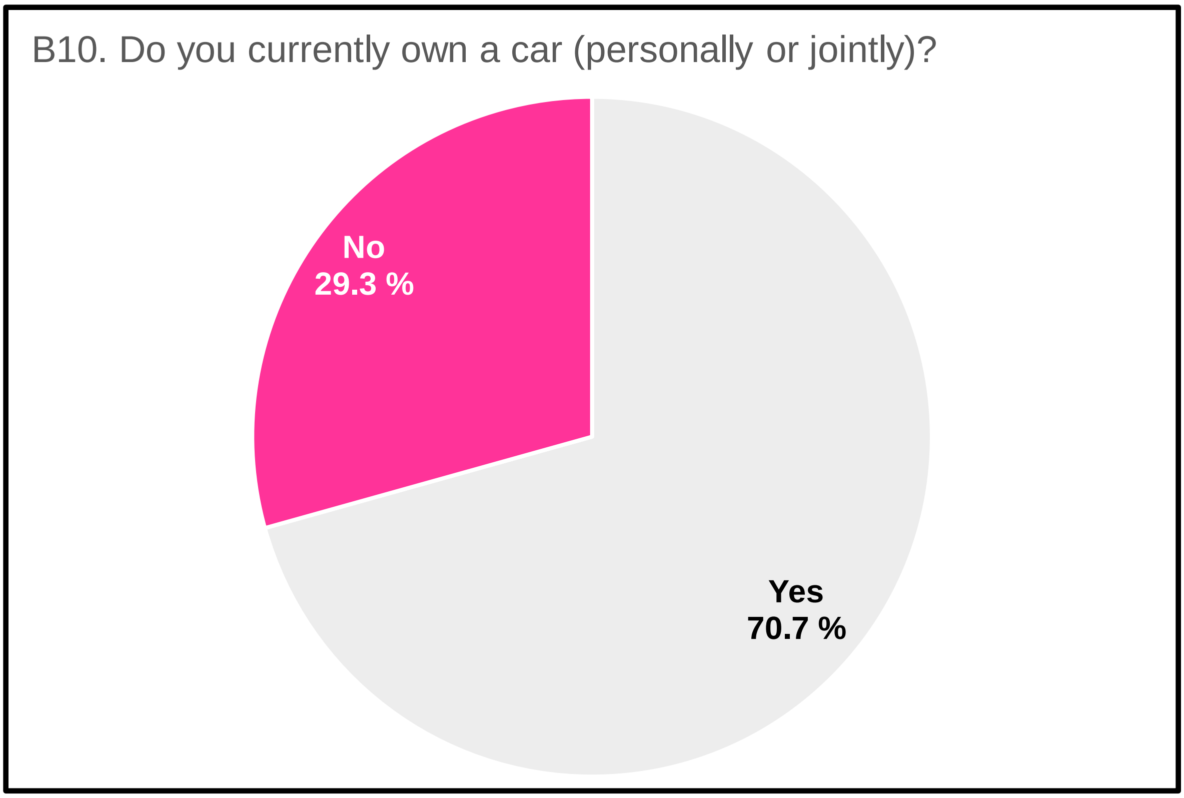
Appendix 3.8 Chart for B8 results, attention to AV related news



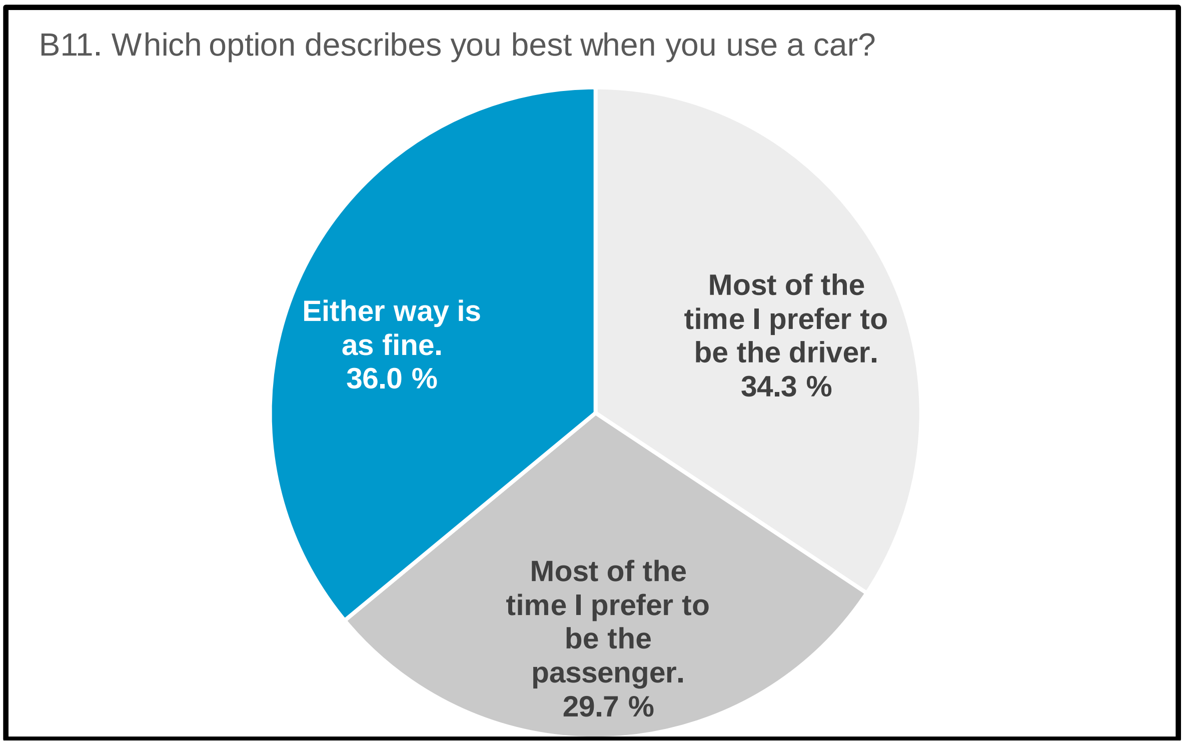
Appendix 3.9 Chart for B9 results, driver's license



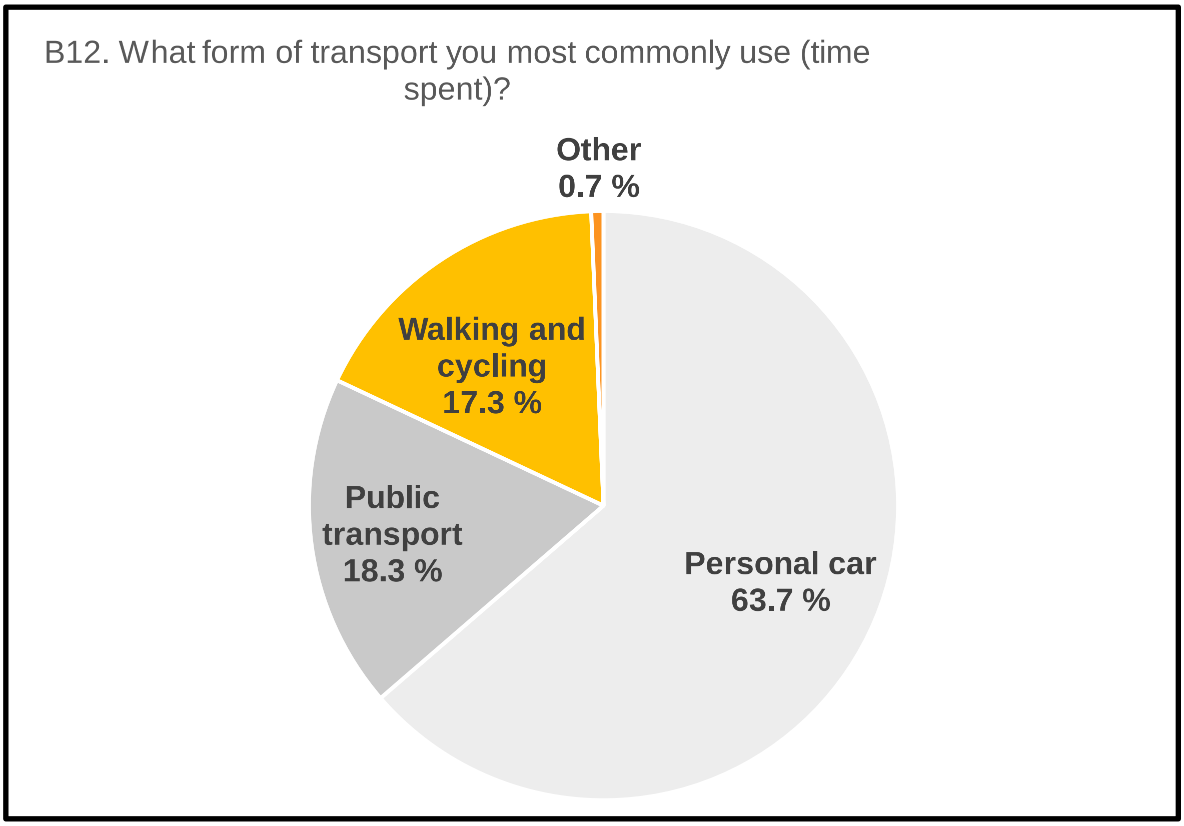
Appendix 3.10 Chart for B10 results, car ownership (personally or jointly)



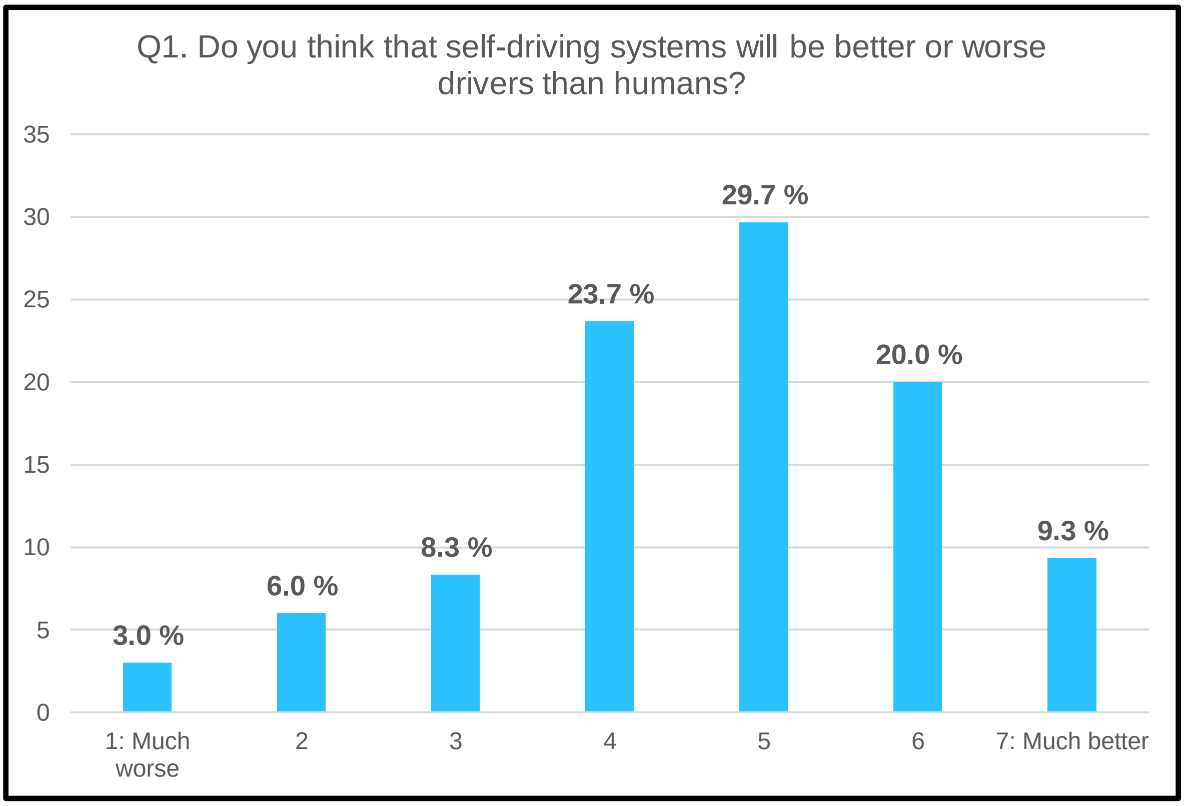
Appendix 3.11 Chart for B11 results, car use preference



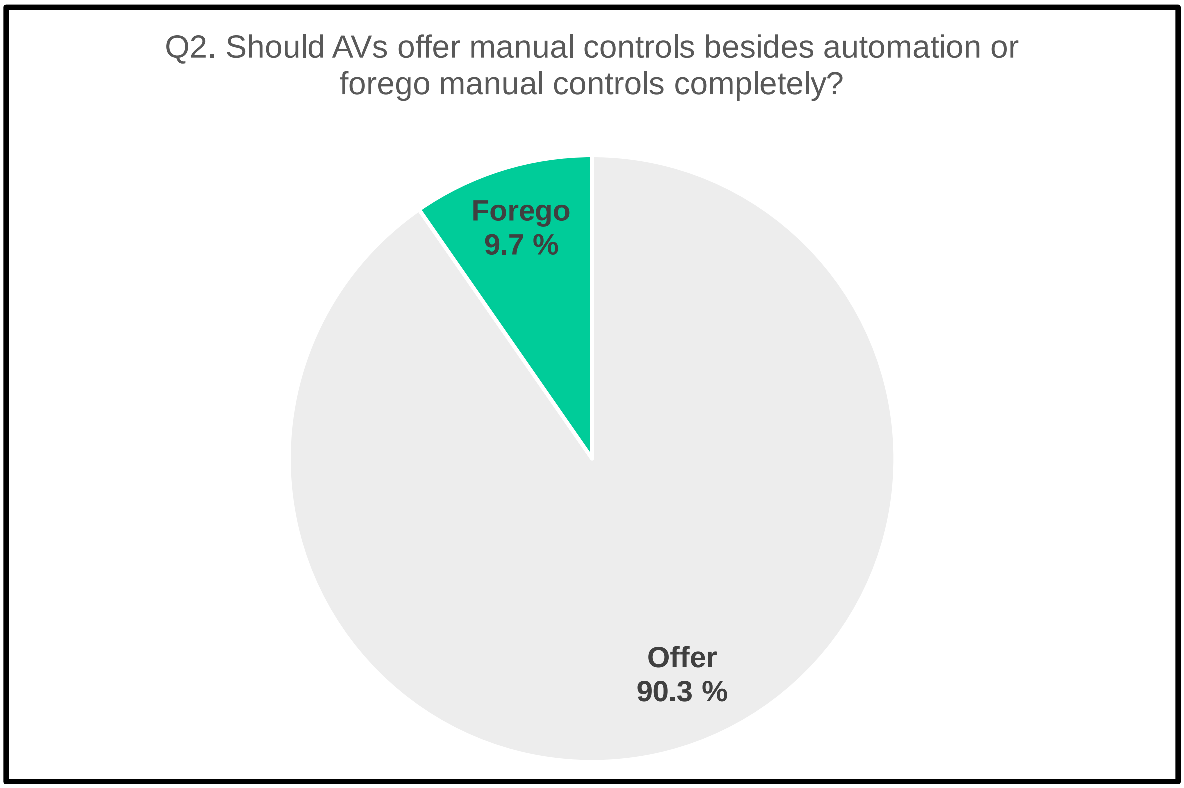
Appendix 3.12 Chart for B12 results, transportation



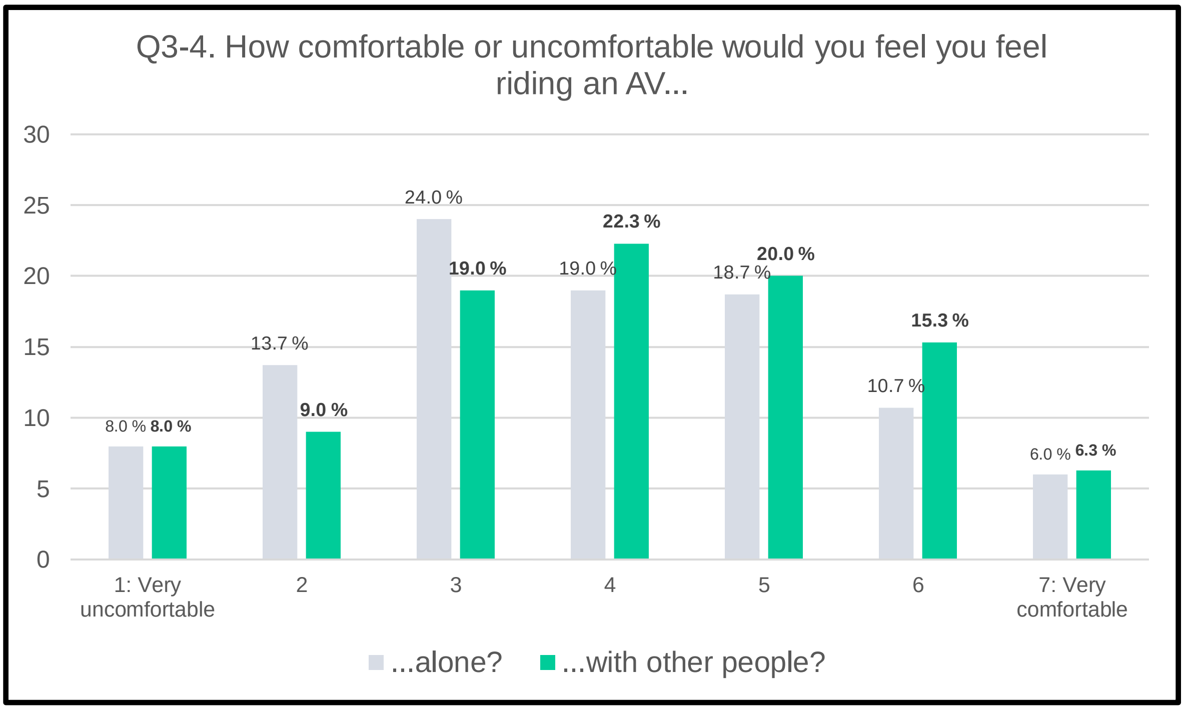
Appendix 3.13 Chart for Q1 results, ability of AVs to drive



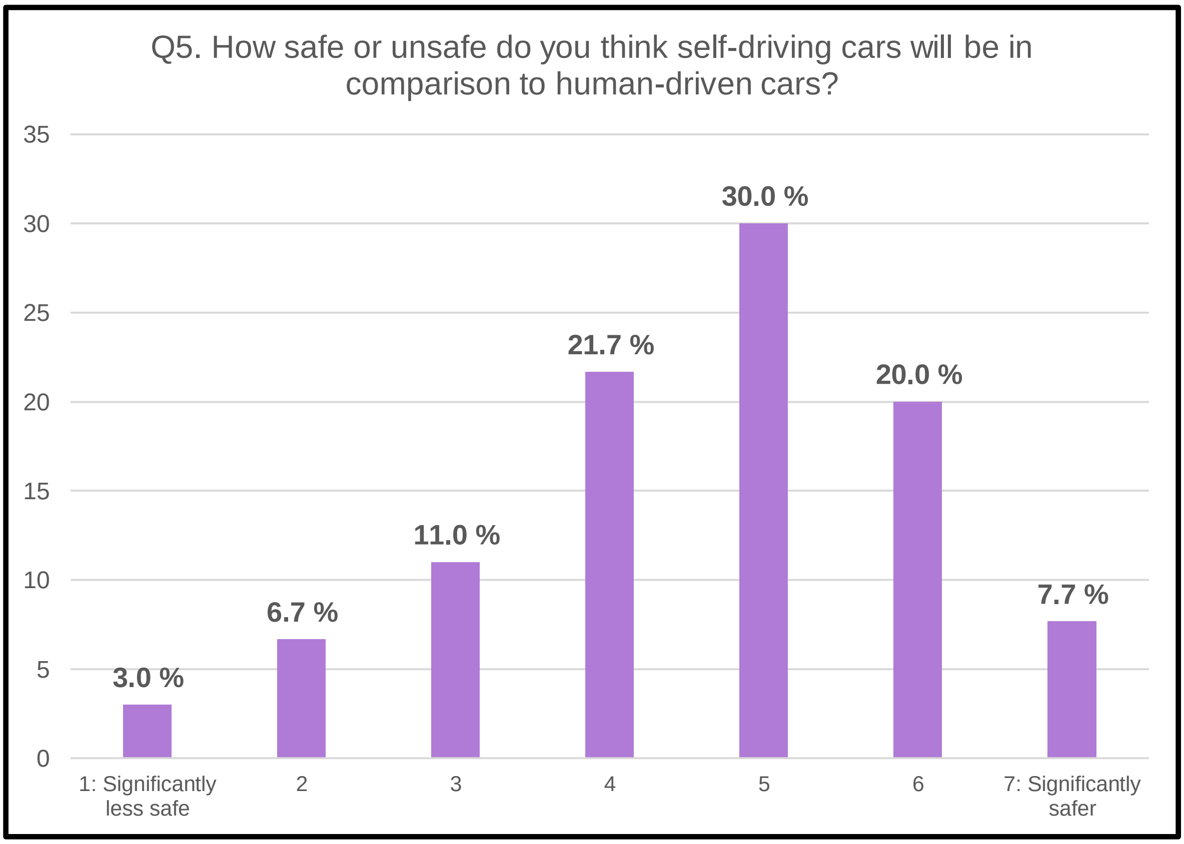
Appendix 3.14 Chart for Q2 results, retainment of manual controls



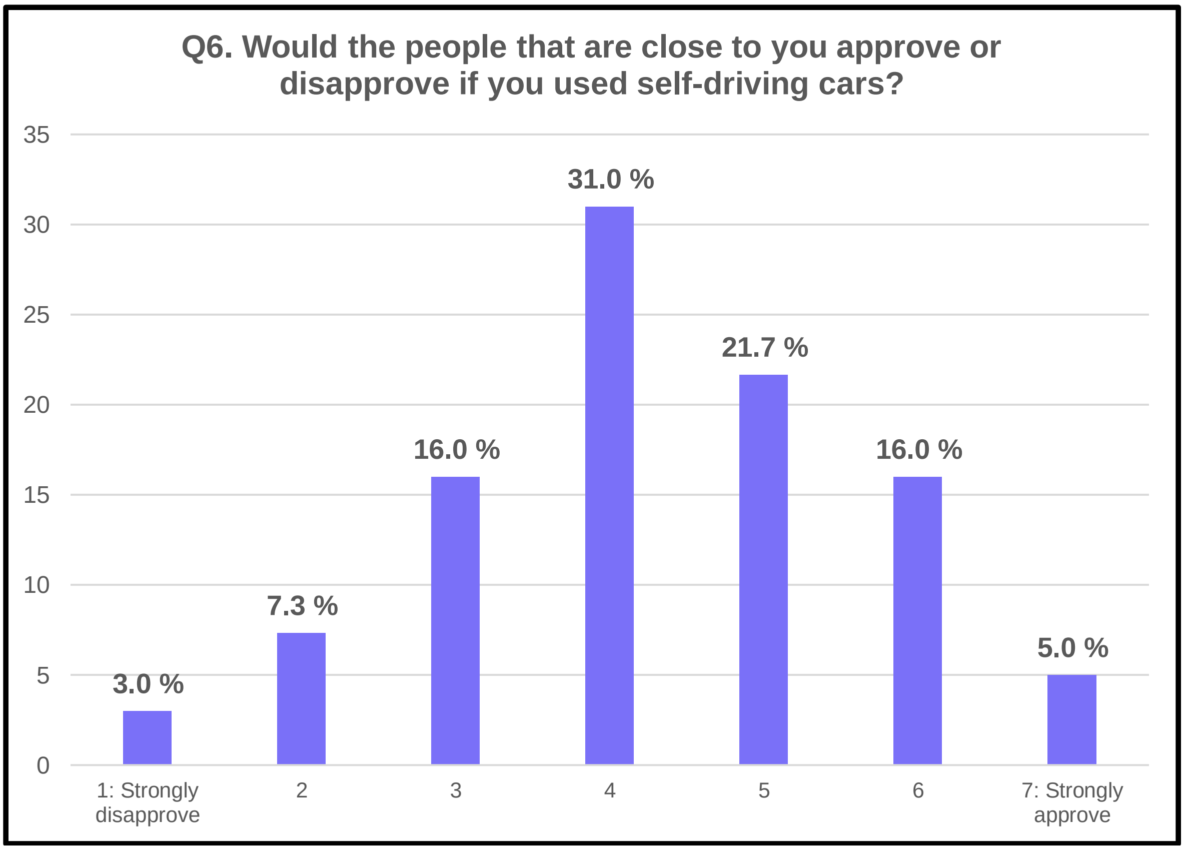
Appendix 3.15 Chart for Q3 and Q4 results, comfort while riding AV



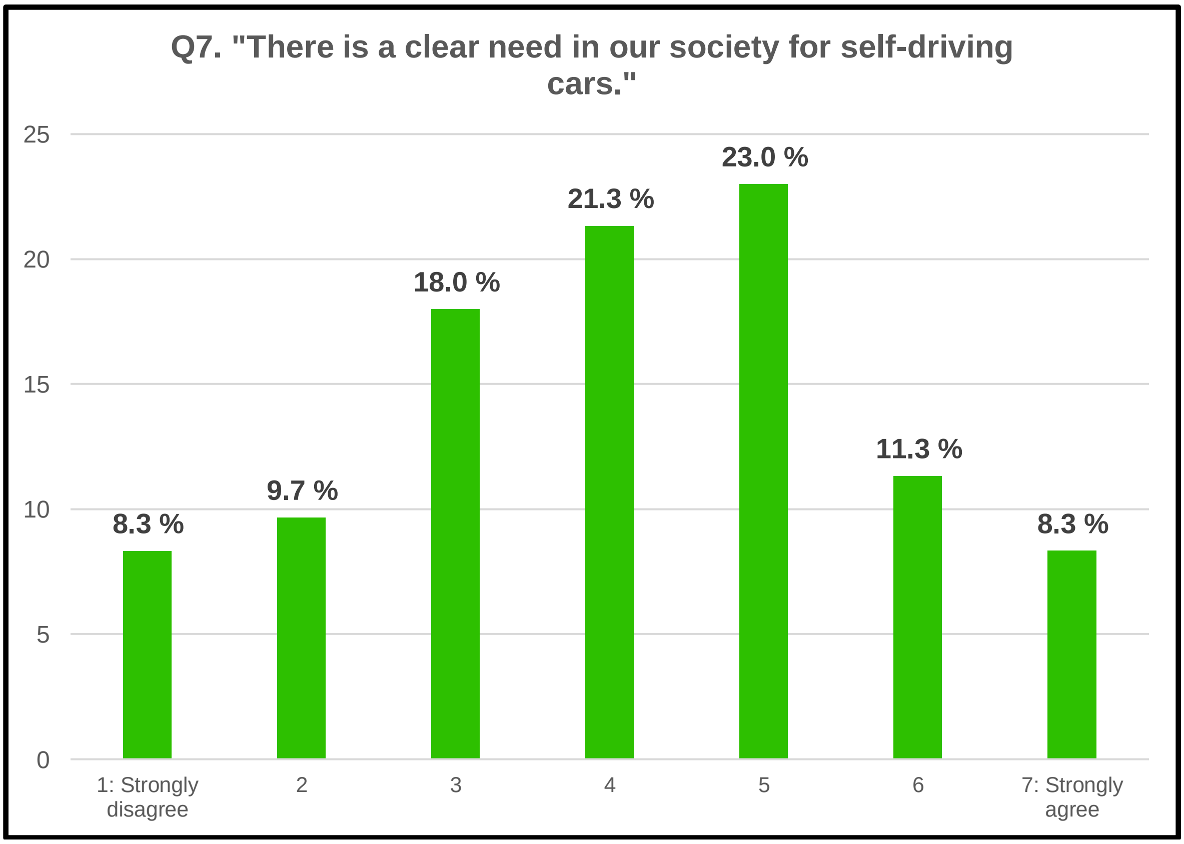
Appendix 3.16 Chart for Q5 results, AV safety compared to HD



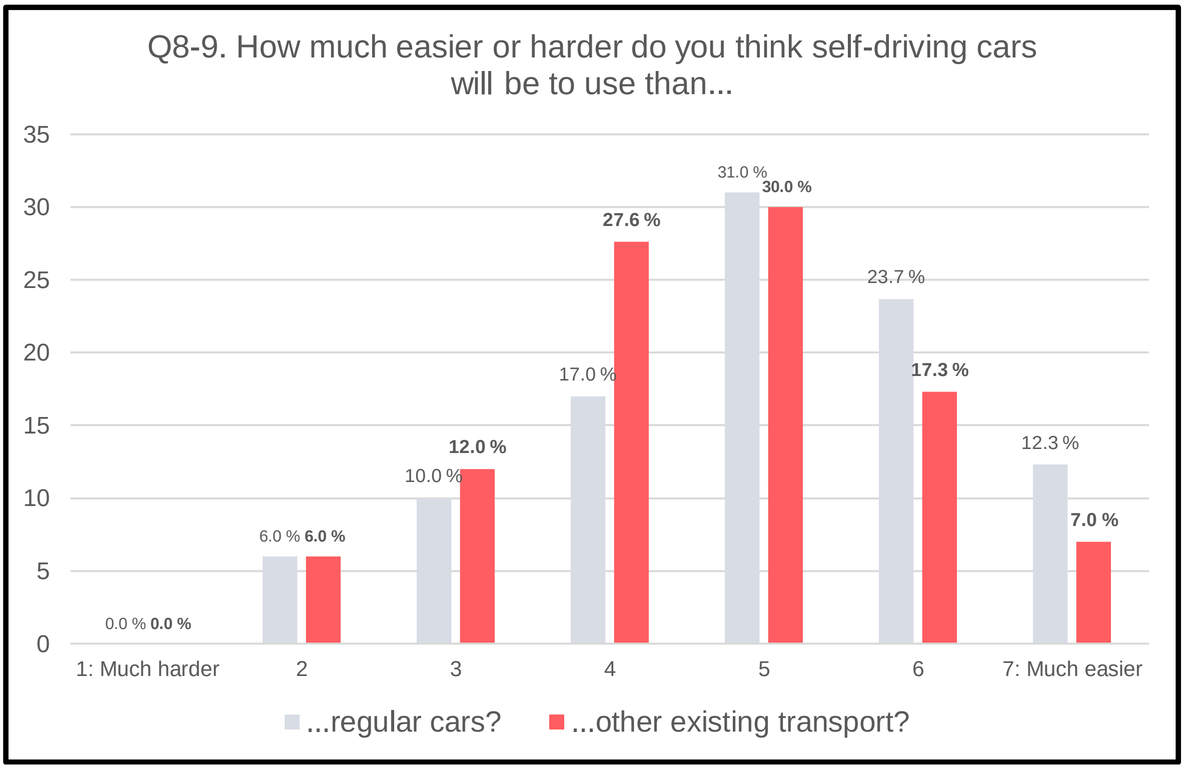
Appendix 3.17 Chart for Q6 results, social influence



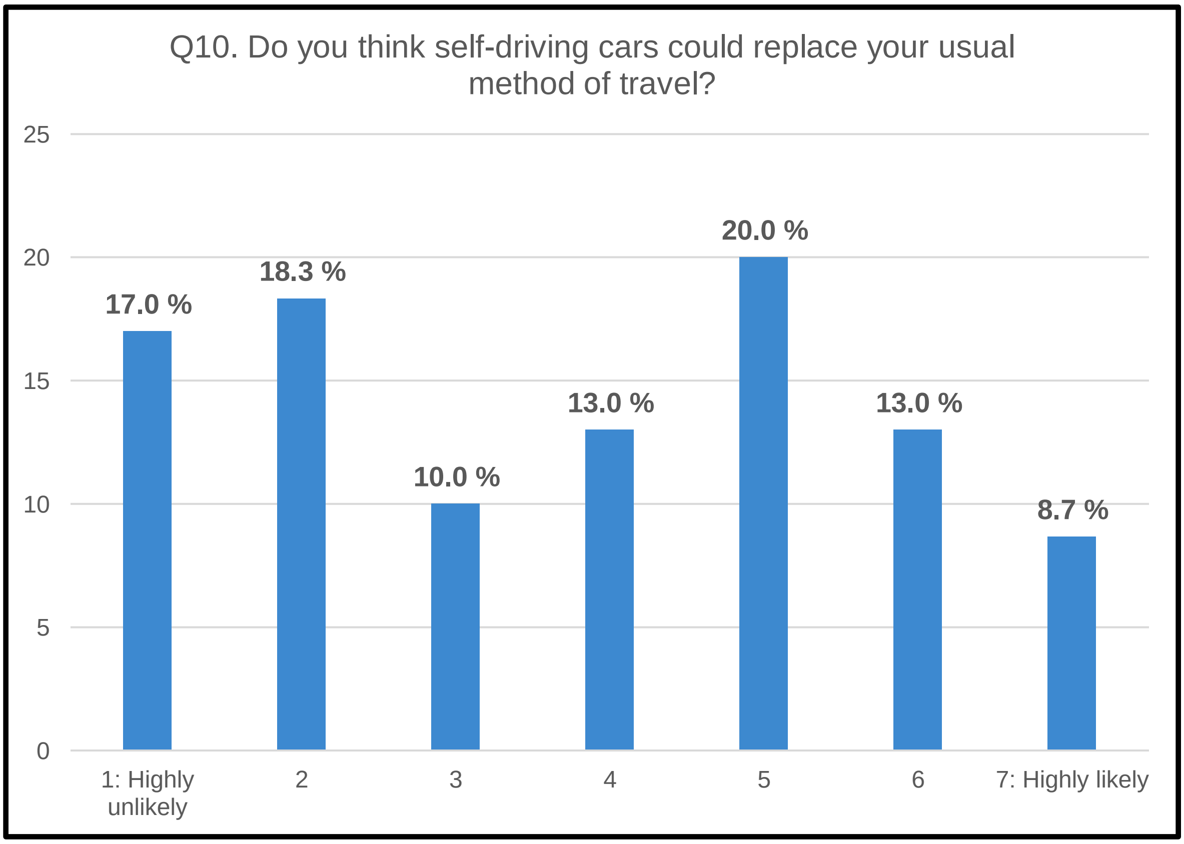
Appendix 3.18 Chart for Q7 results, compatibility



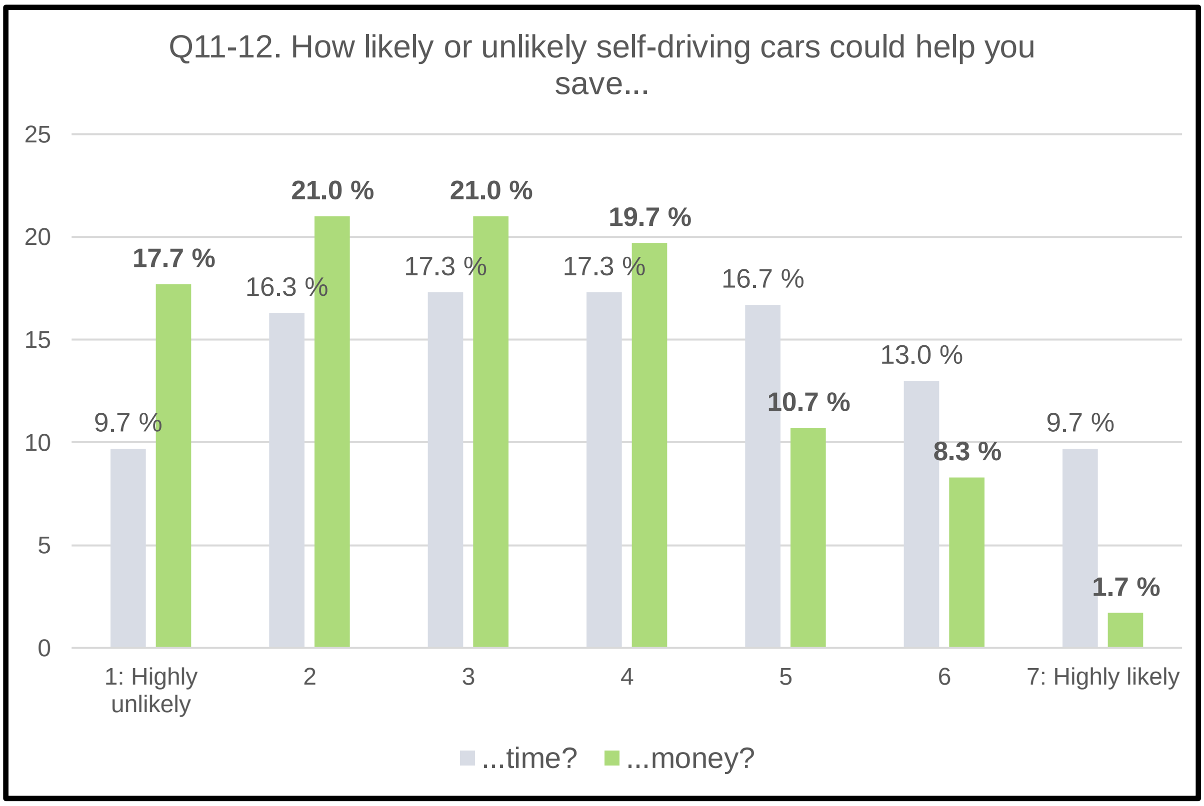
Appendix 3.19 Chart for Q8 and Q9 results, complexity



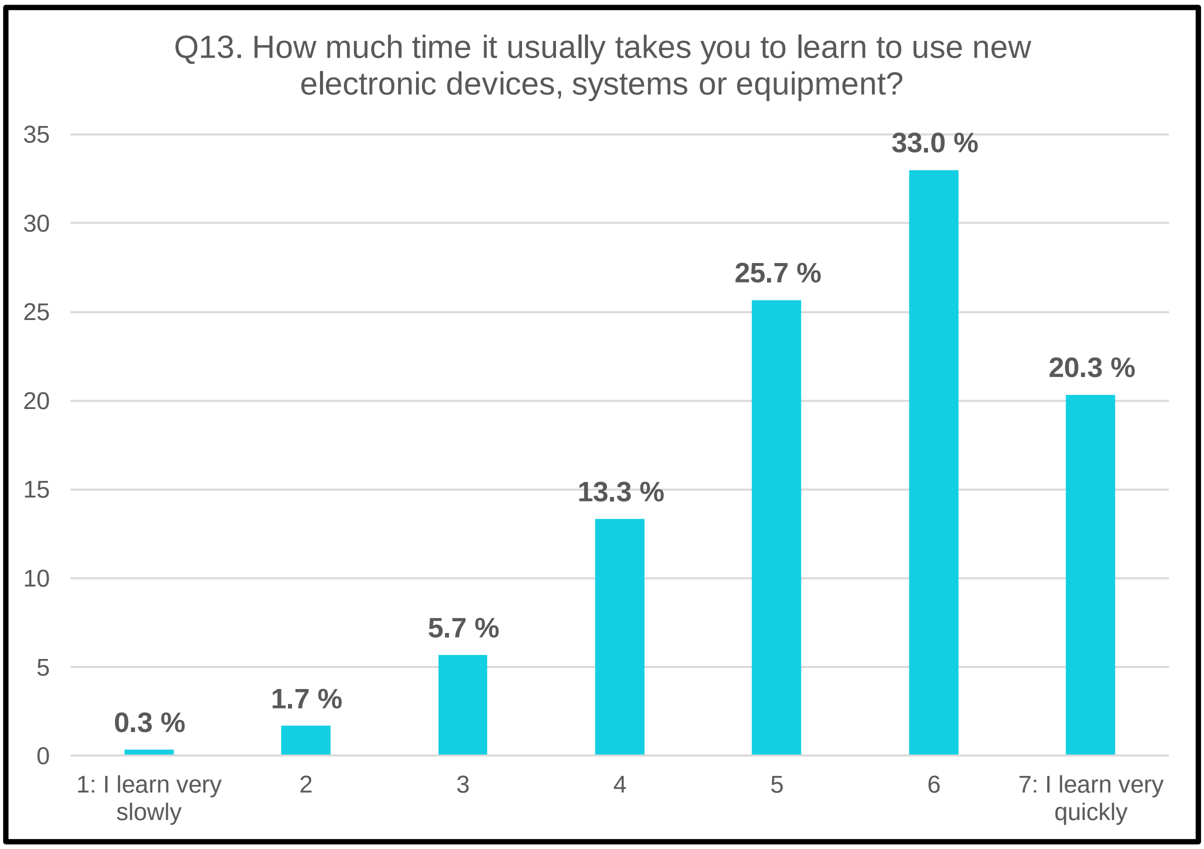
Appendix 3.20 Chart for Q10 results, replacement for current travel



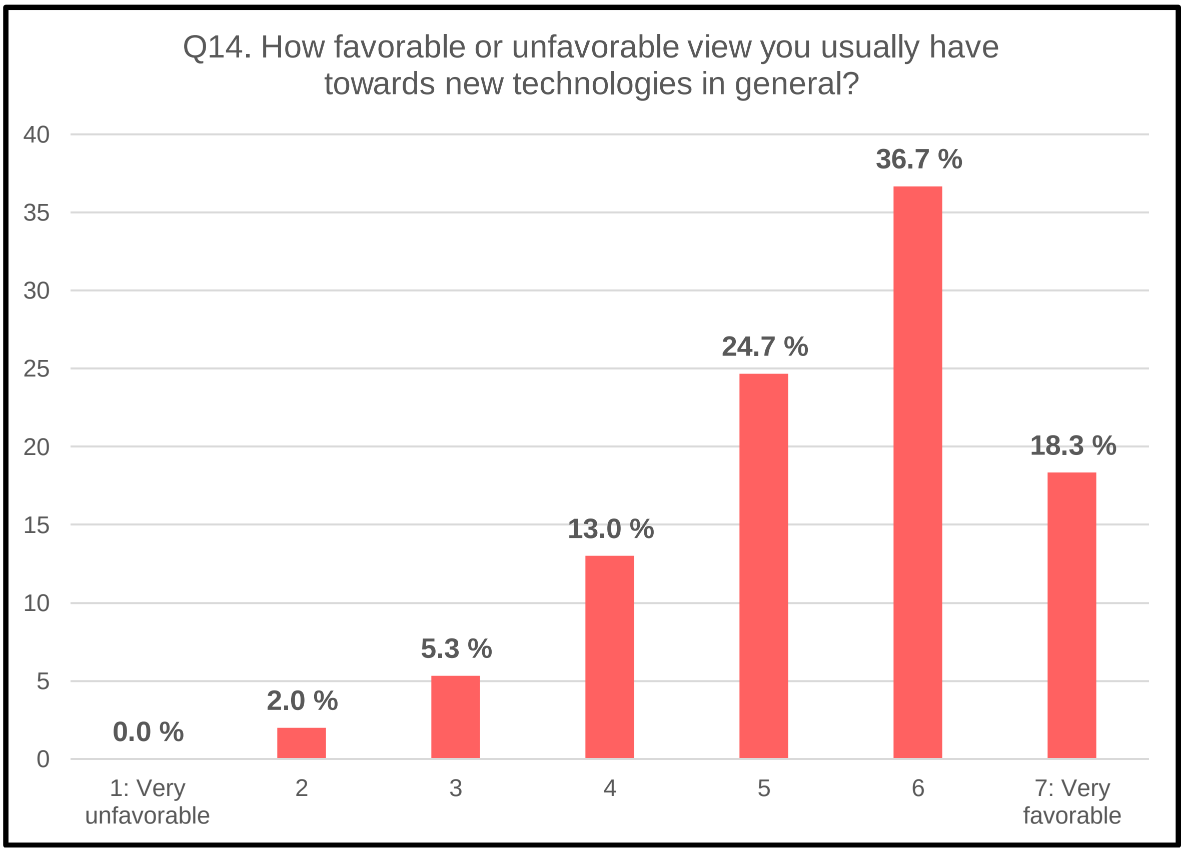
Appendix 3.21 Chart for Q11 and Q12 results, relative advantage



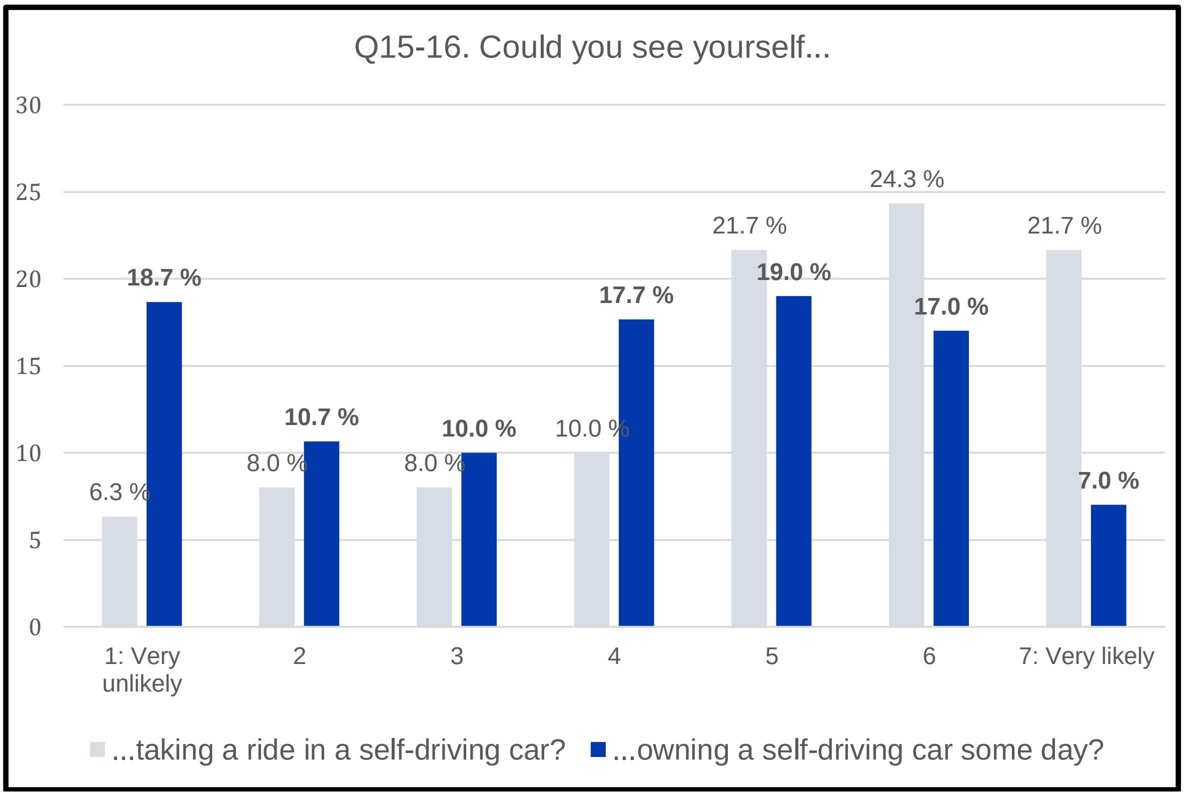
Appendix 3.22 Chart for Q13 results, ability to learn to use new tech



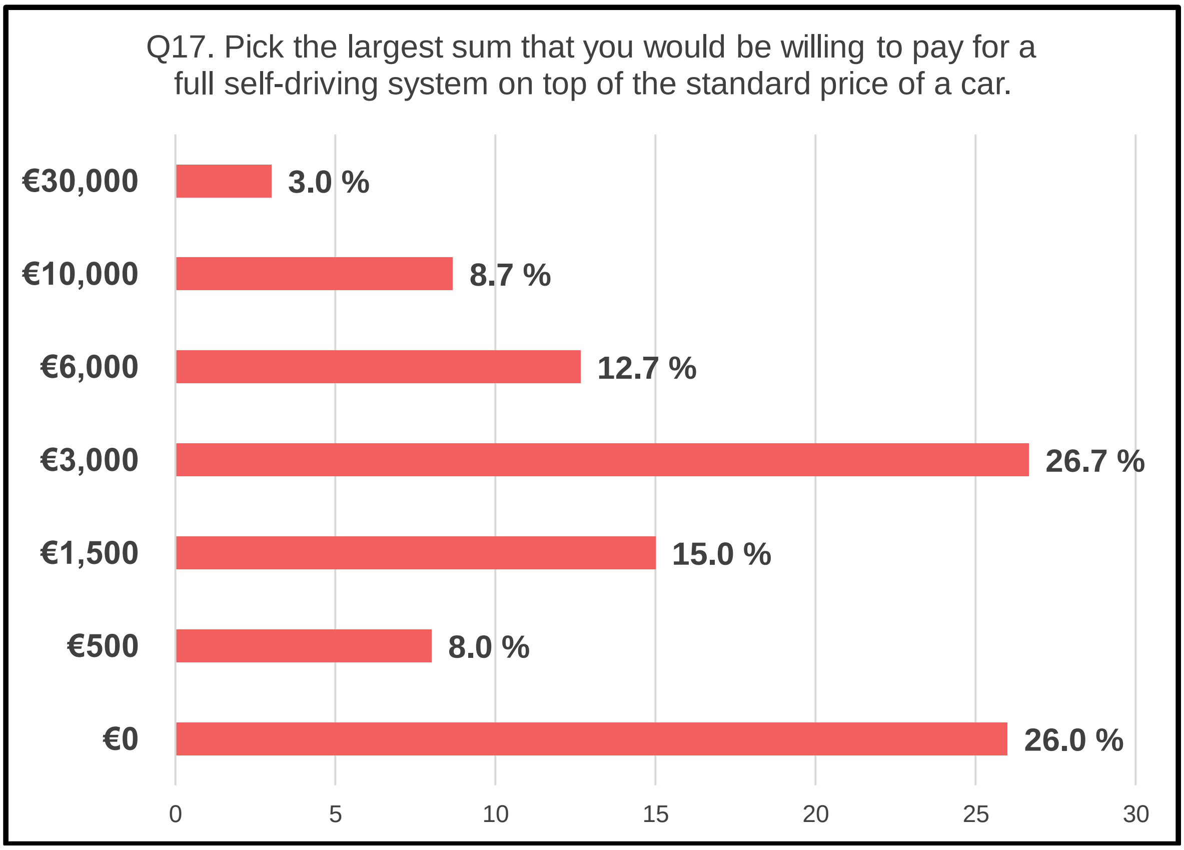
Appendix 3.23 Chart for Q14 results, view towards new tech in general



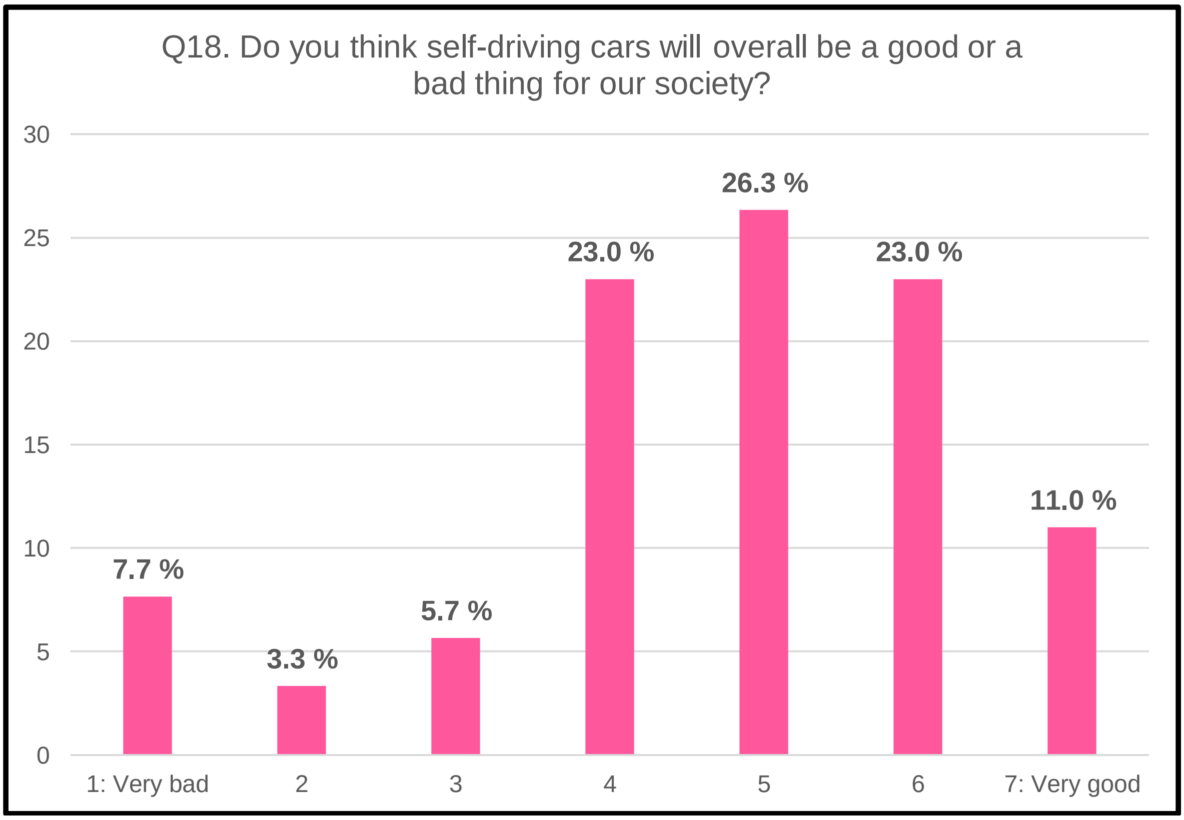
Appendix 3.24 Chart for Q15 and Q16 results, intention to use



Appendix 3.25 Chart for Q17 results, willingness to pay



Appendix 3.26 Chart for Q18 results, general acceptance



Appendix 4. Appendices for measure development

Appendix 4.1 Omitted factor analysis test

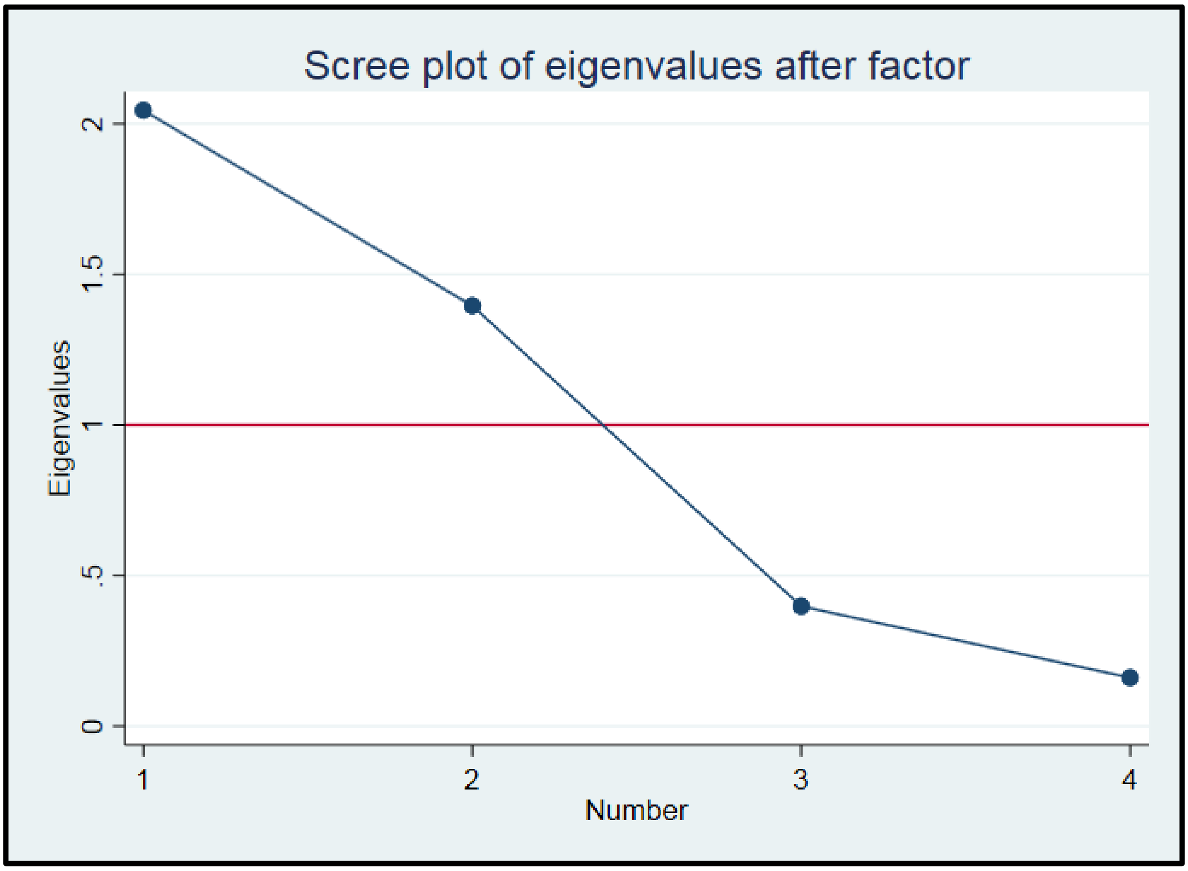
Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor1	5.88230	5.25945	0.9096	0.9096
Factor2	0.62285	0.38617	0.0963	1.0059
Factor3	0.23668	0.00844	0.0366	1.0425
Factor4	0.22824	0.07406	0.0353	1.0778
Factor5	0.15418	0.15906	0.0238	1.1016
Factor6	-0.00487	0.08836	-0.0008	1.1009
Factor7	-0.09324	0.01973	-0.0144	1.0865
Factor8	-0.11296	0.02144	-0.0175	1.0690
Factor9	-0.13441	0.01572	-0.0208	1.0482
Factor10	-0.15013	0.01147	-0.0232	1.0250
Factor11	-0.16160	.	-0.0250	1.0000

Variable	Factor1	Factor2	Factor3	Factor4	Factor5	Uniqueness
Q_three	0.7749	-0.4226	-0.0002	0.0647	0.1194	0.2024
Q_four	0.7361	-0.4431	0.1254	0.0880	0.0475	0.2361
Q_one	0.8197	-0.0332	-0.1126	0.0054	-0.2296	0.2616
Q_five	0.8275	-0.0381	-0.0907	0.0431	-0.2138	0.2580
Q_eight	0.6550	0.2165	-0.0650	0.2670	0.0527	0.4458
Q_nine	0.6193	0.2790	-0.1575	0.1611	0.1299	0.4709
Q_eleven	0.7283	0.2147	0.2295	-0.0002	-0.0180	0.3704
Q_twelve	0.5509	0.1678	0.3150	-0.0078	-0.0489	0.5667
Q_ten	0.7431	0.1747	0.0283	-0.1081	0.1023	0.3943
Q_fifteen	0.7909	-0.0730	-0.1069	-0.1823	0.0532	0.3216
Q_sixteen	0.7476	0.1029	-0.0829	-0.2686	0.0598	0.3479

Appendix 4.2 Factor and aggregate variable correlation matrix

	Anxiety	Tech adapt	Intention	Relative	Complexity	Safety
Anxiety	1.0000					
Tech adapt	-0.0000	1.0000				
Intention	0.6671	-0.1074	1.0000			
Relative	0.4413	-0.2084	0.6384	1.0000		
Complexity	0.4898	-0.0431	0.6094	0.5401	1.0000	
Safety	0.6741	-0.1735	0.7399	0.6007	0.6083	1.0000

Appendix 4.3 Scree plot for factor analysis



Appendix 4.4 Pearson's correlation matrix of the research variables

	V1	V2	V3	V4	V5	V6	V7	V8	V9	V10
V1. Intention	1.000									
V2. WTP	0.595	1.000								
V3. Relative	0.638	0.416	1.000							
V4. Complexity	0.609	0.376	0.540	1.000						
V5. Safety	0.739	0.504	0.600	0.608	1.000					
V6. Anxiety	0.667	0.427	0.441	0.489	0.674	1.000				
V7. Social inf.	0.472	0.307	0.318	0.470	0.475	0.466	1.000			
V8. Compatibility	0.726	0.516	0.601	0.594	0.754	0.659	0.461	1.000		
V9. Self-efficacy	0.168	0.130	0.043	0.176	0.137	0.396	0.081	0.134	1.000	
V10. Attitude	0.381	0.255	0.129	0.275	0.328	0.659	0.145	0.329	0.557	1.000

Appendix 5. Appendices for multiple linear regression analysis

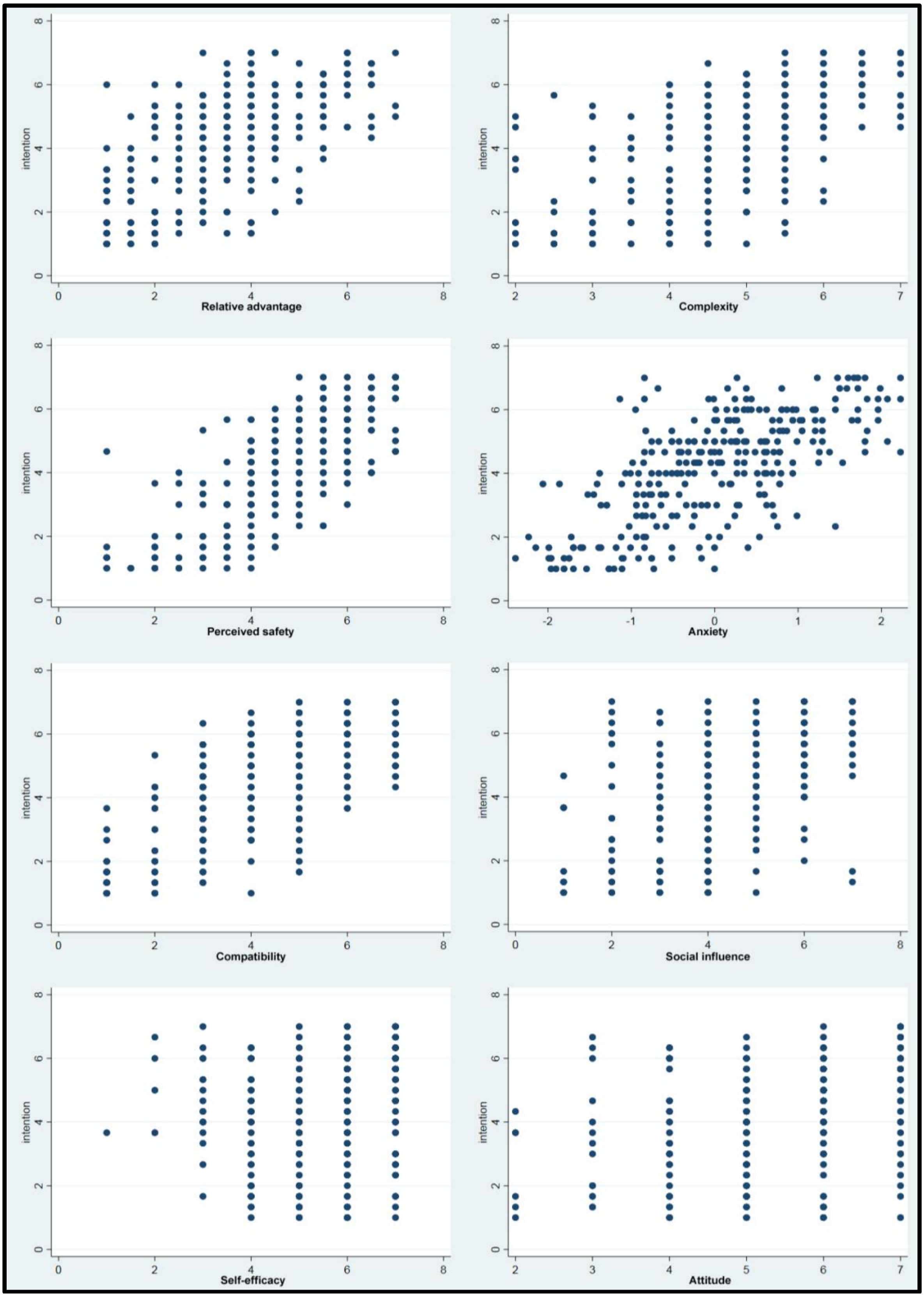
Appendix 5.1. Omitted MLR model with age as the control variable

Dependent variable: Intentions to use an autonomous vehicle					
Independent variables		**Coefficient**	**Std. Error**	**t value**	**P > | t |**
Relative advantage		.2473125	.0491512	5.12	0.000
Complexity		.1448002	.0643778	2.35	0.029
Perceived safety		.2825298	.0696965	4.01	0.000
Anxiety		.2478042	.1034651	2.31	0.020
Social influence		.0825961	.0482379	1.62	0.092
Compatibility		.1948384	.0556448	3.59	0.000
Self-efficacy		-.0471954	.0534993	-0.80	0.392
Attitude		.1183174	.0694681	1.74	0.070
Age (0 – 25 used as reference category)					
26 – 35		-.3292395	.181214	-1.82	0.070
36 – 45		-.4202721	.2212382	-1.90	0.058
46 – 55		-.3132661	.1779157	-1.76	0.079
56 – 65		-.3593552	.2265466	-1.59	0.114
Over 65		-1.213485	.4192938	-2.89	0.007
Constant		.3008398	.6307829	0.48	0.634
Model fit	**N**	**F (13 286)**	**Prob > F**	**R^2**	**Adj. R^2**
	300	40.92	0.0000	0.6516	0.6345

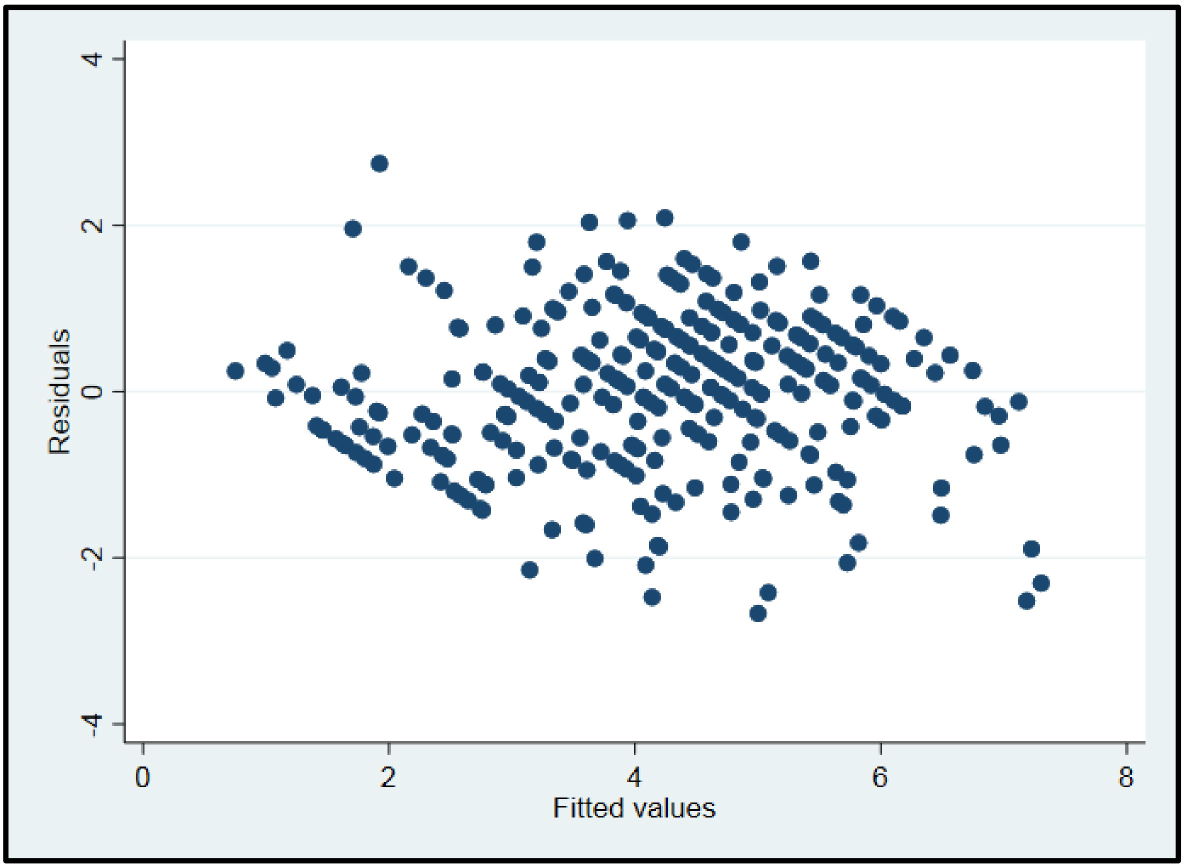
Appendix 5.2. Omitted MLR model with education the control variable

Dependent variable: Intentions to use an autonomous vehicle					
Independent variables		**Coefficient**	**Std. Error**	**t value**	**P > | t |**
Relative advantage		.2516562	.0487466	5.21	0.000
Complexity		.1404115	.0653106	2.25	0.035
Perceived safety		.2974615	.0691835	4.23	0.000
Anxiety		.2275309	.1126716	2.02	0.008
Social influence		.0753194	.0478153	1.53	0.131
Compatibility		.1924891	.0528416	3.54	0.000
Self-efficacy		-.0492429	.0543177	-0.83	0.376
Attitude		.1028192	.0691449	2.05	0.109
Education (Secondary or lower used as reference category)					
Bachelor’s degree		.0397203	.3936167	0.10	0.920
Master’s degree		-.0118332	.4132982	-0.03	0.977
Doctorate		-.850481	.5533342	-1.54	0.125
Constant		-.1833945	.6160432	-0.30	0.766
Model fit	**N**	**F (11 288)**	**Prob > F**	**R^2**	**Adj. R^2**
	300	48.62	0.0000	0.6500	0.6366

Appendix 5.3 Scatter plots for dependent vs. independent variables



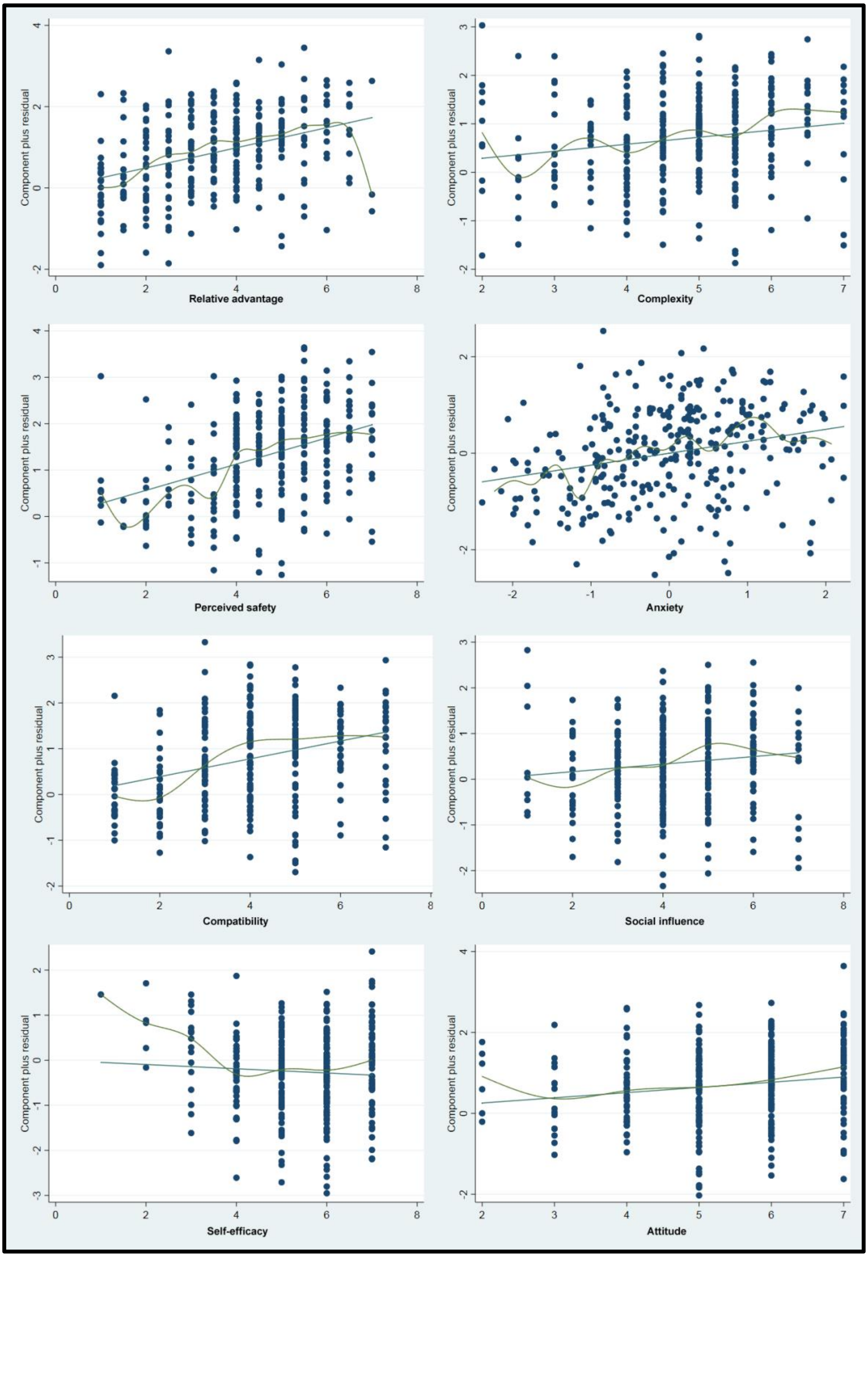
Appendix 5.4 Residual-versus-fitted plot



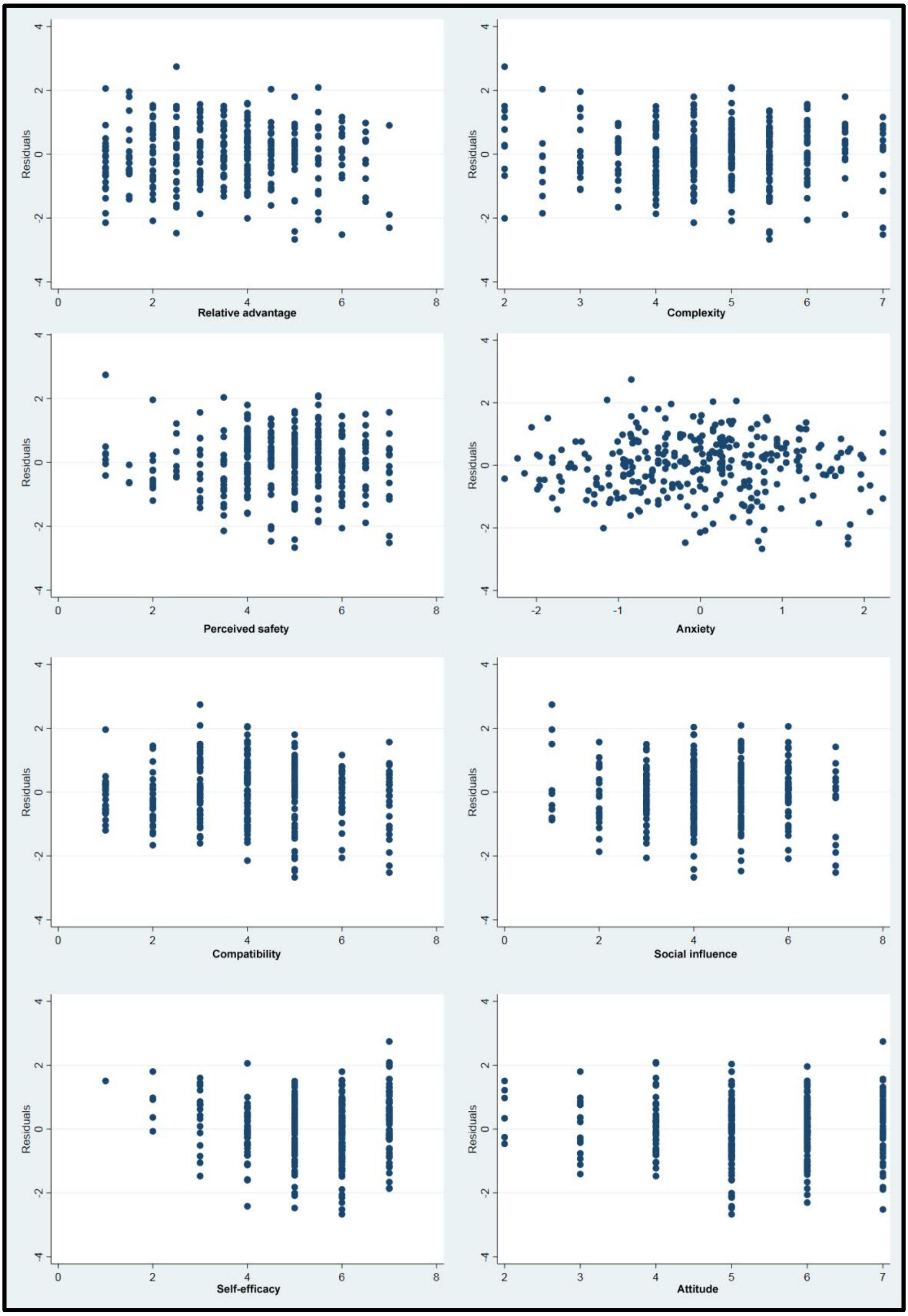
Appendix 5.5 Variance inflation factors and tolerance

Variable	VIF	1/VIF
Anxiety	3.65	0.274001
Perceived safety	3.07	0.326175
Compatibility	2.90	0.344489
Attitude	2.36	0.424459
Complexity	1.94	0.516738
Relative advantage	1.85	0.540322
Social influence	1.53	0.655587
Self-efficacy	1.49	0.670504
Mean VIF	2.35	

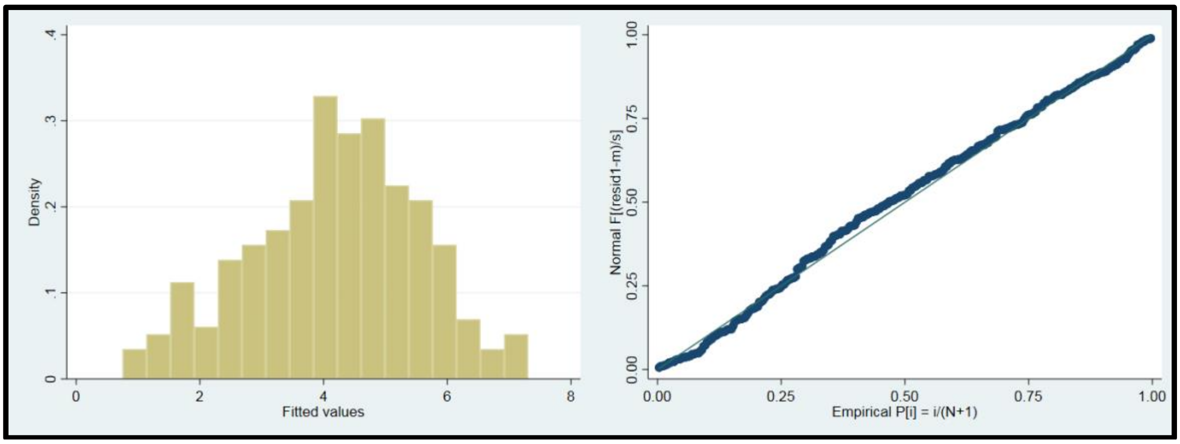
Appendix 5.6 Component-plus-residual plots



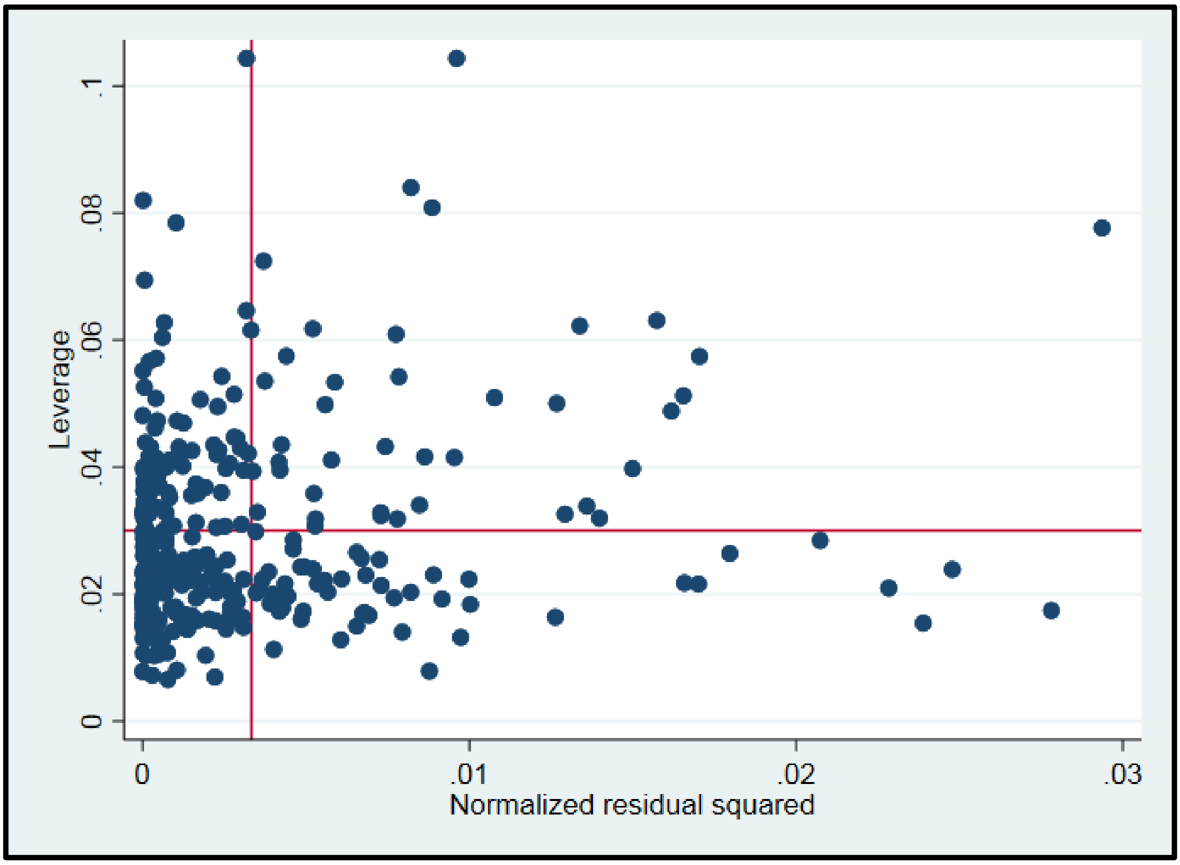
Appendix 5.7 Residual-versus-predictor plots



Appendix 5.8 Histogram and standardized normal PBTY plot for residuals



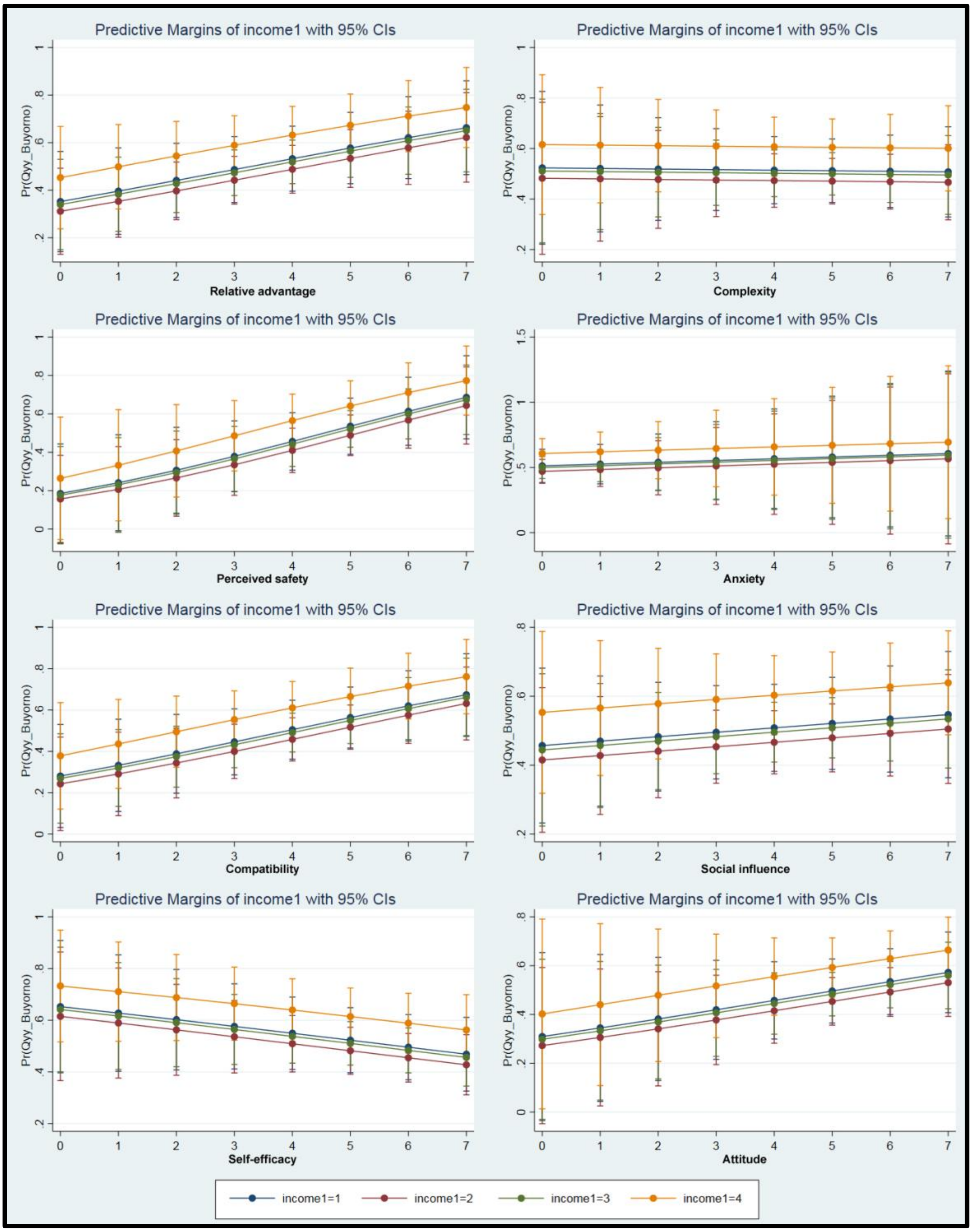
Appendix 5.9 Leverage-versus-squared-residual plot for residuals



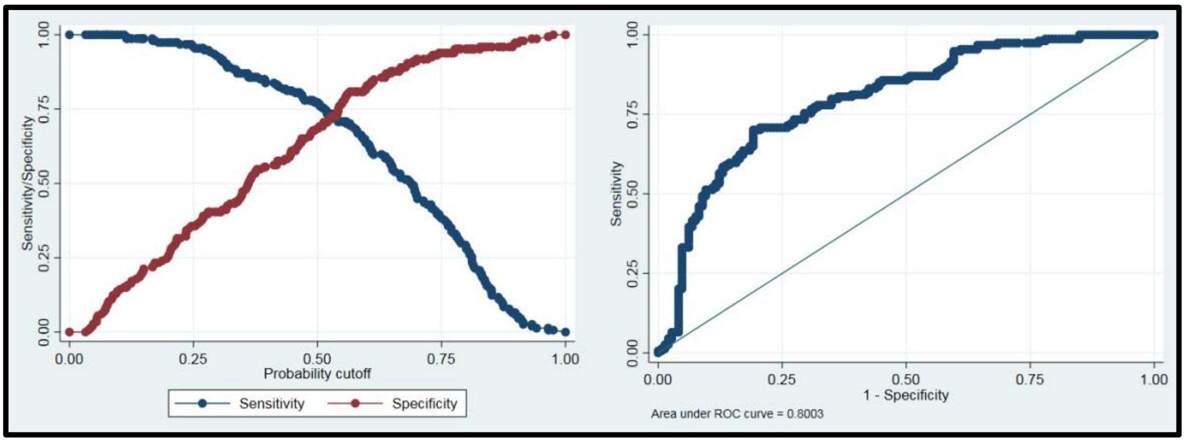
Appendix 6. Appendices for binary logistic analysis

Appendix 6.1 Appendices for BLR1

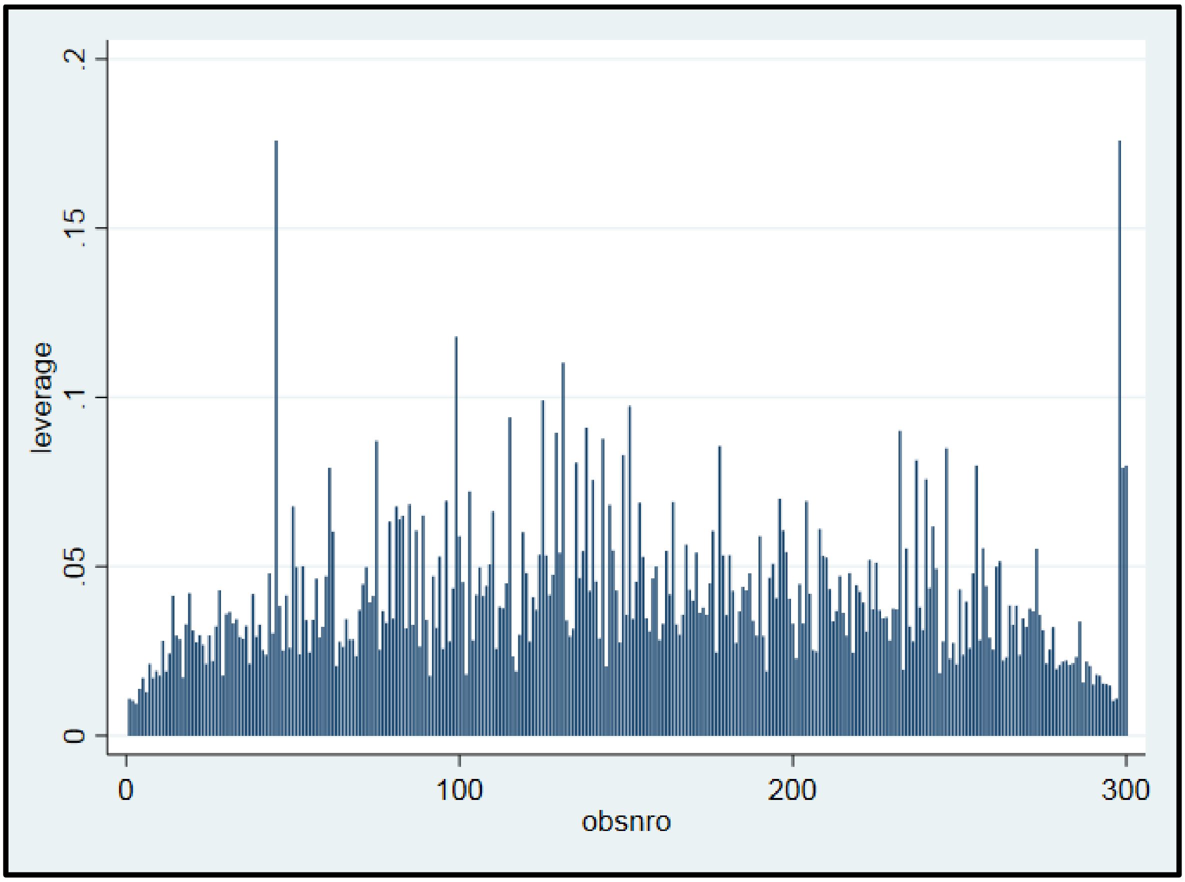
Appendix 6.1.1 Predictive margin graphs for BLR1



Appendix 6.1.2 Sensitivity/specificity graph and ROC-curve for BLR1



Appendix 6.1.3 Spike chart of leverage of observations BLR1



Appendix 6.1.4 Results of logistics regression with time and money

Dependent variable: Willingness to pay at least 3000 euros for SAE level 5 system				
Independent variables	**Odds ratio**	**Std. error**	**z**	**P > |z|**
Time saving potential	1.264633	.1329474	2.23	0.026
Money saving potential	.9649328	.1043937	-0.33	0.741
Perceived safety	1.522784	.2513366	2.55	0.011
Compatibility	1.369965	.1774568	2.43	0.015
Monthly household income (Income 1 used as reference category)				
Income 2	.7808872	.3282047	-0.59	0.556
Income 3	.9674814	.3964134	-0.08	0.936
Income 4	1.819451	.8415685	1.29	0.196
Model fit	n	chi^2 (11)	Prob > chi^2	Pseudo R^2
	300	85.96	0.0000	0.2068

Appendix 6.2 Appendices for BLR2

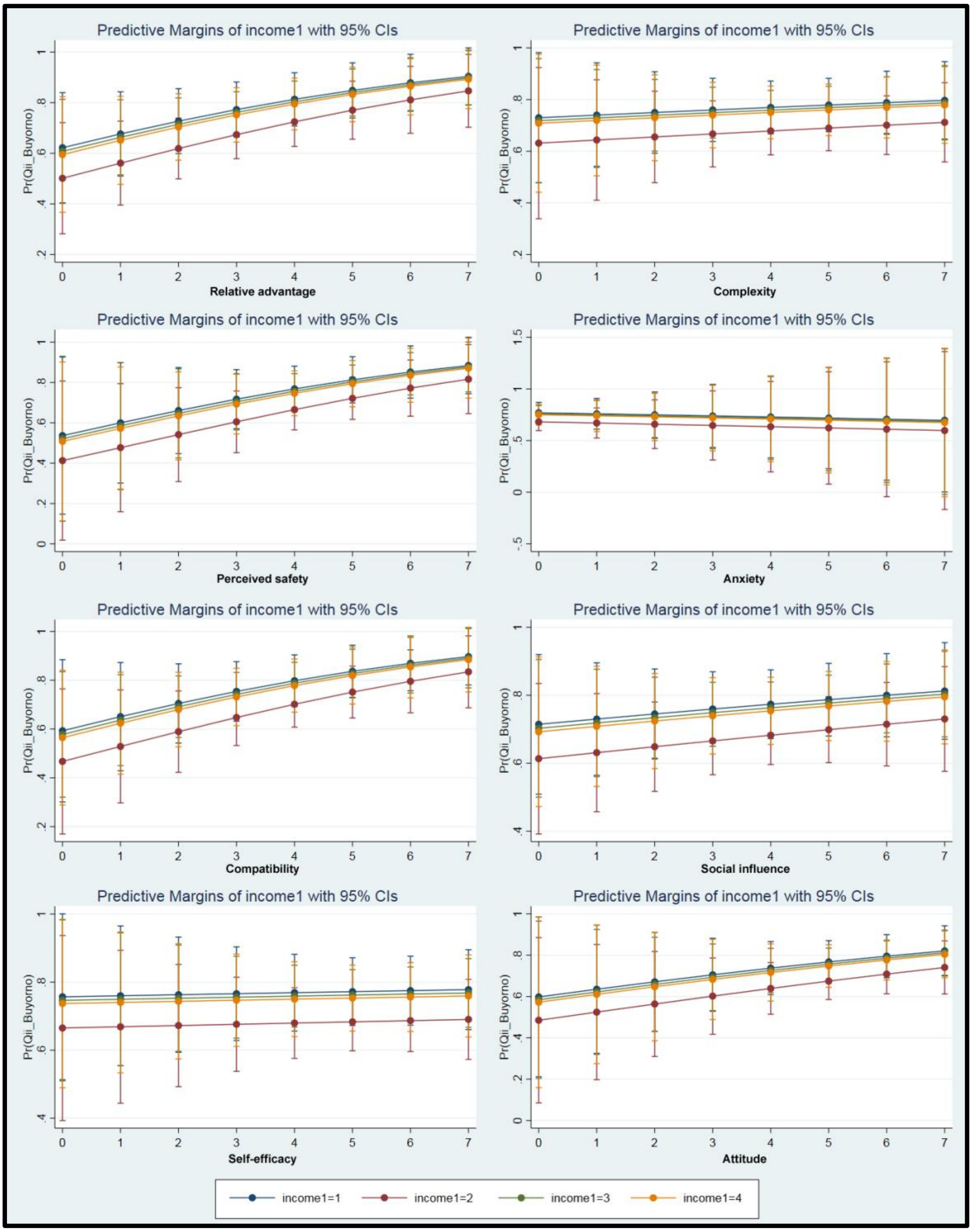
Appendix 6.2.1 Results of logistics regression BLR2

Dependent variable: Willingness to pay at least 500 euros for SAE level 5 system				
Independent variables	**Odds ratio**	**Std. error**	**z**	**P > |z|**
Relative advantage	1.346038	.194081	2.06	0.039
Complexity	1.072932	.1892334	0.40	0.690
Perceived safety	1.374315	.2821138	1.55	0.121
Anxiety	.9288073	.2974569	-0.23	0.818
Social influence	1.107414	.1598558	0.71	0.480
Compatibility	1.344906	.2141607	1.86	0.063
Self-efficacy	1.022859	.157993	0.15	0.884
Attitude	1.234974	.2426034	1.07	0.283
Monthly household income (Income 1 used as reference category)				
Income 2	.5429633	.2556624	-1.30	0.195
Income 3	.9276691	.4423177	-0.16	0.875
Income 4	.8692234	.4534529	-0.27	0.788
Model fit	n	chi^2 (11)	Prob > chi^2	Pseudo R^2
	300	78.96	0.0000	0.2296

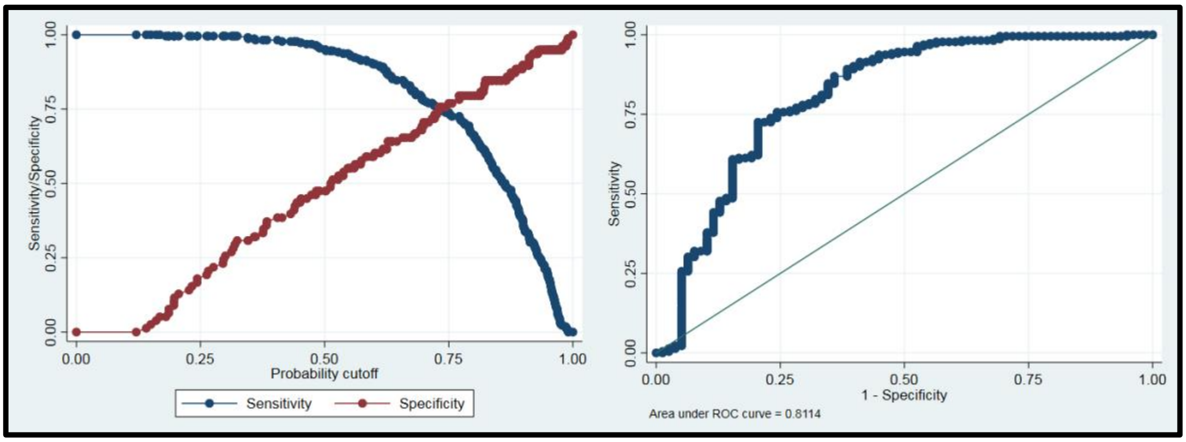
Appendix 6.2.2 Classification table for BLR2

	Actual WTP	**Actual non-WTP**	**Total prediction**
Predicted WTP	211	41	**252**
Pred. non-WTP	11	37	**48**
Total actual	**222**	**78**	**300**
	Sensitivity	Specificity	Correct classification rate
	95.05 %	47.44 %	82.67 %

Appendix 6.2.3 Predictive margin graphs for BLR2



Appendix 6.2.4 Sensitivity/specificity graph and ROC-curve for BLR2



Appendix 6.3 Appendices for BLR3

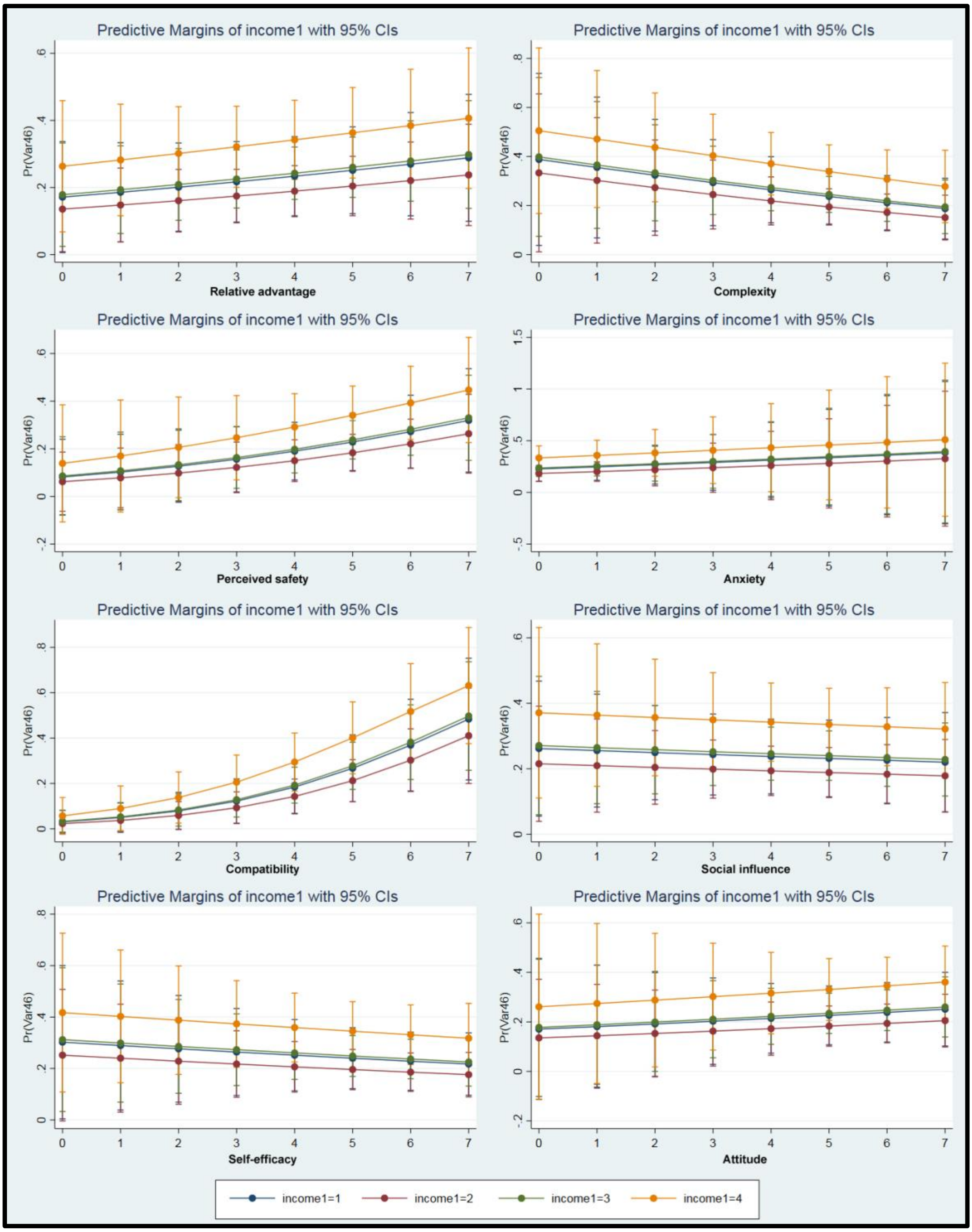
Appendix 6.3.1 Results of logistics regression BLR3

Dependent variable: Willingness to pay at least 6000 euros for SAE level 5 system				
Independent variables	**Odds ratio**	**Std. error**	**z**	**P > |z|**
Relative advantage	1.118892	.1487686	0.84	0.398
Complexity	.8322869	.1522359	-1.00	0.316
Perceived safety	1.299811	.2679364	1.27	0.203
Anxiety	1.138323	.3023779	0.49	0.626
Social influence	.9612087	.1269603	-0.30	0.765
Compatibility	1.639522	.2615052	3.10	0.002
Self-efficacy	.9247956	.133888	-0.54	0.589
Attitude	1.085664	.2136349	0.42	0.676
Monthly household income (Income 1 used as reference category)				
Income 2	.7319735	.3568478	-0.64	0.522
Income 3	1.058867	.4999816	0.12	0.904
Income 4	1.89003	.9780442	1.23	0.219
Model fit	n	chi^2 (11)	Prob > chi^2	Pseudo R^2
	300	56.50	0.0000	0.1697

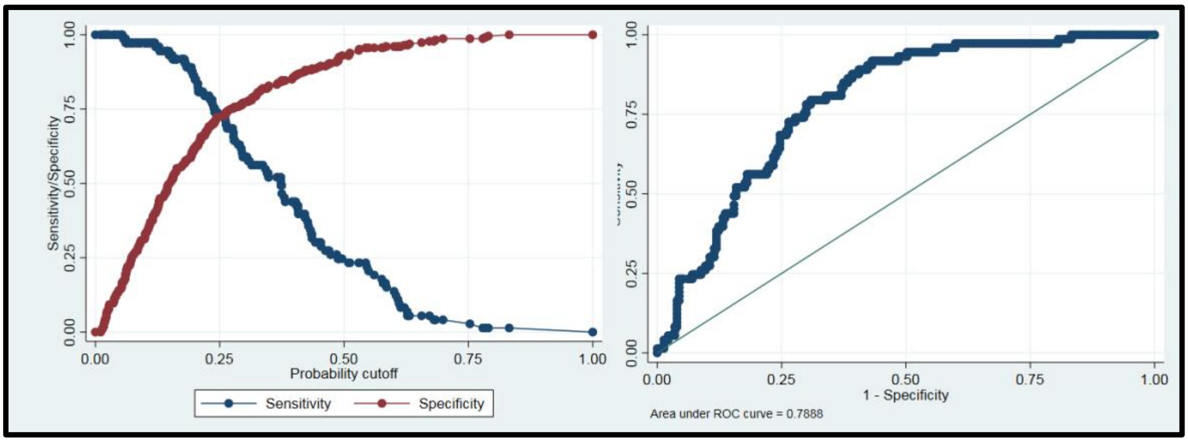
Appendix 6.3.2 Classification table for BLR3

	Actual WTP	**Actual non-WTP**	**Total prediction**
Predicted WTP	17	16	**33**
Pred. non-WTP	56	211	**267**
Total actual	**73**	**227**	**300**
	Sensitivity	Specificity	Correct classification rate
	23.29 %	92.95 %	76.00 %

Appendix 6.3.3 Predictive margin graphs for BLR3



Appendix 6.3.4 Sensitivity/specificity graph and ROC-curve for BLR3



Appendix 7. Appendices for discussion and conclusions

Appendix 7.1 Cross tabulation of comfort while riding AV

	Q4 (together)							
Q3 (alone)	1	2	3	4	5	6	7	Total
1	22 91.7 %	1 3.7 %	1 1.7 %	0 0.0 %	0 0.0 %	0 0.0 %	0 0.0 %	24 8.0 %
2	2 8.3 %	20 74.1 %	14 24.6 %	5 7.5 %	0 0.0 %	0 0.0 %	0 0.0 %	41 13.7 %
3	0 0.0 %	5 18.5 %	34 59.7 %	20 29.9 %	9 15.0 %	4 8.7 %	0 0.0 %	72 24.0 %
4	0 0.0 %	1 3.7 %	4 7.0 %	33 49.3 %	13 21.7 %	5 10. 9 %	1 5.3 %	57 19.0 %
5	0 0.0 %	0 0.0 %	1 1.8 %	4 5.9 %	32 53.3 %	17 37.0 %	2 10.5 %	56 18.7 %
6	0 0.0 %	0 0.0 %	2 3.5 %	4 5.9 %	5 8.3 %	15 32.6 %	6 31.6 %	32 10.6 %
7	0 0.0 %	0 0.0 %	1 1.7 %	1 1.5 %	1 1.7 %	5 10.9 %	10 52.6 %	18 6.0 %
Total	24 100.0 %	27 100.0 %	57 100.0 %	67 100.0 %	60 100.0 %	46 100.0 %	19 100.0 %	300 100.0 %

Appendix 7.2 Cross tabulation of time saved and current transport

	B12. Current primary form of transport			
Q11. AV time saving potential	Walking and cycling	Public transportation	Personal car	Total
1	3 5.6 %	5. 9.1 %	21 11.0 %	29 9.7 %
2	6 11.1 %	5. 9.1 %	38 19.9 %	49 16.3 %
3	7 12.9 %	12 21.8 %	33 17.3 %	52 17.3 %
4	13 24.1 %	6 10.9 %	33 17.3 %	52 17.3 %
5	11 20.4 %	11 20.0 %	28 14.7 %	50 16.7 %
6	7 12.9 %	11 20.0 %	21 11.0 %	39 13.0 %
7	7 12.9 %	5. 9.1 %	17 8.9 %	29 9.7 %
Total	54 100.0 %	55 100.0 %	191 100.0 %	300 100.0 %

Appendix 7.3 Cross tabulation of general acceptance and gender

	B1. Gender			
Q18. General acceptance	Female	Male	Other or non-conforming	Total
1	12 8.9 %	11 6.8 %	0 0.0 %	23 7.7 %
2	3 2.2 %	7 4.3 %	0 0.0 %	10 3.3 %
3	8 5.9 %	9 5.6 %	0 0.0 %	17 5.7 %
4	31 23.0 %	38 23.5 %	0 0.0 %	69 23.0 %
5	38 28.1 %	38 23.5 %	3 100.0%	79 26.3 %
6	33 24.4%	36 22.2 %	0 0.0 %	69 23.0 %
7	10 7.4 %	23 14.2 %	0 0.0 %	33 11.0 %
Total	135 100.0 %	162 100.0 %	3 100.0 %	300 100.0 %

Appendix 7.4 Cross tabulation of likelihood to own AV and news activity

	B8. Attention towards AV related news			
Q16. Probability to own an AV	Inactive	Somewhat inactive	Active or somewhat active	Total
1	24 27.9 %	22 20.0 %	10 9.6 %	56 18.7 %
2	10 11.6 %	10 9.1 %	12 11.5 %	32 10.6 %
3	12 13.9 %	13 11.8 %	5 4.8 %	30 10.0 %
4	19 22.1 %	18 16.4 %	16 15.4 %	53 17.7 %
5	11 12.8 %	25 22.7 %	21 20.2 %	57 19.0 %
6	10 11.6 %	15 13.6 %	26 25.0 %	51 17.0 %
7	0 0.0 %	7 6.3 %	14 13.4 %	21 7.0 %
Total	86 100.0 %	110 100.0 %	104 100.0 %	300 100.0 %