University of Glasgow

School of Social & Political Sciences

Urban Studies

Public Acceptance and Adoption of Autonomous Vehicles over time:

A case study for Seattle

Presented in partial fulfilment of the requirements for the degree of

M.Sc. in Urban Transport

August 2018

Word count: 14821

Abstract

This study focuses on the factors affecting the public acceptance of fully autonomous vehicles over partial automation, investigating the possible future scenario of “SAVs” (Shared Autonomous Vehicles) and the implications related to this scenario. Following this approach, a comparative analysis is being conducted based on repeated cross-sectional data derived from PSRC, in order to examine differences and changes in acceptance over time.

The results of the multinomial logistic regression models deployed suggest that socio-demographics, mobility characteristics, travel attitudes, tech-savviness, current vehicle, and contextual characteristics are associated with public perspectives regarding shared driverless cars and their automation level, revealing that younger male workers, who are more educated and tech-savvy, residents of high-density urban areas and currently having more active/sharing travel attitudes to be more likely to embrace the new technology.

As far as the changes over time, we conclude that the list of factors significantly affecting acceptance is not the same over time. A quite significant increase in interest is observed, considering the fact that the intermediate time between the two surveys is only two years. However, the percentage of people that show no willingness to accept such a radical change and their level of concern is still substantially high, confirming the fact that technology often moves faster than acceptance.

Keywords:

CAVs, AVs, SAVs, self-driving, driverless, acceptance, adoption, preferences, car ownership, car-sharing, ride-sharing, repeated cross-sectional study, comparative study, multinomial logistic regression

Table of contents

List of figures

List of tables

Acknowledgments

A very long journey ends with this dissertation, which in turn marks the start of a new era in my life, moving me one step closer to my dreams. Thus, I should not fail to offer my heartfelt thanks to the people who gave me the strength to fight for fulfilling them by all means.

I would first like to thank my dissertation supervisor Dr. David Mcarthur of the School of Political and Social Sciences at the University of Glasgow, not only for his guidance in the process of researching and writing this thesis but also for all of his help and support from the very beginning of my postgraduate studies.

I would also like to express my endless gratitude to my friends and closest people for standing by me during this marathon, emotionally supporting me and sharing all the bad and good moments with me throughout the year, making it even more special. I feel blessed having you in my life.

Finally, nobody has been more important to me in this journey than my parents and my family. I wouldn't be who I am, and where I am today without them in my life, unconditionally loving me, giving me the strength to keep going, keep trying, keep breathing, keep dreaming... I hope to find the way to return a piece of all that support and love.

1. Introduction

The launch of autonomous vehicles (“AVs”, “self-driving”, “driverless” or “robotic”) represents the biggest technological advance in personal transportation over the last century, introducing radical changes and promising interconnected socioeconomic benefits. Possibly the most vital expected benefit of their deployment is the prevention of a considerable number of fatal accidents, achieved through their enhanced throughput, along with the drastic ease of congestion caused by humans’ delayed response time (Willumsen and Kohli, 2016; Le Vine *et al.*, 2016). Moreover, the lower gap acceptance accomplished due to the vehicle-to-vehicle communication and sensors for collision avoidance could lead to enhanced road and highway capacity (Anderson *et al.*, 2015), while they could contribute on land-use optimisation by freeing up space from parking areas (Liu, 2018). We should not fail to mention the expected energy conservation and the efficient control of carbon dioxide emissions, with fuel consumption to be potentially reduced at least 25%, due to better route choices, less congestion, and optimal drive cycles (Fagnant and Kockelman, 2015). In addition, AVs have been identified as a potential and permanent solution for mobility impaired people, since they will facilitate their access to education and employment, improving their living standards and leading to tremendous socioeconomic benefits. According to surveys, AVs can help more than one million people in the United Kingdom pursue a university degree (KPMG, 2015). On the top of bringing new perceptions of mobility, the concept of in-vehicle-time (commute time) and its cost is also expected to be radically disrupted by AVs, which would allow “drivers” to use it more productively (Piao *et al.*, 2016).

However, the majority of these benefits might be significant only after a complete transition from conventional to self-driving cars. Litman (2014) suggests that AVs’ beneficial impacts on safety and congestion is expected to emerge between 2040 and 2060 and may require the restriction or even prohibition of human-involvement in driving. That would gradually lead to a 100% market penetration of fully autonomous vehicles and consequently to the eradication of human drivers’ error, which is credited as the main reason for 90% of crashes (Science and Technology, Lords Select Committee 2017). Hence, an essential assumption that has to be done before a cost-benefit analysis can be conducted refers to the rate and the nature of future demand, which, in turn, depends on the level of public interest and willingness to embrace the innovative transportation mode. This analogous relationship highlights the need for developing an adoption model regarding autonomous driving, as an attempt to explain and predict the evolution of public acceptance. Modelling the factors affecting public attitudes towards AVs would allow us to adequately estimate the future demand and narrow the implementation scenarios, leading to more specifically oriented predictions. Therefore, in this study, we sideline the technical and regulatory challenges that apparently arise, focusing on the social implications, in terms of public confidence and acceptance, which appears to be crucial for the effective deployment of AVs as well as the nature of their usage. Many researchers (Howard, 2014; Rödel *et al.*, 2014; Payre *et al.*, 2014; Schoettle and Sivak, 2014; Kyriakidis *et al.*, 2015; Bansal *et al.*, 2016; Krueger *et al.*, 2016; Zmud and Sener, 2017) and consulting firms (Silberg *et al.*, 2013; Deloitte, 2014; Stephen *et al.*- Atkins, 2016) have conducted surveys in order to explain public acceptance and perceptions on AV's benefits and limitations. Their results are controversial and in certain cases statistically insignificant, failing to indicate how individual's socio-demographics (e.g. age, education), current travel characteristics (e.g. mode choice, trip frequency) and built-environment variables (e.g. population density, area type) affect their opinions for such technologies. Furthermore, the fact that acceptance may differ with regard to the ownership model adopted and the level of vehicles' automation is usually neglected. Thus, the present research aims to investigate the social perception of AVs under different implementation scenarios, by distinguishing the two following groups:

1.1 Ownership model

The main reason for our first classification is that public opinion depends on whether we refer to a future ride-sharing or a more similar to the current car ownership model. The concept of driverless taxis ("Autonomous Car-as-a-Service"), which is one of the first implementations of AVs in real traffic situations, is analogous to the car and ride-sharing services. These services are based on the Mobility-as-a-Service (MaaS) distribution model, in which a person's transportation needs are met over one interface, offered by a service provider and presented to the user as an integrated solution through a smartphone app (Spulber and Dennis, 2016). Car and ride-sharing is already a thriving business model, so the first scenario is considered as the most possible, since it is consistent with the predictions that there will be little incentive to own a car in the future and it is expected that other transportation systems (Dial-A-Ride Industry, MaaS) will dominate (Bagloee *et al.*, 2016).

However, the experts opinions on the predicted benefits of this potential shift, from a policy-making point of view, are controversial, with some of them expressing their hesitation on how positively public transport and active travel could be affected by a MaaS system and highlighting the risk of public transport getting marginalised to serving the non-profitable routes, the difficult areas to serve, or only the disadvantaged areas, while private operators take commercially profitable routes and areas. On the top of that, the willingness of people to change their travel behaviour switching in a shared-ownership model does not conform to this idea, as reflected in a recent analysis of Piao (2016). Thus, in any case, we still have to take into consideration the second scenario, even though it may appear to be less efficient and desirable, while it is crucial to investigate how AVs could affect the attractiveness of traveling by car, how this, in turn, could affect car ownership, mode choice and the broader transportation system (Gruel and Stanford, 2016).

1.2 Levels of automation

The second group of scenarios introduced examines the intention and willingness of people whether to use a driverless car or eventually appear ready to accept only a partially AV instead (presence of back-up driver). The National Highway Traffic Safety Administration proposes a formal classification of automation spanning from no automation (Level 0) to full automation (Level 5). As summarised in Figure 1, the intermediate categories of assisted automation are gradually leading to full automation by adding tasks automatically performed by the system (NHTSA, 2016).

The common ground of previous studies is that they assess public acceptability in an unclarified way, investigating the general perception about automation, rather than Level 5 AVs in specific. A study conducted by Payre et al. (2014) attempted to measure the “a priori acceptability” of fully automated cars, defining it as the evaluation of a new technology before having any interaction in practice. Concerns around technology failures and security seem to be the principal reasons why many consumers are circumspect about full automation.

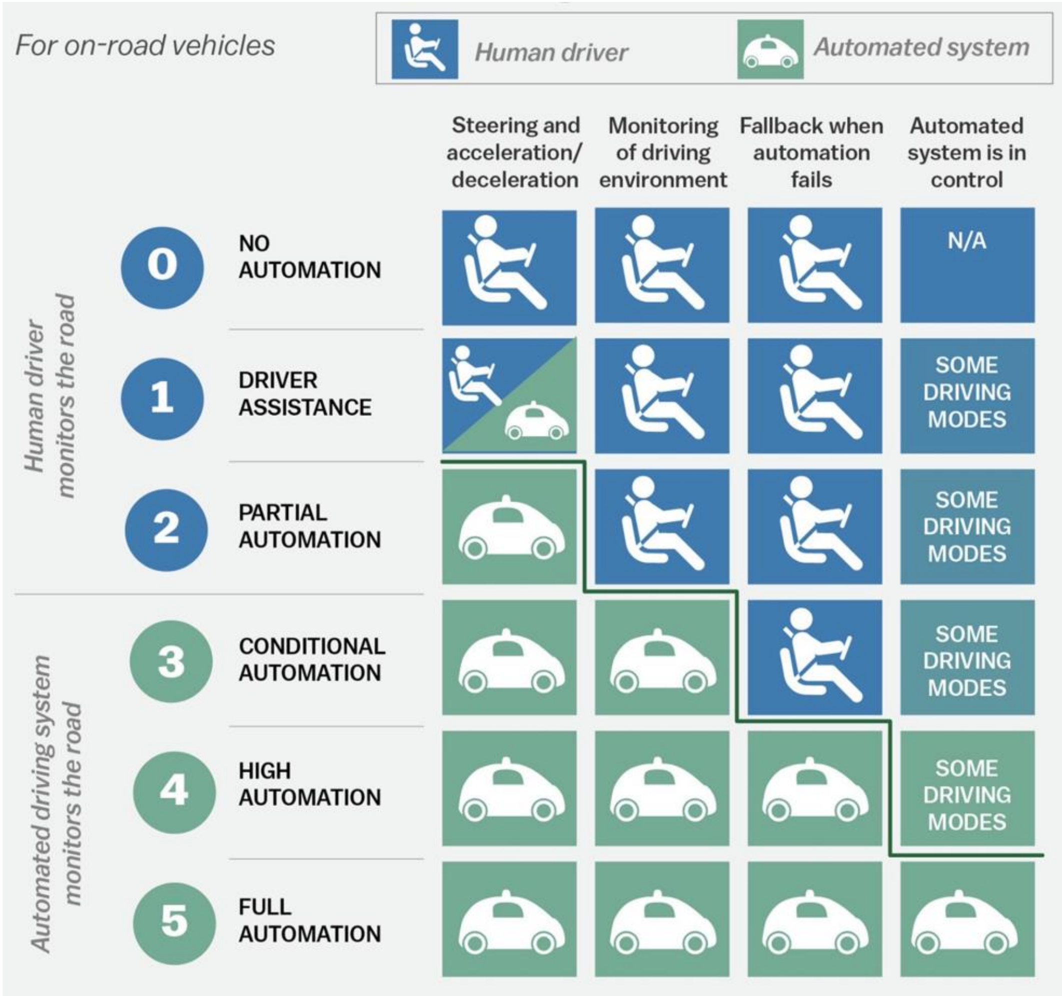

Figure 1: Levels of Automation (NHTSA, 2016)

A recent survey polled people in the U.S. and Germany and found that more than 50% of respondents would not consider riding in a driverless car, while significantly more would consider riding in a partially autonomous vehicle (Meyer, 2016). This survey is consistent with a comparative study conducted by MIT AgeLab researchers (Abraham *et al.*, 2017). Since their first survey was deployed, numerous strides and setbacks had occurred on the path to fully automated vehicles, including the first fatality related to a highly automated driving feature (Forbes, 2016).-Therefore, they decided to re-deploy their survey in an effort to gain updated and deeper insight into consumers' willingness to accept varying levels of automation. A substantial decrease of trust levels regarding a fully self-driving car, along with a noticeable shift toward more limited automation was observed, leading to less optimistic results (only 13% on the side of full autonomy and 59% on the side of partial autonomy), emphasising the crucial role of time dimension on the configuration of public's acceptance.

1.3 Changes over time

In contrast to these comparative surveys, the vast majority of those conducted up to the present include responses collected at one time-point, excluding the factor of time, which is essential for the investigation of the dynamic concept of acceptance and adoption. One of the main aims of analysing human's behaviour towards innovative technologies is to forecast their long-term adoption, which means that the framework of a related study should consider changes over time. Technology progression, changes in household socio-demographics, urbanisation and numerous other exogenous factors affect public opinion on AVs, thus the exact interpretation of these swifts is objectively challenging, but some useful insights can be offered by comparing specific groups of people with same or similar characteristics over time.

1.4 Research questions

The research questions emerging from the discussion are the following:

1) Which are the factors configuring public acceptance on autonomous vehicles at a statistically significant level and how the adoption patterns are shaped under different implementation scenarios?
2) How does public perception towards these scenarios change over time?

The groups of scenarios investigated are the following:

A) Ownership model
- SAVs (Shared Autonomous Vehicles): AVs as part of a MaaS ("Mobility as a Service") transportation system
- AVs ownership: AVs used as a private transport mode

B) Levels of automation
- Fully Autonomous Vehicles (Level = 5)
- Partially Autonomous Vehicles (Level <5)

2 Literature Review

2.1 Technology Acceptance: Concepts, Research and Characteristics

In order to effectively address the issue of acceptance, it is important to have defined the term accurately. The subject of technology acceptance is decidedly inhomogeneous and multiple scientific disciplines (e.g. psychology, sociology, and economics) have mutual bonds with it. In the early 80s, Davis (1985) formed a fundamental technology acceptance model (TAM), which has been widely used in relevant studies. The model in its initial form had only two constructs, namely “perceived usefulness” and “perceived ease of use” for predicting the extent of adoption of new technologies at individual level and was originally tested in the context of adoption of email service and file editor at IBM Canada (Sharma and Mishra, 2014). The main idea behind the development of the first TAM model was that the acceptance of a new technology depends on believing that the technology is useful for achieving higher standards of living and decidedly easy to use (Davis, 1989). A visual representation of the initial model is shown in Figure 2.

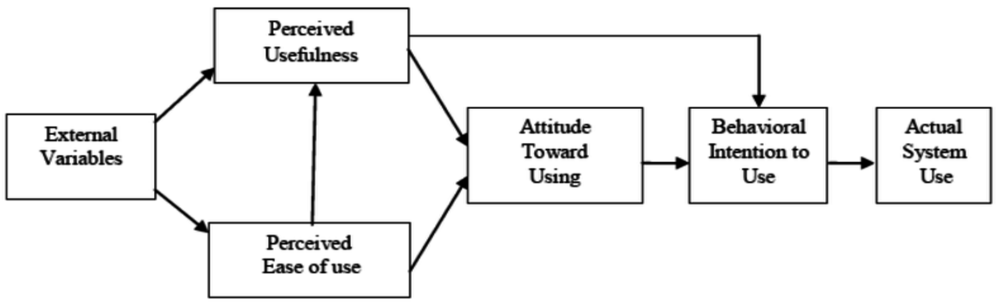

Figure 2: Technology Acceptance Model (Davis, 1985)

The evolution of this arguably simplistic approach included several modifications to date, in terms of additional external variables (e.g. age, gender, experience, social influence) and higher standards of precision in explaining the process of acceptance, even by distinguishing separate types of acceptability. Venkatesh and Davis (2000) developed a theoretical extension of TAM (TAM2), which extended TAM’s effects by encompassing both social influence and cognitive instrumental processes, providing a detailed account of the key forces underlining judgements of perceived usefulness, while breaking down the main groups of Ease of Use further (Hutchins and Hook, 2017). These configurations eventually led to the Unified Theory of Acceptance and Use of Technology (UTAUT), which is now over a decade old and has been used extensively in information systems and other fields (Venkatesh *et al.*, 2003). Recently, Venkatesh *et al.* (2016), in a review of the original paper concluded that it was one of the highest cited documents in the area of technology acceptance, as evidenced by its 1,267 citations by that time. In UTAUT – as presented in Figure 3 – it is assumed that the four constructs which are significantly important determinants of acceptance are performance expectancy, effort expectancy, social influence and facilitating conditions, which are impacted by four key moderators: gender, age, voluntariness, and experience. In this way, the model managed to outperform existing models by explaining approximately 70 percent of the variance.

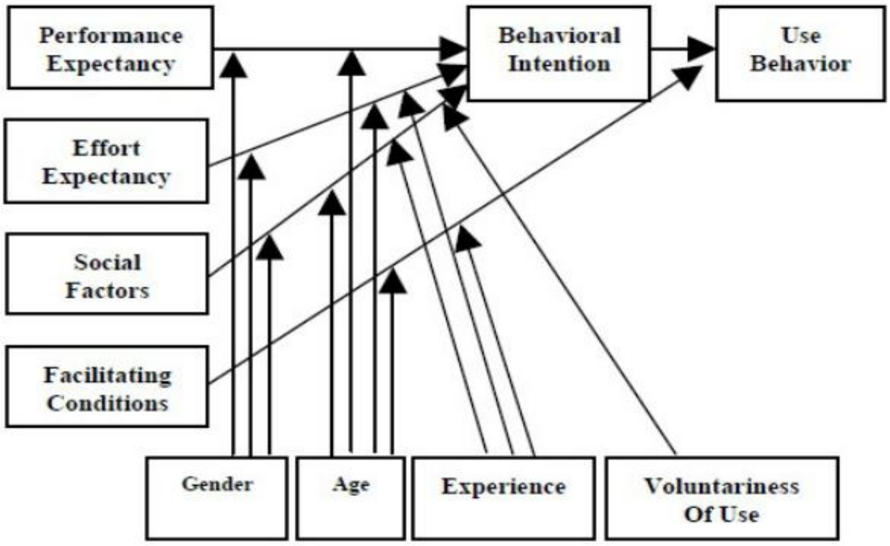

Figure 3: The UTAUT Model (Venkatesh et al., 2003)

It is worthwhile mentioning that UTAUT development relied on the Technology Acceptance Framework of Huijts *et al.* (2012), which uses psychological factors in interpreting acceptance and was initially created with sustainable energy technologies in mind. However, many researchers stated that the framework can also be used as a baseline for studying the acceptance of other technologies with social or environmental benefits, potential risks, and costs, after being modified by adding or eliminating some factors. UTAUT configuration is the most widely accepted, and it is currently used as a starting point in technology adoption studies.

Based on the UTAUT, researchers usually adapt the model depending on their field of study by combining it with other theories in order to derive a conceptual model of acceptance. For example, Nordhoff *et al.* (2016) applied the UTAUT in the context of highly automated vehicles in order to investigate users' acceptance on AVs inside and outside of them, developing a conceptual model that integrated UTAUT and other psychological/behavioural models to address the multidimensional nature of acceptance through a holistic and comprehensive set of variables, capable to explain, predict, and improve public acceptance of automated transportation. Buckley *et al.* (2018) also draws our attention to distinct categories of acceptance observed in relevant model expansions, specifying citizen (public's behavioural response to the implementation or forthcoming implementation of the technology), consumer (public's response to the availability of the technology, in terms of willingness to purchase and use of the product) and socio-political acceptance (public's response to regional, national or international events or policy-making that is not always directly affecting their own situation). Finally, Im *et al.* (2011) in their exploratory research applied UTAUT model in the U.S. and South Korea, investigating differences in adoption process between dissimilar cultures and revealed that the interactive effects of three models' constructs (effort expectancy - behavioural intention – use behaviour) were substantially diverse.

Evidently, technology acceptance is a complex, multi-layered construct that is not directly measurable but depending on the acceptance object in question and the relevant dimensions and adjusting our model according to the data availability, we can derive measurable indicators to capture acceptance patterns (Lenz, 2015). This study, with respect to the available data, focuses on citizen acceptance, taking into account sociodemographic, mobility and contextual characteristics, as will be detailed in the methodology chapter.

2.2 Acceptance of Connected Autonomous Vehicles and future scenarios

Autonomy in automobiles has been in the research phase in academia and in large companies' research and development departments for several decades and some semi-autonomous features are already offered on current vehicle models, while connected autonomous vehicles implementations have already been realised.

The first experiment with autonomous and connected cars has been conducted in 1925, on streets of Milwaukee, where a driverless car was radio-operated from a second car, introducing a kind of V2V communication (Gora and Rüb, 2016). In order the term "connected" to be explained, it refers to the following three types of vehicles' communication, as distinguished by literature: V2V (vehicle-to-vehicle), V2I (vehicle-to-infrastructure) and I2V (infrastructure-to-vehicle) communication. In the early 80s, research led to the design of the first truly autonomous cars, capable of driving without any human intervention, in an era of computers with limited computational power. Advancements in self-driving technology accelerated in the 2000s and at the present, trials are being undertaken worldwide by research institutes, car, and IT companies. Recent examples are the CityCar (Massachusetts Institute of Technology), the AdaptIVe (Volkswagen) and the Waymo Project (Google). Inevitably, due to the stage of development, many of these trials are taking place in protected areas (e.g. university campus) and their primary objective is restricted in testing the capability of the vehicles or improving the design. However, existing projects include trials on public roads, aiming to improve AVs' understanding through empirical data collections and demonstrate their potential. Representative on-going projects are the CityMobil2 Bus (France/Greece/Italy), the VENTURER (UK), the SARTRE (Spain), the YUTONG (China), the One-North (Singapore) and the autonomous vehicle testing of Uber and Volvo (USA, Pittsburgh).

The prospect of commercially available self-driving cars and trucks has perceptibly gone from a futuristic fantasy to a likely near-term reality and various models for accessing their acceptance have been introduced up to date. By getting a comprehensive overview of existing models and methods and the influencing factors that have already been found, we can effectively proceed to the set up of the right methodology for our research.

Many of these models originate from the technology acceptance models mentioned in the previous section, having emerged from a configuration of them in order to appropriately adapt to self-driving cars. Payre *et al.* (2014) extended the TAM to incorporate additional constructs, while another example is the combination of TAM with prior research on trust in automation by Choi and Ji (2015), which identifies ten constructs that significantly affect acceptance, as shown in Figure 4.

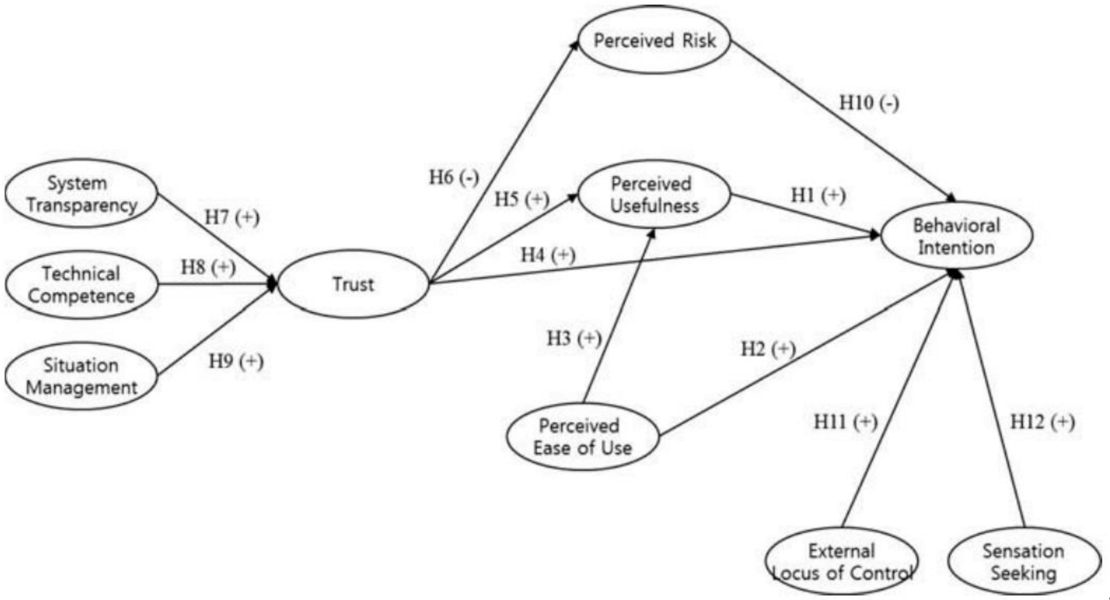

Figure 4: Autonomous Vehicle acceptance research model (Choi and Ji, 2015)

Similar studies include the use of extended versions of TAM by Nees (2016) for setting up a 24-item measurement scale under the name “Self-driving Car Acceptance Scale” (SCAS) to explain acceptance and the use of the Unified Theory of Acceptance and Technology (UTAUT) by Nordhoff *et al.* (2016), who proposed a combined conceptual model to explain, predict and improve user acceptance of AVs, in which they distinguished four categories of characteristics that may affect peoples’ perspectives: socio-demographics, mobility, vehicle and contextual characteristics (Figure 5). Among others, they conclude that young, tech-savvy, higher educated, full-time male workers, residents of urban areas with children in their household and some experience with vehicle automation are likely to use AVs more frequently, while elderly people or people who are too young to hold a driving license are more likely to accept them (socio-demographic and mobility characteristics). They also refer to the negative impact of higher levels of automation and heavier traffic situation on acceptance (vehicle and contextual characteristics).

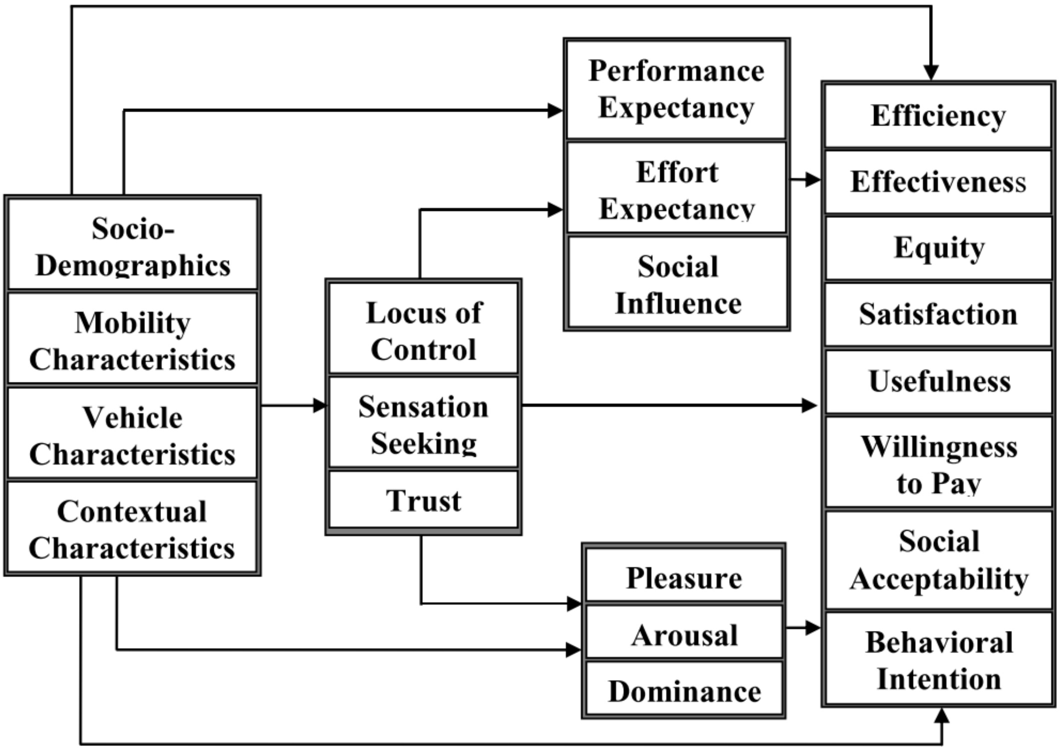

Figure 5:Conceptual Acceptance Model (Nordhoff et al., 2016)

A frequent conclusion made on existing studies is that young people are more likely to use driverless cars, compared to older age groups, even if AVs is a promising efficient solution for older or disabled people (König and Neumayr, 2017; Ellis et al., 2016), Furthermore, those having a high annual VMT (Vehicle Miles of Travel) and long-distance commute trips are found to be more willing to choose automated options (Shabanpour *et al.*, 2017). Kyriakidis *et al.* (2015), in a large longitudinal online survey (5000 respondents from 109 countries) observed that males and those who drove more were willing to invest more in the new technology, while the results of a survey conducted by Bansal *et al.* (2016) showed that technology-savvy males have a greater inclination towards AVs, while higher-income individuals are also expected to benefit more from automation because of their higher perceived value of time, which can be used more productively through full automation (Wadud, 2017).

Although analogies to other technologies (smartphones, e-learning, intelligent tutoring systems) and thus their experience of acceptance tend to be difficult to make, autonomous driving could be logically placed alongside existing examples of transport automated systems (e.g. airplanes, trains). For instance, surveys on public perception of UTO (Unattended Train Operations) demonstrate similar results, highlighting the factor of safety as a psychological barrier of users. An interesting finding that showcases the psychological factors was that almost 50% of a recent survey's respondents agreed that there should be a driver's room on the train, even if it is obviously not necessary, but surprisingly, almost 90% of the participants appeared willing to trust the technology (Fraszczyk *et al.*, 2015). The confidence and awareness levels in the case of AVs are lower and much higher respectively, because of the limited number of real-traffic trials. In a survey of public opinion on AVs in the U.S., the U.K. and Australia showed that the percentage of people who were not even familiar with them was approximately 30%, while a promising 60% was positive in using the technology (Schoettle and Sivak, 2014). In a recent combinatorial investigation into consumer preferences on electric and autonomous vehicles, Shabanpour (2017) points out similarities on the factors affecting participants' adoption behaviour (demographics, driving patterns, experience with technology) on the two types of vehicle. However, AVs place unique demands on acceptance, since we do not yet have a widely used mobility system without any human authority to supervise them and consequently the public's interaction in practice is still limited.

Focusing on concerns about AVs, in analyses carried out to date, consumers appear reluctant to adopt the technology because they feel uncomfortable with liabilities and absence of control (Deloitte, 2017). Howard (2014) collected data and opinions about self-driving cars in Berkeley and California and reported that their enhanced safety was the most attractive feature to individuals, while lack of control was their top concern. In another recent analysis, the possibility of imperfect performance in response to unexpected traffic situations was indicated as the most critical concern of respondents (Shabanpour *et al.*, 2017). Considering this fact, researchers investigate new acceptance models which incorporate considerations for safety, focusing on the psychology of control, acceptance and trust and the factors that influence the use of a safety critical technology (Hutchins and Hook, 2017).

Although the literature provides some insights on user preferences and concerns regarding AV technologies, there is considerable heterogeneity in results of the existing studies, which have moderate success in explaining the variance in acceptance of autonomous. Therefore, it is unanimously consented that much remains to be investigated in this particular domain.

2.3 Shared Autonomous Vehicles

While AVs are set to emerge on the public market, a considerable amount of literature suggests that they may quickly offer another mode of transportation, shared autonomous vehicles (SAVs), offering short-term, and on-demand rentals with self-driving capabilities, like a driverless taxi. According to Fagnant and Kockelman (2015), each SAV could potentially replace up to 10 household-owned vehicles and equally serve the same number of trips, reducing the total service times and travel costs, even after incorporating extra passenger pick-ups, drop-offs and non-direct routings, while the same view is supported by Anderson *et al.* (2015), who estimate an average cost reduction by 30% to 85%, depending on the cost of the autonomous technology and the expected returns on the fleet operator's investment. In a case study in Singapore, researchers modelled the potential replacement of all modes of personal transportation by a fleet of SAVs and the results revealed that the mobility needs of the entire population may be met by an estimated one-third of total private vehicles currently in operation (Spieser *et al.*, 2014). Subsequently, urban residents could avoid the fixed costs associated with car ownership as well. However, the assumption of SAVs being utilized more intensively may lead to more frequent required replacement in comparison with conventional cars (Milakis *et al.*, 2017).

A significant analysis and discussion on the subject of SAVs was recently presented by Haboucha *et al.* (2017), who developed a vehicle choice model to investigate individuals motivations for choosing to own or share autonomous vehicles, proposing methods to encourage SAV use (increase cost of conventional cars, educate/inform the public about the benefits of SAVs). The pro-AV attitude (current travel behaviour and lifestyle) was the strongest of the latent variables in the configuration of public preferences, with the majority being more interested in owning a fully automated vehicle. This result is consistent with the findings of a survey conducted by Bansal *et al.* (2016) in Texas, where 80% of the respondents were resistant to changing their current car-ownership profile.

Consumers' preferences in the nature of usage of AVs is associated with current car-sharing attitudes (use of Uber, Lyft etc.). Schaefers (2013) in her qualitative analysis concludes that the sense of community and identification with the lifestyle of other users are important motivating factors for car-sharing usage, while Correia and van

Arem (2016) note that despite recent signs of shift in travel patterns brought on by the shared-economy, 'owning an automobile is still linked to both instrumental and symbolic-affective motives'. The results of another stated choice survey conducted and analysed by Krueger *et al.* (2016) imply that the adoption of SAVs may differ across cohorts, whereby young individuals and those with multimodal travel patterns may be more likely to adopt SAVs. Therefore, lifestyle preferences, consumer attitudes, and travel patterns need to be taken into account when modelling public acceptance and adoption of transformative transportation technologies.

2.4 Acceptance and levels of automation

Public attitudes toward self-driving cars are increasingly important, as the public shapes the demand for the technology, the policies involved and the future investments in digital infrastructure. As we already suggested, the potential benefits and costs of AVs are analogous with the level of automation and the penetration rate, which in turn depend on the level of public confidence and acceptance, and subsequently the willingness to pay for it. A higher level of automation, cooperation and penetration rate could theoretically double the road capacity (penetration rate 100%) and lead to substantially higher fuel savings and limitation of emissions (Milakis *et al.*, 2017).

Whilst the level of automation seems to be a critical factor, it has not been always included in a clear way in relevant surveys, because of the fact that autonomous vehicles' implementation is in a quite germinal stage. Reviewing the previous research studies that include a classification of the level of automation, we observe that individual's acceptance varies. The initial predictions that systems restricting driver's behaviour are less likely to be accepted than non-restrictive, informative systems, made by Van Der Laan et al. (1997) were eventually rejected two decades later by Kyriakidis *et al.* (2015). In their international survey's questionnaire, they included technical information and provided the respondents with the definitions of all levels of automation (manual driving, partially automated driving, highly automated driving, and fully automated driving), investigating their acceptability, concerns and willingness to buy for each level. Respondents indicated that fully automated driving would be more convenient and enjoyable than manual driving, whereas driving partially automated car could potentially be somewhat more difficult in comparison with a conventional vehicle, while they would have been more willing to purchase for full than high automation. However, the findings of Van Der Lann *et al.* (1997) about the level of automation being negatively correlated with acceptance was supported by Schoettle and Sivak (2015) and Nordhoff *et al.* (2016).

Regarding the comparison between fully and partially automated driving, Banks *et al.* (2018) conducted an on-road study to further explore whether partially automated functions can appropriately support the driver in completing their new monitoring role. The analysis of the video results suggested that drivers demonstrated behaviour indicative of complacency and over-trust, which may encourage them to take more risk during driving. However, on-road testing is not available in the vast majority of the surveys and that is the reason why acceptance of AVs is so challenging to understand. Payre *et al.* (2014), in their attempt to measure the "a priori acceptability" of fully automated cars, found that the predictors of intention to accept fully automated driving (FAD) was mainly attitudes, contextual acceptability and interest in impaired driving and driving-related excitement-seeking, finally gender.

2.5 Autonomous Vehicles' adoption over time

After reviewing the existing literature, we observe that the vast majority of quantitative academic studies around autonomous vehicles' acceptance concentrate on the behavioural analysis and do not adopt a chronological approach since they are based on surveys conducted in one time-point. However, there is a small number of papers and reports principally delivered by consulting companies, which have considered the effect of time, evaluating the present situation, making use of repeated cross-sectional data to compare the statistical results over time and attempting future predictions.

According to a recent analysis (McKinsey, 2016), we should not expect to observe significant differences on acceptance statistics between short periods of time (a few years), since the adoption levels still present stability or fluctuation. The report distinguishes different disruption scenarios concerning the progressive diffusion of fully autonomous vehicles, placing their potential commercial introduction not earlier than 2020 – 2025. As far as the present situation, if we look at the five phases of adoption (innovators, early adopters, early majority, late majority, and laggards), as they have been defined by Rogers (1995), we can safely say that highly automated vehicles are currently in the early adopters phase and we are possibly crossing the chasm (Figure 6).

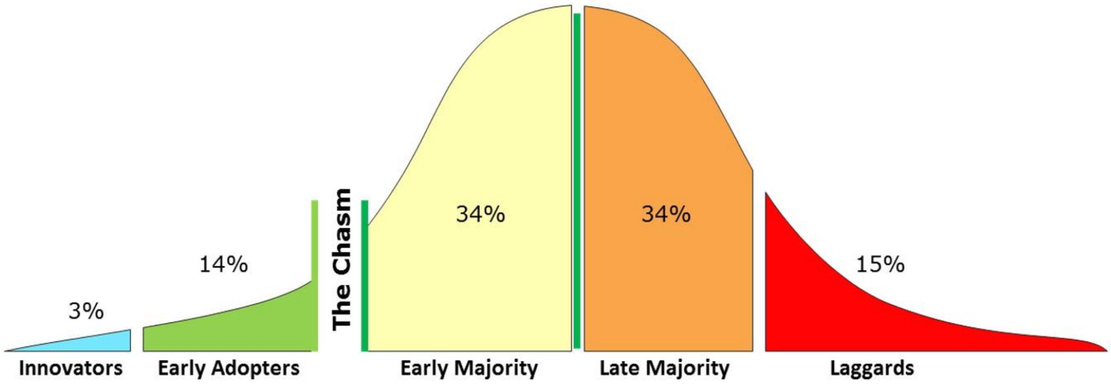

Figure 6: Technology Adoption Life Cycle (Rogers, 1995)

Based on the technology adoption life cycle, Gartner's research and annual reports have also been of considerable interest to researchers, stakeholders, and consumers. The so-called "hype cycle" is developed by the American research and IT firm, for graphically present the maturity, adoption and social application of specific technologies. The hype cycle provides a graphical and conceptual presentation of the maturity of emerging technologies through five phases: technology trigger, peak of inflated expectations, trough of disillusionment, and slope of enlightenment and plateau of productivity (Linden and Fenn, 2003). After integrating the last few year's reports' data, the evolution of the hype cycle for autonomous vehicles between 2012 and 2017 is presented in Figure 7. An interesting point is that the predictions for autonomous vehicle reaching the "Plateau of Productivity" in 5-10 years remained unchanged for four years until 2016-17 when they changed to "more than 10 years". This is probably due to numerous incidents taking place during this period, including the first fatality related to a highly automated driving feature (Forbes article, 2016) and the proportional shift away from comfort with automation –especially full automation, as the recent MIT AgeLab repeated survey confirms (Abraham *et al.*, 2017).

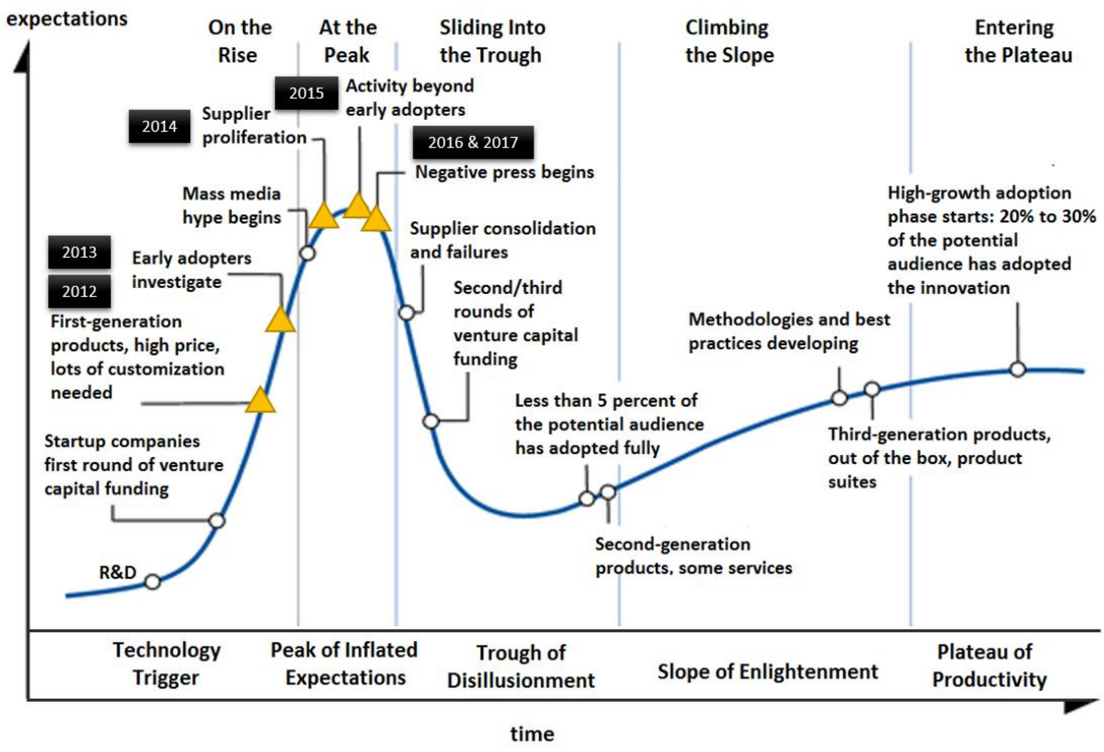

Figure 7: Hype Cycle for Autonomous Vehicles (Gartner, 2012-2017):

A longitudinal study conducted by Kohl *et al.* (2017) attempted to measure the level of disruption of individual mobility by self-driving cars over time in terms of risk and benefit perception, using an alternative and interesting approach, by analysing a huge amount of text posted in Twitter throughout fifteen consecutive months (March 2015 – July 2016). The results showed that the risk and benefit perceptions developed over time and were influenced by certain events, leading to domination of tweets mentioning the risks and indicating a lack of acceptance, while the total number of tweets about risks or benefits for autonomous vehicles were dramatically decreased during 2016.

There are clearly so many aspects that someone could investigate about public perspectives on autonomous vehicles and the future scenarios to assume, predict and analyse are numerous. The definition "autonomous vehicles" itself includes so many different features, in terms of the level of automation or the type of the transportation system. Many scientific papers refer to the term to describe a wide range of possible usage of autonomous features, as autonomous underwater vehicles, autonomous golf cars, autonomous delivery vehicles, and drones. Besides that, there are more points of view except for the user's, such as pedestrians' receptivity toward automated vehicles and the impact on their safety

Overall, quite a large number of international studies on public acceptance of autonomous vehicles have been conducted up to date, which include surveys of members of motoring organisations (conducted by consulting companies, insurance companies or roadside recovery companies), population-representative opinion polls (conducted by recognised polling companies and published online or reported in the media) and in-depth academic studies of specific dimensions of perceptions of self-driving cars (conducted on small or bigger samples, which are not necessarily representative of well-defined population groups).

The present study appertains to the third category, making use of repeated cross-sectional data, derived from two travel surveys in an urban residential area in U.S. conducted in 2015 and re-deployed in 2017 and aims at exploring the scenario under which people would prefer to use the new technology and to what extent would accept automation, while investigating public acceptance on fully autonomous vehicles over time in an attempt to follow up the existing studies and estimate the current phase of their public acceptance and adoption.

3 Study Area, Data, and Methods

3.1 Study Area

Our study area is the Puget Sound region, located on the northwestern coast of the U.S. state of Washington. The region makes an interesting case study, including urban centres such as Seattle and satellite cities such as Bremerton and Bellevue, which are fairly considered to be innovation hubs, as they compete with each other for pioneering self-driving cars. It is worth noting that Seattle traffic congestion was listed as ninth worst among U.S. cities, according to a recent scorecard released by traffic technology and data firm INRIX (Cookson and Pishue, 2017). As a consequence, the city is embracing innovative solutions able to lead in traffic congestion decrease as well as number and consequences of car accidents, a fact that may have a positive impact in citizens' awareness regarding AVs.

The total population of the four main counties, namely King, Pierce, Snohomish, and Kitsap is 4,063,713. The region is characterized by a significantly young population. Specifically, according to official age distributions (United States Census Bureau), the average percentage of people belonging to the age group 18-44 is 37.7%, which is higher than the corresponding 35.3% in the state of Washington and 34.7% in the United States. It is worth noting that the most populated county (King) holds a young population percentage equal to 39.4%, while Seattle holds an impressive 47.7%. Having a higher proportion of young people makes the area more appropriate for our study since the specific age range is practically the most crucial in the adoption of AVs during the next years.

3.2 Data

In the framework of the development of regional planning strategies, Puget Sound Regional Council conducts household travel surveys in a two-year basis, to collect current data and representative information of residents, including detailed information about socio-economic, demographic, literacy, technology use, attitudes and activity-travel characteristics needed for monitoring and modelling travel and land use patterns. The open data used in this paper are the final datasets of the spring 2015 survey and 2017 survey (which became available on the 2nd of April 2018) and they are the most recent in terms of availability. A total of 4786 people from 2419 households completed the 2015 survey, while the total sample size of 2017 survey was even larger (6254 people from 3285 households). Within all final samples used, individuals younger than 18 years old were excluded.

During the survey, autonomous vehicles were defined as follows: "Autonomous cars, also known as "self-driving" or "driverless" cars, are capable of responding to the environment and navigating without a driver controlling the vehicle". The questionnaires of the two surveys include several (same in both years) questions concerning autonomous vehicles, in terms of the level of interest and level of concern, covering a range of aspects, given the comparatively early stage of AVs evolution and the general lack of more detailed evidence and data.

The objective of the current research is to analyse traveller's interest in adopting full automation and determine the extent to which they are inclined to acquire such vehicles for private ownership or use them in a shared mobility service configuration. In addition, we conduct a comparative analysis of the two surveys' results, in order to reveal possible changes in public perceptions, preferences, and level of concern over time, including safety, liability, security, capability, and performance.

3.3 Methodology

In our first question, we examine the future potential of AVs as part of a share-riding transportation system, by constructing a four-alternative multinomial choice variable that captures the level of interest in AV use. The two questions that were used for this purpose are the following:

- Level of interest in owning an autonomous car
- Level of interest in participating in an autonomous car-share system (SAV) for daily travel

Correspondingly, for our second question, which aims to investigate the acceptance of autonomous vehicles depending on their automation level, we are making use of the following questions.

- Level of interest in riding a fully autonomous car (no driver present)
- Level of interest in riding a partially autonomous car (back-up driver present)

All four questions are included in both 2015 and 2017 datasets, in the exact same structure, while the answer is measured using a six-point Likert scale, anchored by not interest at all and very interested ("not at all interested", "somewhat interested", "neutral", "don't know", "somewhat interested", "very interested").

Given the big amount of data, the datasets are analysed using RStudio, which is a free and open-source integrated development environment (IDE) for R, a programming language for statistical computing and graphics (Available at https://www.rstudio.com/products/rstudio/download/). After experimenting with ordinal regression models for our analysis, we carried out a likelihood ratio test (Brant test), from which we obtained evidence that the parallel regression assumption had been violated. This means that the coefficients that describe the odds of being in the lowest category vs. all higher categories of our response variable are not the same with those that describe the odds between the second lowest category and all higher categories, etc. Therefore, we choose the following alternative approach, which will enable us to deploy multinomial logistic regression models instead:

Taking into consideration the ambiguity of the "neutral" category and the slight hesitation entailed in the "don't know" category, we express the level of interest with a binary variable. Respondents who were somewhat interested and very interested were considered as being interested in AVs, while all others were treated as being uninterested. This configuration should also allow us to provide a conservative estimate of adoption rates, which can be considered as prudent since the survey did not offer detailed explanations about the new technology to the participants, but only leaned on the preconceived level of their awareness. The binary indicators of the level of interest in owning or sharing an autonomous car were then combined into a single four-alternative multinomial variable as follows:

- Not interested in sharing or owning an AV
- Interested in owning an AV only
- Interested in sharing an AV only
- Interested in sharing and owning an AV

Following the same rationale and procedure, we construct a second four-alternative multinomial variable, by combining the binary indicators of the level of interest in full or partial automation, as follows:

- Not interested in fully or partially autonomous vehicles
- Interested in fully autonomous vehicles only
- Interested in partially autonomous vehicles only
- Interested in fully and partially autonomous vehicles

The selected target sample for this study includes adult workers (divided into three age groups), having access to at least one vehicle within their household. The main reason behind this selection is the fact that people being employed are the most critical group, in terms of being able to purchase an AV or pay for a sharing service. Thus, the investigation of how willing they appear to become potential purchasers and eventually how quickly they would be ready to shift from their current conventional vehicles to an innovative type of mobility is crucial. Besides that, the selection enables us to investigate individuals' intentions~~,~~ using "Working Hours", "Commuting Mode", "Commuting Frequency", "Vehicle Age" and "Vehicle Fuel Type" as independent variables, the meaning of which will be detailed below. The factors that were taken into account as potentially significant in the adoption of fully autonomous vehicles and the context in which the technology can transform the future transportation systems are presented in Table 1, along with the descriptive statistics of our two final samples (2015 and 2017).

A substantial percentage of the participants in both surveys belong in the "not interested" category. However, this percentage is lower in 2017 survey, and approximately 50% compared with 60% of the survey conducted only two years earlier. Before conducting any analysis, we can observe that in 2017 survey, the sample population is slightly younger, has a higher average level of education, a higher level of tech-savviness and more developed sharing attitudes, while a higher percentage lives in overpopulated residential areas, own comparatively newer cars and choose more often their personal vehicles over public transport and active travel modes to commute.

Based on the existing literature, we distinguish four categories of characteristics that we initially hypothesize as important determinants of public acceptance, which in turn include the most closely related variables chosen to capture the corresponding factors, in respect with the availability of the surveys' datasets. The procedure of selection, the categorization and the meaning of the variables that are eventually being used in constructing our two combined analytical models, are described elaborately as follows:

Table 1: Descriptive Statistics for final samples

	2015		2017	
	Mean	SD	Mean	SD
Sociodemographics				
Age (5 = 18-24 to 12 = 85 or older)				
Generation 1 (18-44)	54,46%		69,24%	
Generation 2 (45-64)	40,92%		26,85%	
Generation 3 (65+)	4,62%		3,91%	
Gender (Male)	53,13%		49,87%	
Education (1 = Less than high school to 7 = Graduate/Post-graduate degree)	5,44	1,62	5,68	1,53
Children (1 or more)	29,03%		27,10%	
Income				
<25000	5,16%		3,48%	
25000-50000	13,62%		10,28%	
over 50000	81,22%		86,24%	
Working hours (1 = more than 50 hours to 6 = 10 hours or fewer)	2,67	1,08	2,50	0,87
Disability	4,62%		3,57%	
Mobility characteristics, Travel Attitudes & Tech-savviness				
Number of trips	9,35	6,40	9,71	13,34
Commute mode (public transport/active travel)	21,28%		13,85%	
Commute frequency ((1 = 6-7 days/week to 7 = never)	2,53	1,18	2,29	0,86
Transit frequency (1 = 6-7 days/week to 7 = never)	5,80	1,28	5,85	1,15
Walk frequency (1 = 6-7 days/week to 7 = never)	3,46	1,85	3,59	1,80
Bike frequency (1 = 6-7 days/week to 7 = never)	6,10	1,35	6,32	1,04
Important to be close to public transit (1 to 5 = very important)	3,24	1,35	3,28	1,39
Important to be within 30-min commute to work (same scale)	4,12	1,19	4,17	1,20
Ride sharing (at least once)	7,75%		50,13%	
Car sharing (potential 2015) (yes) / Carpool (2017) (at least once)	23,79%		12,15%	
License	98,51%		98,90%	
Smartphone (have or plan to get)	85,76%		-	
Smartphone age (less than 4 years old)	-		89,89%	
Smartphone qualified	-		89,89%	
Vehicle characteristics				
Fuel type (gas/diesel alternatives/renewables)	5,48%		6,12%	
Car age (new car: two years old or newer)	29,19%		48,17%	
Contextual characteristics				
High population density (>8000 persons/square mile)	28,79%		37,81%	
Parking availability in workplace (park seekers)	59,55%		97,45%	
Importance of space (1 to 5=very important)	3,59	1,20	3,44	1,24
Interest in owing or sharing an autonomous vehicle				
Not interested in sharing or owing an AV	61,27%		50,89%	
Interested in owning an AV only	9,55%		12,57%	
Interested in sharing an AV only	8,29%		8,24%	
Interested in sharing and owing an AV	20,89%		28,29%	
Interest in riding a fully or partially automated vehicle				
Not interested in full or partial automation	61,74%		51,66%	
Interested in full automation only	8,22%		8,50%	
Interested in partial automation only	7,20%		9,52%	
Interested in full and partial automation	22,85%		30,33%	
Sample size	1278		1177	

3.4 Variables selection

3.4.1 Socio-demographics ("SD")

Age: The reference age group used refers to the population lying from 18 to 44 years old, which we hypothesize that is more likely to adopt the new technology

Gender: Although the heterogeneity of previous studies' results regarding gender, they generally show differences in the level of acceptance between males and females. Thus, gender is included as an explanatory variable in both models (Reference: Male)

Education: The statement that an individual of higher education level could be less resistant to the idea of participating in an SAV system is to some extent sensible. However, the discipline in which people are specialised may also significantly affects the extent to which they are willing to trust AVs (Reference: High school or lower)

Children: The fact that, in general, families with children tend to realise a larger number of trips may positively influence their perspectives on autonomous vehicles, but also boost their psychological barrier of taking the responsibility for their children to ride a car that doesn't provide any human control (Reference: No children)

Income: The variable captures the impact of income distribution on acceptance, and specifically consumer acceptance (Buckley *et al.*, 2018). We logically expect that people with lower income may prefer sharing an AV, instead of owing it, while more wealthy people may present higher levels of interest, because, except for their higher perceived value of time, they are also more likely to afford it (Reference: over 50,000)

Working Hours: The employment status is considered to be a critical factor in the configuration of public willingness to use autonomous vehicles, as they would provide them with additional productive commute time. The effect is expected to be more noticeable in those exceeding the typical working hours (Reference: ≤ 40 hours/week)

3.4.2 Mobility characteristics, Travel Attitudes & Tech-savviness

This category includes the underlying lifestyle factors that may affect the propensity to adopt autonomous vehicles, divided into these key subcategories. The variables appertaining to the "Mobility characteristics" category are used in both models. The "Travel Attitudes" category includes variables incorporated in our first model (for the public adoption of SAVs) since they capture the extent to which individuals have an active and multimodal travel profile and attitudinal variables concerning their current sharing habits. Finally, the “Tech-savviness” category includes variables being deployed in our second model (for public acceptance of full autonomy), considering them as more critical to capture the acceptance associated with the level of autonomy, with full automation to represent the most cutting-edge technology.

3.4.2.1 Mobility characteristics (“Mobil”)

Commute mode: The survey asks what is participants’ typical commute mode and the responses are related either to private transport (e.g. “drive alone”, “drive only with other household members”) or active travel (e.g. “bicycle”, “walk”, “skateboard”) and public transport modes (e.g. “bus”, “train”). We expect that individuals with multimodal travel patterns may be more likely to adopt an innovative transportation system, especially in the form of SAVs. (Reference: Private Transport)

Number of trips: We rationally expect that those making a larger number of trips will be more interest in the new technology in any form, even to shift to full automation (Reference: <10)

Disability: The expected impacts of AVs’ introduction on the travel behaviour of mobility impaired travellers are radical, especially given the currently low car availability for these vulnerable groups, which are likely to be early adopters of the technology, in a future where impairments will be no longer a reason for not using a car (Reference: No)

3.4.2.2 Travel & Sharing Attitudes (“Travel”)

In some of the existing literature, the pro-AV attitudes (current travel behaviour and lifestyle) was the strongest of the latent variables in the configuration of public preferences towards driverless cars. In particular, we expect that those characterised by more active and multimodal travel patterns and car-sharing attitudes may be more likely to be the early adopters and advocators of SAVs. The variables used are the following:

Walk & bike frequency (Reference: Never)

Transit frequency and importance: The survey, except for transit frequency (Reference: Never), asks how important is for each individual to be close to public transit, as a factor for choosing a home location (Reference: Not important/Neutral)

Commute frequency and importance: In a similar way, the survey includes a question measuring the commute frequency (Reference: ≤2 days/week), while another one asks how important is for each individual to be within a 30-minute commute to work (Reference: Not important/Neutral).

Ride and car sharing: The two surveys provide information about the ride and car sharing habits of respondents by requesting answers to how many times the individual used car-share or ride-share services in past 30 days (e.g. car2go, RelayRides, Zipcar, Lyft, Sidecar, Uberx, Pronto or other) (Reference: Never)

Because of the null percentages of positive answers, in terms of making usage at least one time of carpooling services among 2015 survey's responses, this question is replaced – in lack of an identical variable – by an alternative combined variable emerging from six questions asking 2015 participants how they would potentially change their travel attitudes, by commuting more frequently by carpool/vanpool (if an optimisation of these services could lead to time or money savings), practically capturing their intentions to use it (Reference: No)

3.4.2.3 Tech-savviness / Other variables ("Tech")

Smartphone ownership: Through this category, we are making an effort to capture the tech-savviness of individuals, in terms of technology awareness. Both surveys ask participants if they currently own or plan to get a smartphone within the next year, while the 2017 survey includes two additional questions, about smartphone age and installed apps, which are used instead (since everyone owns a smartphone):

- Smartphone is more than four years old (yes/no) (Reference: Yes)
- Owns rMove qualified smartphone (yes/no) (Reference: No)

License ownership: Fully autonomous vehicles could potentially lead to the eradication of driving licenses, in favour of those who don't hold one. Partial automation would not allow this, therefore we expect that people not holding a license will be less keen in a partially autonomous vehicle (Reference: Yes)

3.4.3 Vehicle Characteristics (“Veh”)

Car age: We assume that individuals owning a considerably newer car have experienced vehicle automation in some way and in some extent and consequently they may are more likely to use autonomous cars in any future scenario (Reference: old car)

Fuel type: The second vehicle characteristic included in our models refers to current vehicle fuel type (Gas, Diesel, Hybrid, Flex Fuel, Electric, Biofuel, Natural gas). We rationally assume that people who currently own vehicles consuming renewable and sustainable kinds of energy would be more likely to trust the new disruptive mode since they have already been early adopters of alternative transportation-related technologies (Reference: Gas/Diesel)

3.4.4 Contextual Characteristics (“Cntx”)

Population density: The population density was calculated for each resident completing the survey, making use of their corresponding household’s census tract. The data was derived from the official website of the Washington State Department of Health (https://www.doh.wa.gov/), which provides detailed population distribution datasets. We consider that the blocks that had a density of over 8000 persons per square mile are high-density regions (the average is approximately 7000 per/sqm). We expect that individuals living in high-density residential areas will be more interested in fully or partially autonomous vehicles, and especially in a shared-vehicle mobility-on-demand system, rationally assuming that these areas are associated with heavier traffic situation, which accounts some of the variance in acceptance, as also hypothesised on the conceptual model of user’s acceptance on driverless vehicles, developed by Nordhoff *et al.* (2016) (Reference: <8000 persons / square mile)

Importance of space: In the same direction, it is predicted that fleets of shared autonomous vehicles could meet the mobility needs of the entire population by using only an estimated one-third of total private vehicles currently in operation, leading to substantial space savings (e.g. parking areas reduction) and activating more efficient land utilization. It is worth noting that the estimated total area dedicated to parking space is on average equivalent to 31% of distinct areas (Bagloee *et al.*, 2016). This variable measures the level of importance of people having space in their residential area and we can expect that it will be positively associated with acceptance. (Reference: Not important/Neutral)

Parking availability: The variable emerges from questions asking people about their usual parking location in the workplace and if their work provides them with a free or subsidised parking. We expect that those required to daily seek a parking spot near their workplace or even pay for using a parking lot (limited parking availability) will be more interested in sharing an AV. As far as the level of automation, we can expect the parking seekers to be more willing to try a fully autonomous car, which would completely exempt them from the park seeking process (Reference: Yes)

3.5 Analytical Models

The final variables selection for each analytical model have been made after experimenting with a wide range of different combinations and it is presented in the next chapter tables, along with the results and the discussion. Furthermore, the selection of the variables has been made in a way, in order for each pair of models deployed to answer our two main research questions to be identical, or almost identical. This should enable us to compare the results more effectively and safely since identical variables have the same gravity/weight/effect for our dependent variable estimate in both years. The majority of the variables are totally identical since they emerge from the very same questions, but in lack of identical ones, we choose closely related in cases where the variable is crucial. For instance, in the pair of models for public acceptance of full autonomy, the variable of "smartphone ownership" of 2015 is replaced by two different but smartphone related variables ("smartphone age" and "smartphone qualified"), given their critical role for capturing the tech-savviness. Additional information about the models' construction procedure and the final equations are presented as follows:

3.5.1 Analytical models for public adoption of SAVs

After transforming our response variable into a multinomial four-choice variable – as explained earlier in this chapter – two identical multinomial logistic models were employed (one for each year). The probability that Y is equal to one of the outcomes (e.g. "Interest in sharing an AV only"=m) can be written as follows:

$$\Pr(y_i = m|x) = \frac{\exp(\beta_m x_i)}{\sum_{j=1}^{J} \exp(\beta_j x_i)}$$

where x includes x_{SD}, x_{Mobil}, x_{Travel}, x_{Veh} and x_{Cntx} (based on the variable categories detailed in the text above). In practice, one of the outcome categories is set as a baseline category, constraining all coefficients to be 0 to identify estimates. In this analytical model, the category "Not interested in sharing or owning an AV" is assumed as a baseline, and the relative impacts of $\boldsymbol{x}$ on other answers (i.e., "Interested in owning an AV only", "Interested in sharing an AV only", "Interested in sharing and owning an AV") compared to the baseline category were examined

3.5.2 Analytical models for public acceptance of full

In a similar way, we employ a second pair of identical multinomial regression models to investigate the public acceptance of full autonomy. The probability that y is equal to one of the outcomes (e.g. m) can be written again as above:

$$\Pr(y_i = m|x) = \frac{\exp(\beta_m x_i)}{\sum_{j=1}^{J} \exp(\beta_j x_i)}$$

where, in this case, x includes x_{SD}, x_{Mobil}, X_{Tech}, X_{Veh} and x_{Cntx} (based on the variable categories detailed in the text above). Correspondingly, the category "not interested in fully or partially autonomous vehicle" is assumed as a baseline, and the relative impacts of $\boldsymbol{x}$ on other answers (i.e., "Interested in fully AV only", "Interested in partially AV only", "Interested in fully and partially AV") compared to the baseline category were examined.

4 Results and discussion

In this chapter, the outcomes of our investigation are being aggregated initially in two combined tables, where the results of each pair of our analytical models are presented together (2015 and 2017). The results of the multinomial logistic models for public's adoption of SAVs are presented in Table 2, while the results of the models for public acceptance of full autonomy in automobiles are presented in Table 3. The side-by-side presentation of the results will allow us to solidly interpret them, highlighting the statistically significant relationships, and effectively compare them, examining changes over time. The comparison of the results is supported by figures and tables. An assessment of the adequacy and validity of our fitted multinomial logistic regression models (goodness of fit) is also included.

Given the quite large number of significant associations emerging from our results and the fact that our study has two directions, in order the reader to be more easily led to refer to the corresponding part in accordance with interest, we consider it meaningful to organise the structure of this chapter as follows:

The presentation of the results initially follows the variables' categorisation, as detailed in the previous chapter, analysing what are the impacts of each category's corresponding factors in public acceptance of the different autonomous vehicles future scenarios. Following this, we make a further analysis of the results from a different point of view, classifying our discussion depending on our two research questions. More specifically, we examine the effects of our explanatory variables in workers' perceptions depending on different potential ownership model choice and following this, we investigate what are their effects on acceptance depending on the level of automation, while pointing out significant changes over time. An additional discussion is made to review the factors that somehow impact acceptance towards AVs over time, regardless of any particular future scenario.

Table 2: Multinomial Logistic Model for public adoption of SAVs

	Interested in owning an AV only						Interested in sharing an AV only						Interested in owning and sharing an AV					
	2015			2017			2015			2017			2015			2017		
	Estimate	SE	Pr(>|t|)	Estimate	SE	Pr(>|t|)	Estimate	SE	Pr(>|t|)	Estimate	SE	Pr(>|t|)	Estimate	SE	Pr(>|t|)	Estimate	SE	Pr(>|t|)
(Intercept)	-2.87	0.79	0.00**	-1.23	0.39	0.00**	-5.89	1.13	0.00**	-3.70	0.97	0.00**	-3.07	0.59	0.00**	-1.62	0.37	0.00**
Socio-demographics																		
Age (Reference: 18-44 years old)																		
45-64 years old	-0.40	0.22	0.00**	-0.55	0.23	0.00**	-0.29	0.24	0.00**	-0.24	0.27	0.00**	-0.87	0.17	0.00**	-1.07	0.19	0.00**
65+ years old	0.11	0.41	0.79	-1.42	0.64	0.03*	-0.10	0.57	0.87	-1.48	1.05	0.16	-1.19	0.50	0.02*	-0.89	0.43	0.04*
Gender (Reference: Male)	0.22	0.20	0.28	-0.82	0.20	0.00**	0.20	0.22	0.36	-0.53	0.24	0.00**	0.54	0.15	0.00**	-0.94	0.15	0.00**
Education (Reference: Highschool or lower)	0.95	0.49	0.05*	0.93	0.51	0.07†	1.55	0.75	0.04*	-0.30	0.53	0.57	0.46	0.32	0.15	-0.02	0.33	0.94
Income (Reference: 50,000+)																		
25,000-50,000	-0.30	0.32	0.36	-0.12	0.33	0.72	0.03	0.31	0.93	0.13	0.36	0.71	0.01	0.23	0.96	-0.19	0.26	0.46
under 25,000	0.02	0.44	0.96	-1.15	0.76	0.13	-0.18	0.52	0.73	-0.29	0.66	0.66	-0.26	0.36	0.47	-0.35	0.42	0.41
Working hours (Reference: ≤40 hours/week)	-0.47	0.31	0.12	0.50	0.21	0.02*	-0.01	0.38	0.98	0.46	0.25	0.07†	0.31	0.28	0.26	0.38	0.16	0.02*
Mobility Characteristics & Travel Attitudes																		
Commute mode (Reference: Private Transport)	-0.33	0.29	0.25	0.75	0.77	0.33	0.11	0.28	0.70	-0.72	0.53	0.17	-0.16	0.20	0.44	-0.12	0.42	0.78
Commute frequency (Reference: ≤2 days/week)	0.13	0.38	0.73	0.02	0.26	0.93	1.05	0.62	0.09†	0.32	0.32	0.32	0.20	0.31	0.52	0.11	0.20	0.59
Transit frequency (Reference: Never)	0.20	0.23	0.37	0.29	0.22	0.18	0.53	0.27	0.05*	0.71	0.32	0.03*	0.23	0.18	0.20	0.44	0.18	0.01*
Number of trips (Reference: <10)	-0.28	0.22	0.21	0.15	0.23	0.52	-0.34	0.25	0.18	0.36	0.26	0.16	-0.12	0.16	0.48	0.43	0.18	0.02*
Bike frequency (Reference: Never)	-0.29	0.22	0.17	-0.49	0.21	0.02*	0.08	0.23	0.74	0.21	0.24	0.38	0.41	0.16	0.01*	-0.15	0.16	0.34
Important to be close to public transit (Reference: Not important/Neutral)	0.08	0.22	0.72	-0.15	0.21	0.48	0.28	0.24	0.24	0.13	0.25	0.60	0.41	0.17	0.01*	0.16	0.16	0.33
Important to be within 30-min commute to work (Reference: Not important/Neutral)	-0.10	0.24	0.68	0.18	0.24	0.46	0.29	0.29	0.31	0.83	0.35	0.02*	0.00	0.19	0.99	0.18	0.19	0.34
Ride sharing (Reference: Never)	0.22	0.41	0.59	0.03	0.22	0.90	0.73	0.36	0.04*	0.34	0.27	0.20	0.90	0.27	0.00**	0.64	0.17	0.00**
Car sharing (Reference: No/Never)	-0.19	0.26	0.46	-1.24	0.46	0.01*	0.83	0.24	0.00**	0.33	0.31	0.28	0.54	0.17	0.00**	-0.05	0.23	0.82
Disability (Reference: No)	0.75	0.41	0.07†	0.70	0.50	0.17	0.97	0.46	0.04*	0.58	0.57	0.31	0.28	0.39	0.47	-0.32	0.48	0.50
Vehicle characteristics																		
Fuel type (Reference: Gas/Diesel)	-0.01	0.46	0.99	0.10	0.40	0.79	0.58	0.45	0.20	-0.54	0.64	0.39	0.41	0.32	0.19	0.50	0.30	0.10†
Car age (Reference: old car)	0.25	0.22	0.24	0.59	0.20	0.00**	0.07	0.24	0.78	-0.23	0.24	0.34	0.13	0.16	0.43	0.36	0.15	0.02*
Contextual characteristics																		
Pop. Density (Reference: <8000 per / sq.mile)	0.43	0.24	0.07†	0.01	0.22	0.96	0.73	0.25	0.00**	0.88	0.25	0.00**	0.20	0.18	0.27	0.02	0.16	0.92
Parking availability (Reference: Yes)	0.18	0.22	0.41	-1.03	0.51	0.04*	0.51	0.25	0.04*	-0.07	0.69	0.92	0.19	0.17	0.25	0.28	0.53	0.59
Importance of space (Reference: Not important/Neutral)	0.08	0.21	0.72	-0.07	0.20	0.72	-0.15	0.22	0.51	0.11	0.24	0.63	0.15	0.16	0.34	0.26	0.15	0.09†
Sample size	1278			1177			1278			1177			1278			1177		

†significant at the 0.10 level, *significant at the 0.05 level, **significant ate the 0.01 level.

Table 3: Multinomial Logistic Model for public acceptance of full autonomy

	Interested in fully autonomous vehicle only						Interested in partially autonomous vehicle only						Interested in fully and partially autonomous vehicle					
	2015			2017			2015			2017			2015			2017		
	Estimate	SE	Pr(>|t|)	Estimate	SE	Pr(>|t|)	Estimate	SE	Pr(>|t|)	Estimate	SE	Pr(>|t|)	Estimate	SE	Pr(>|t|)	Estimate	SE	Pr(>|t|)
(Intercept)	-4.71	1.24	0.00**	-2.38	0.64	0.00**	-16.77	0.58	0.00**	-2.32	0.56	0.00**	-2.55	0.71	0.00**	-1.29	0.34	0.00**
Socio-demographics																		
Age (Reference: 18-44 years old)																		
45-64 years old	-0.54	0.24	0.00**	-0.6	0.26	0.00**	-0.66	0.26	0.00**	-0.73	0.25	0.00**	-0.87	0.16	0.00**	-1.05	0.17	0.00**
65+ years old	-0.79	0.64	0.22	-0.82	0.64	0.20	0.29	0.45	0.53	-1.63	0.76	0.03*	-0.63	0.39	0.10†	-1.35	0.44	0.00**
Gender (Reference: Male)	0.91	0.22	0.00**	-0.86	0.23	0.00**	-0.22	0.24	0.00**	0.03	0.22	0.89	0.36	0.15	0.00**	-0.55	0.14	0.00**
Education (Reference: Highschool or lower)	1.23	0.54	0.02*	0.35	0.51	0.50	2.23	1.02	0.03*	1.02	0.63	0.10†	0.87	0.33	0.01*	0.33	0.33	0.32
Children (Reference: No children)	-0.88	0.29	0.00**	-0.51	0.27	0.06†	-0.22	0.29	0.44	-0.21	0.25	0.39	-0.33	0.18	0.06†	-0.39	0.16	0.02*
Income (Reference: 50,000+)																		
25,000-50,000	0.48	0.30	0.12	-0.12	0.37	0.74	0.33	0.32	0.30	-0.42	0.37	0.26	-0.07	0.22	0.76	-0.66	0.26	0.01*
under 25,000	-0.11	0.57	0.85	0.11	0.59	0.86	0.69	0.47	0.14	0.19	0.49	0.69	-0.05	0.35	0.89	-0.91	0.46	0.05*
Working hours (Reference: ≤40 hours/week)	0.10	0.22	0.67	0.62	0.24	0.01*	-0.12	0.24	0.61	-0.12	0.22	0.59	0.03	0.15	0.83	0.22	0.15	0.13
Mobility characteristics & Tech-savviness																		
Smartphone (Reference: don't have one)	0.41	0.35	0.25				0.42	0.38	0.27				0.44	0.24	0.07†			
Smartphone age (Reference: "old")				0.14	0.20	0.50				-0.26	0.16	0.10†				0.01	0.12	0.94
Smartphone qualified (Reference: No)				0.14	0.20	0.50				-0.26	0.16	0.10†				0.01	0.12	0.94
License (Reference: Yes)	-0.67	1.08	0.54	-0.48	1.14	0.68	-12.00	0.58	0.00**	-0.07	1.15	0.95	-0.46	0.61	0.45	-1.04	0.69	0.13
Commute mode (Reference: Private Transport)	0.11	0.28	0.69	-0.08	0.58	0.89	0.16	0.31	0.62	-0.11	0.57	0.85	0.38	0.19	0.04*	0.39	0.43	0.36
Number of trips (Reference: <10)	0.31	0.24	0.20	0.37	0.26	0.16	-0.13	0.27	0.63	0.60	0.24	0.01*	-0.12	0.17	0.47	0.64	0.17	0.00**
Disability (Reference: No)	0.86	0.45	0.06†	0.00	0.65	0.99	0.40	0.51	0.44	0.89	0.48	0.06†	0.20	0.36	0.57	-0.25	0.46	0.59
Vehicle characteristics																		
Fuel type (Reference: Gas/Diesel)	0.70	0.42	0.10†	0.11	0.48	0.82	-0.03	0.55	0.95	0.29	0.48	0.54	0.41	0.30	0.17	0.55	0.29	0.06†
Car age (Reference: old car)	-0.15	0.24	0.53	-0.02	0.22	0.92	-0.01	0.25	0.97	-0.15	0.21	0.49	0.21	0.16	0.17	0.24	0.14	0.09†
Contextual characteristics																		
Pop. Density (Reference: <8000 per / sq. mile)	0.53	0.24	0.03*	0.44	0.23	0.06†	0.49	0.25	0.05*	0.46	0.22	0.04*	0.46	0.16	0.00**	0.29	0.15	0.05*
Parking availability (Reference: Yes)	0.30	0.23	0.20	0.09	0.67	0.89	0.76	0.26	0.00**	0.19	0.66	0.77	0.45	0.16	0.00**	0.68	0.49	0.16
Sample size	1278			1177			1278			1177			1278			1177		

†significant at the 0.10 level, *significant at the 0.05 level, **significant ate the 0.01 level.

4.1 Impacts of variables

4.1.1 Socio-demographics

A substantial amount of statistically significant associations between sociodemographic factors and acceptance can be observed from the results of both pairs of models, as presented in Table 4 and Table 5. As expected, individuals belonging to the younger category (18-44) are more likely to adopt the new technology in any form. The coefficients corresponding to the second **age** group (45-64) are all negative and significant at the 1 percent level of significance, while their values range in a quite similar way between the two years, revealing a stable inverse relationship between age and AV acceptance. The older group results indicate an even bigger gap on acceptance levels, when compared with the younger group, leading to the same conclusions. However, the significance level of the results is lower and differs between the two years in this case, possibly due to the smaller number of workers belonging to the third age group (65+). The magnitude of the coefficients' values suggests that younger generations are more interested especially in owing an AV or riding a partially autonomous vehicle when compared to the older age groups. These results are consistent with the findings of Rödel *et al.* (2014), while other studies investigating the intention to use AVs conclude to controversial or not significant associations *(*Payre *et al.*, 2014; Bansal *et al.*, 2016).

Table 4: Interest in owning or sharing an AV by age

	18-44		45-64		65+		Total	
	2015	2017	2015	2017	2015	2017	2015	2017
Not interested	53,02%	43,93%	71,32%	65,51%	69,49%	73,91%	61,27%	50,89%
Interested	**46,98%**	**56,07%**	**28,68%**	**34,49%**	**30,51%**	**26,09%**	**38,73%**	**49,11%**
Breakdown for those interested:								
Own only	20,80%	23,85%	30,00%	33,03%	50,00%	25,00%	24,65%	25,61%
Share only	19,88%	15,32%	24,67%	23,85%	22,22%	8,33%	21,41%	16,78%
Both	59,33%	60,83%	45,33%	43,12%	27,78%	66,67%	53,94%	57,61%

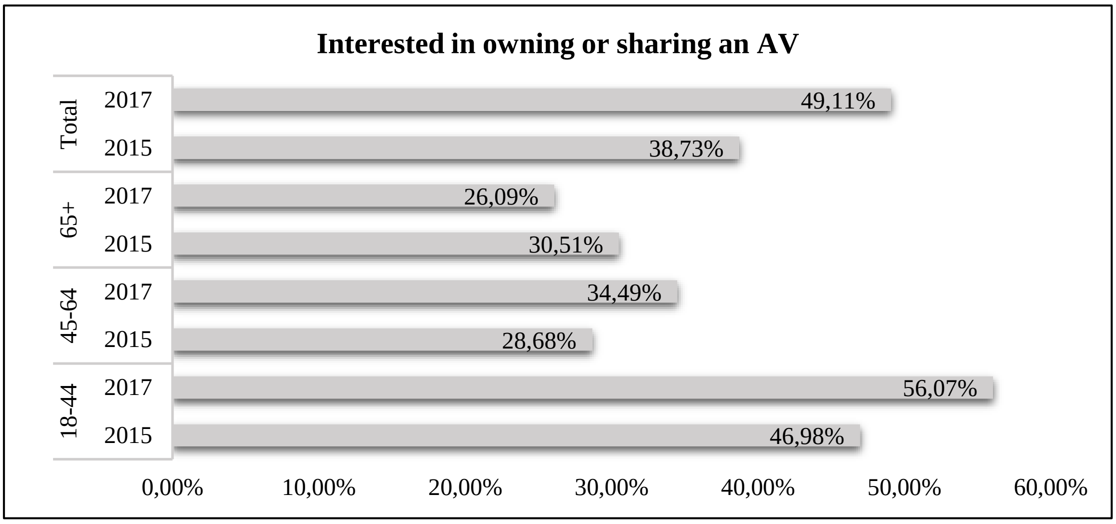

Figure 8: Interest in owning or sharing an AV over time

Given the critical role of younger generations in the adoption of driverless cars, we conduct some further analysis to investigate the levels of acceptance distributed by generation and their evolution over time. As shown in Figure 8 and Figure 9, although the acceptability of older people (65+) towards the new technology declined by 5 percentage points between 2015 and 2017, younger people (Generation 1 and Generation 2) are getting more willing to adopt the new technology in any form, especially those belonging to the first age group (18-44), where the percentage was significantly increased by up to 10 percent, only after two years, from an original value of 46% in 2015. However, a slight shift to a specific preference on owning an AV is observed in younger generations, which along with the overall decrease of interest by elderly, eventually leads to a slightly more pessimistic prediction regarding the implementation of a shared-mobility scenario.

Table 5: Interest in full or partial automation by age

	18-44		45-64		65+		Total	
	2015	2017	2015	2017	2015	2017	2015	2017
Not interested	53,74%	44,54%	72,08%	66,77%	64,41%	73,91%	61,74%	51,66%
Interested	**46,26%**	**55,46%**	**27,92%**	**33,23%**	**35,59%**	**26,09%**	**38,26%**	**48,34%**
Breakdown for those interested:								
Full only	19,88%	16,37%	26,03%	21,90%	14,29%	25,00%	21,47%	17,57%
Partial only	17,39%	19,03%	19,18%	22,86%	38,10%	16,67%	18,81%	19,68%
Both	62,73%	64,60%	54,79%	55,24%	47,62%	58,33%	59,71%	62,74%

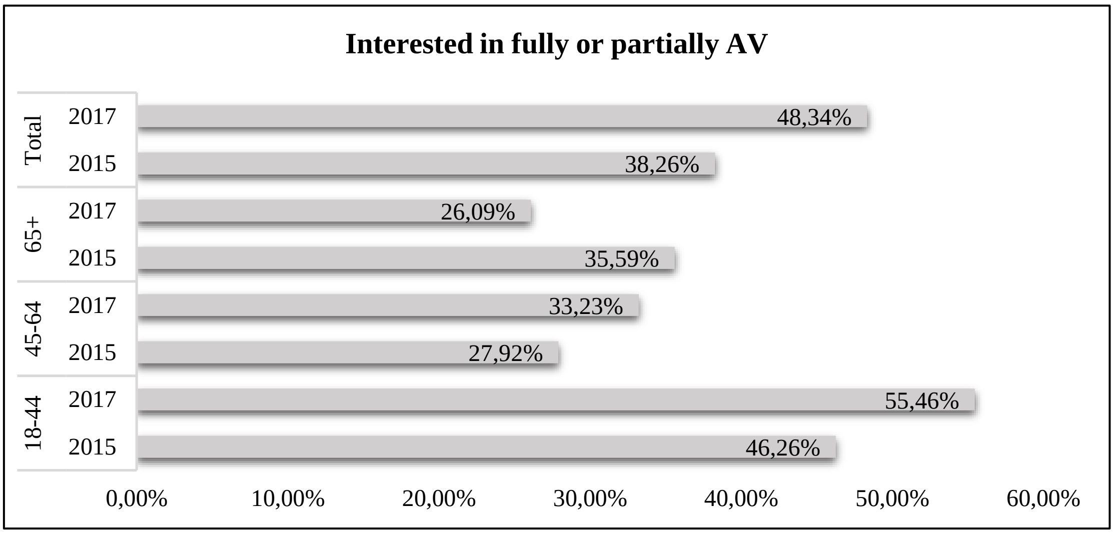

Figure 9: Interest in fully or partially AVs over time

As far as the level of automation, the elderly's interest in full automation is increased, possibly because they are physically unable to drive. On contrary, younger generations tend to prefer having the option of partial participation in the navigation of their automobile, as suggested by the decline of the corresponding percentages of those interested only in partial or only in full automation, while this is also the case for the total population interested in AVs. Finally, the absolute percentages of people interested in any type of the innovative transportation system are increased by up to 10 percentage points, which is a significant change over such a short period of time.

The factor of **gender** also presents statistically significant relationships with the acceptance of AVs. According to the most recent survey's results (2017), females are less likely to embrace autonomous vehicles, since the corresponding coefficients ("interested in fully and partially AV" and "interested in owing and sharing an AV") are negative and significant at the 1 percent level of significance, while the 2015 survey's data leads us to draw the opposite inference. An interesting observation is that the results emerging from the older survey and related to a specific preference (apart from the abovementioned, referring to the answers of "interested in both") suggest that females were less likely to trust a partially automated vehicle and more likely to trust full automation at that time. We can rationally assume that a shift of interest between genres occurred during these two years, possibly because of the fatal accidents have taken place in the meantime and their negative impact especially in females' trust upon the new technology. Nonetheless, the fact that the results are characterised by heterogeneity, leading to controversial conclusions is consistent with the literature. It is interesting to point out that only a few older studies conclude that females are more likely to adopt the technology, like the one conducted by Silberg *et al.* in 2013.

Although the absolute number of statistically significant results related to the **education level** and their level of significance differs between the two years (0.05 level in 2015 and 0.10 level or lower in 2017), the correlation is positive in every statistically significant estimate from both surveys. This is not the case for a recent study conducted by Zmud and Sener (2017), who included an education representative variable in their model but no sign of statistically significant association emerged. Based on our analysis, we conclude that having higher education qualifications generally increases the odds of being an early adopter of AVs (owning or sharing), while both surveys agree that those having a higher education level are more likely to own a partially autonomous vehicle compared to the less educated group.

The association between **income** and acceptance of AVs doesn't appear as statistically significant according to the 2015 survey. However, some statistically significant results about the income levels are emerging from the 2017 sample's second analysis, which indicates that the workers earning lower amounts of money are gradually less interested in fully or partially automated cars. This result is consistent with recent surveys, which reveal that bigger income has a positive effect on intention to use, the willingness to pay for owing an AV and the adoption time (Kyriakidis *et al.*, 2015; Bansal *et al.*, 2016).

The same phenomenon is observed when looking at the impact of **working hours**, which does not appear statistically significant in 2015 analysis. Surprisingly, the survey conducted two years later reveals a strong and positive relationship even if the mean of the working hours on 2017 sample is slightly lower compared to 2015. The results suggest that working beyond the typical weekly hours leads to a strengthened interest in AVs, especially in full automation, while hard-working people are generally more likely to either own or share a driverless car in the future.

Finally, individuals having **children** seem more reluctant to the new technology, conversely with our initial hypothesis that they may have a positive perception because of the potentially increased number of trips. Although the number of trips is positively correlated with acceptance (as discussed in the next section), they are not significantly associated with procreation in our data. The results suggest that parents are less likely to implicate themselves on any form of AVs' implementation, but especially in a full automation scenario. That agrees with our second speculation that in case that an individual has children, their feeling of responsibility and the psychological barriers are possibly escalated. This finding confirms the negative association between procreation and interest in AVs suggested by Zmud *et al.* (2016).

4.1.2 Mobility characteristics, Travel Attitudes & Tech-savviness

In this category, the results emerging from the variables used to capture possible important factors of adoption of the technology in any form partially agree with our hypothesis that tech-savvy individuals, having more active and multimodal travel patterns and current sharing travel attitudes would may be more likely to foster the idea of fully autonomous transportation systems and especially SAVs. Indeed, all selected variables lead to statistically significant associations, which on the other hand present some diversity between the two years.

The current travel patterns of workers are initially captured by the question asking what their usual **mode of commuting** is. We observe that only the 2015 results of the model for public acceptance of full autonomy suggest that those usually choosing public transport modes and the advocates of active travel and alternative ways of commuting are more likely to embrace AVs (either full or partial automation). However, there is no statistically significant association regarding their interest particularly in SAVs, since the corresponding analysis doesn't include any significant outcome at all. On contrary, the **frequency of commuting and transiting and the level of their importance** for each individual seems to lead to a higher propensity for sharing autonomous vehicles relative to no interest at all in the technology, interest in owning an AV or interest in both owning and sharing an AV. In particular, according to both surveys' results, those who transit more frequently are more likely to favour SAVs, while the commute frequency is significant at the 0.10 level only at the 2015 sample and the importance of being within a 30-minute commute to work is significant at the 0.05 level only at the 2017 sample. At the same time, those **cycling** more frequently appear to be less inclined towards AV ownership, as shown in the 2017 results. In addition, after analysing the 2015 dataset, it seems that those cycling more frequently and those who consider transit locations as an important factor in choosing a residence appear a higher likelihood of embracing a combined system. Finally, workers realising a larger **number of trips** are expectantly more likely to support any form of AV system. Interestingly, except for the fact that all statistically significant coefficients are coming exclusively from 2017 analysis, the only one related to a specific preference is found under the "interested in partially AV only", reflecting the total population desire to have some control of their automobile and their hesitation on trusting full automation.

The results emerging from the variables capturing workers' current **car and ride sharing** attitudes confirm our initial assumption regarding their direct relationship with public intentions in AVs use, indicating that people who have already experienced (at least once) transport-related sharing services are more likely to favour a future AV-share system, while they would not reject a mixed-use scenario. As a reminder, in 2015 survey the variable related to car sharing captures the intentions of people using this kind of services more frequently under optimised circumstances and, as expected, the coefficient corresponding to the answer "interest in sharing an AV only" is positive and significant at the 0.01 level, on contrary to 2017 coefficient, which is also positive but not statistically significant. However, the analysis of the second survey leads to an equivalent conclusion, since it suggests that those who have experienced car-sharing more times are associated with a greater indifference towards AV ownership.

The chance of more efficient mobilisation of user groups with **mobility impairments** and travellers without driver **license** is also reflected in our analysis' results. According to 2015 survey, workers suffering from disabilities are more likely to be the early adopters of fully autonomous vehicles, as suggested by the positive coefficient in Table

3, which is significant at the 0.10 level, while their choice between owning and sharing it is not clear. Surprisingly, the disabled participants of 2017 survey responses lead to only one statistically significant result, related to their interest only in partial automation, following the general decline of trust in full automation. As far as the coefficient of license ownership, it is the most noticeable in 2015 results. As expected, the workers lacking a driving license show a very negative propensity to partial automation, since in case of implementation of this scenario, a license would be still a requirement in order to legally drive.

Although the variables deployed for capturing the **tech-savviness** are not identical for both years, lead to similar and statistically significant associations. The first survey's results suggest that those who own a smartphone are more likely to be the fervent supporters of AVs. Reasonably, technology awareness usually has a positive effect on the adoption of innovative systems, as confirmed by relevant – AV focused – studies (Schoettle and Sivak, 2014; Bansal *et al.*, 2016). On contrary, the 2017 survey's results imply that those having an old phone and are less qualified in smartphone apps are more likely to accept only partial automated vehicles, and vice versa, more tech-savvy are less likely to adopt partial automation, maybe because they are aware of the possible negative impacts, which include sleepy drivers, over-trust or taking more risks while driving (Banks *et al.*, 2018). In defence of this speculation, respondents of existing study indicated that full automation would be more convenient and enjoyable, whereas driving a partially automated car could potentially be somewhat trickier and more difficult compared to a conventional one (Kyriakidis *et al.*, 2015).

4.1.3 Vehicle characteristics

In lack of possibly more suitable variables (i.e. "current vehicle automation level"), current vehicle characteristics are described by the **age of the car and the type of fuel** used. As we initially hypothesised, people driving newer cars would be less reluctant to additional automated features embedded in their future car. Partial automation in lower levels already exists, thus those driving modern vehicles have possibly experienced or at least have more familiarity with automation. Kyriakidis et al. (2015) found that people who currently use adaptive cruise control or automated safety functions in their vehicles are more likely to pay for fully autonomous cars. This fact substantially influences acceptance and is being reflected in the results of both years.

The age of the current personal vehicle presents statistically significant results only in 2017 survey, possibly because of the technological evolution of the automobile industry and the launch of vehicles offering higher levels of automation in the meantime. The factor of fuel type, in terms of choosing alternative types of energy, is associated with a greater proclivity towards AVs, already since 2015, while it is worthwhile highlighting the fact that the only statistically significant result of the specific variable that year is related to a selective interest in fully autonomous cars.

4.1.4 Contextual characteristics

This category is included in our analysis after assuming that the manner in which autonomous vehicles become available to the public influences the way and the extent to which they will be accepted, implemented and practically used. The first variable chosen is the **population density** of workers' residential areas, through which we made an effort to measure the traffic situation around each household, theorising that those characterised by higher density are interconnected with heavier **traffic and space limitations**. Indeed, according to the results of both years, residing in higher density neighbourhoods seems to lead to a higher propensity for sharing autonomous vehicles relative to no interest at all in the technology, interest in owning an AV or interest in both owning and sharing an AV, since the corresponding coefficients are statistically significant at the 0.01 level of significance. Concerning the level of automation, the overall pattern observed suggests an unambiguous favour of both partially automated and driverless automobiles by those living in blocks associated with congestion, while a slight difference between the two years' significance levels can be noticed. Equivalent results emerge from a report published by an American-based information services company, which suggest that urbanization is positively associated with public's opinions on AVs, also confirmed by follow-up research but failing to include any comments on significance (JD Power, 2012; Bansal *et al.*, 2016). In the same manner, participants of 2017 survey considering the concept of **space** availability important are rationally more likely to appear willing to embrace a transportation system (either own or share-configured).

Finally, the **parking availability** variable is somehow capturing the traffic situation near individuals' workplace, as well as their interest in an automated parking function, which is one of the already embedded functions in partially autonomous cars currently in consumer supply. As expected, according to 2015 results, those who enjoy limited parking availability are more likely to adopt any type of autonomous vehicle (fully or partially automated) and specifically join into a share mobility transportation system. Equivalent conclusions emerge from 2017 survey, in which the results suggest that those who daily seek for a parking when commuting to work are significantly less interested in owning an AV. Their preference between partial and full automation is not clear, but the statistically significant positive coefficient (0.01 level) related to the category “interested in partially AV only” may signify a slight hesitation in trusting full automation and a greater inclination to a partially automated design.

4.2 Ownership model and levels of automation

Overall, the factors captured by the variables chosen to be included in our analytical models were proven to be significant in some way in the configuration of public acceptance, and specifically on employed population’s perceptions towards the imminent arrival of autonomous vehicles. In order to have a clearer picture of which factors influence workers in a specific way, in terms of **what type of ownership model and what level of automation** they would prefer in a future scenario, we present in Table 6 and Table 7 the corresponding variables which had statistically significant results under the categories “interested only in…”, as they arise from the two datasets.

Table 6: Statistically significant variables for interest in a specific **ownership model**

2015		2017
	Age	
		Gender
	Education	
		Working hours
Commute frequency		
		Importance of commute
	Transit frequency	
		Bike frequency
Ride sharing		
	Car sharing	
Disability		
		Car age
	Population density	
	Parking availability	

The factors stably affecting the preferences of workers regarding the potential **ownership** model adopted, are the age, the education level, their mobility characteristics and sharing attitudes (including transit frequency and car-sharing frequency), and the population density along with the parking availability, which represent the traffic situation in their residential areas and their workplaces. However, part of these common results over time are inconclusive, in terms of not clearly pointing out which is the most preferred system for AVs' implementation. More specifically, they reveal that **younger, more educated male workers, residing in high-density urban areas are generally more likely to adopt the new technology in some way.** On contrary, those who **transit more and currently experiencing car-sharing seems to especially favour a share-mobility** system of AVs. Surprisingly, the variable capturing the participants usual way of commuting ("commute mode") doesn't appear any significance in models' results, with no obvious explanation to be proposed However, despite some differences in significance levels of variables related to the commute frequency, the importance of commute, the bike, and the ride-sharing frequency, they all conclude that **a more active/green lifestyle is associated with a greater inclination towards SAVs**. Mobility impairments present statistically significant results only in 2015 analysis for ownership alternatives, maybe because of the bigger proportion of disabled people at that time (4,62% in 2015 and 3,57% in 2017), which suggest that **mobility impaired workers plausibly tend to be less resistant in either owing or sharing an AV**. Another particularly interesting point also noted in the discussion above is that the effect of the number of working hours, despite the fact that 2017 workers seem to work fewer hours based on the sample means, are significant only in the most recent survey's analysis. This can be explained by a possible increased demand for productivity by employers throughout the years, concerning the daily workload required and depending on the sector and the nature of work. For instance, a greater proportion of individuals belonging to 2017 sample may be employed in an office environment, which means they could potentially make use of the commuting time more productively by riding an autonomous vehicle, increasing their leisure time. Reasonably, **working overtime is positively correlated with acceptance of AVs in any ownership mode**. Contrarily, current vehicle age becomes significant only in 2017, possibly due to the incremental launch of vehicles with automated features in the market, abetted by leading automobile manufacturers. Rationally, **those driving modern vehicles are more like to participate in an AV transportation system, especially as owners**. Finally, it is worthwhile mentioning that as evidenced from the magnitude of explanatory variables coefficients estimates and their weight in the dependents' estimates, the factors that seem to affect acceptance (ownership-oriented) the most is education, sharing attitudes and the current traffic situation.

Table 7: Statistically significant variables for interest in a specific **level of automation**

2015		2017
	Age	
	Gender	
	Education	
	Children	
		Working hours
		Smartphone
Licence		
		Number of trips
	Disability	
Fuel type		
	Population density	
Parking availability		

The second pair of our models, deployed to explain the way in which possibly significant factors affect the acceptance, subject to whether individuals are willing to accept full automation or not, shows us that age, gender, education level, the presence of children in a household, the mobility impairments and the traffic situation in workers' residential areas steadily affect their perceptions towards the **levels of automation** over time. In particular, we conclude that **younger, higher educated workers, residing in high-density urban areas, suffering from disabilities appear to be more inclined towards fully or partially autonomous vehicles.** The most noticeable change over time is that females' initial trust in driverless cars compared to males in 2015 decreased during the next two years, with the most recent results concluding that **men are expected to be more zealous advocates of full automation**. Both surveys suggest that **parents express their hesitation on fully autonomous cars**, maybe because of their growing need to be protective of their children and their reluctance on giving the total control of their driving in a machine. Another interesting point to note is that while license ownership was the most significant factor of workers' opinion configuration in 2015, suggesting that **those who currently don't hold a license are less likely to embrace partial autonomy**, no statistically significant result is observed after two years. That may be justified either because of the scant percentages of this category in both samples, or due to the big leap in ride-sharing usage (7,75% in 2015 and 50,13% in 2017), which enable them to use alternative transport options instead of driving.

However, the more developed sharing attitudes of 2017 workers along with their slight increase in walking and cycling appear to contradict with the substantial decrease of the percentage using public transport modes to commute (21,28% in 2015 and 13,85% in 2017). **Tech-savviness**, as captured by our corresponding variables, and according to the most recent results has an **inverse relationship with acceptance of partial automation** in cars, while the 2015 variable (smartphone ownership) is not statistically significant under a specific preference regarding the level of automation. Current vehicle characteristics, as captured by the variable referring to the fuel type of workers' car leads to statistically significant results, suggesting that those currently owning cars consuming **alternative types of energy for their movement are associated with a greater indifference towards fully autonomous vehicles.** This result, referring exclusively in acceptance of full automation emerges only from the older survey, possibly reflecting on the early adopters of alternative kinds of fuel and electric cars, the market penetration of which was increased later on. Similarly, **those working beyond the typical amount of weekly hours (>40 hours/week) are reasonably more likely to embrace full automation**, in order to use more productively the commuting time and increase their free time. It is worth to note that, in this case, this is the only statistically significant result implying a strong association between working overtime and the interest in driverless cars, while it emerges only from 2017 survey. Finally, **those realising a larger number of trips are more likely to accept a partially autonomous car**. For consistency purposes, we should not fail to mention that the factors that seem to affect acceptance (automation level-oriented) the most is license ownership, the number of working hours and the current traffic situation.

Table 8: Variables with statistically significant influence in acceptance

2015		2017
	Age	
	Gender	
	Education	
	Children	
		Income
		Working hours
		Number of trips
	Disability	
	Smartphone	
Licence		
Commute mode		
Commute frequency		
		Importance of commute
	Transit frequency	
Importance of transit		
	Bike frequency	
	Ride sharing	
	Car sharing	
	Disability	
	Fuel type	
		Car age
	Population density	
		Importance of space
	Parking availability	

After analysing the effect of the different factors in specific directions of acceptance, we summarise all the representative variables leading to statistically significant results towards any type of AVs ownership mode or level of automation, in order to highlight the changes of their influence **over time**. As shown in Table 8, the factors that – regardless of their exact effect i.e. males for gender, wealthier for income etc. – have a **constant** statistically significant influence in acceptance towards AVs over time **is age, gender, education level, household composition (children), tech-savviness, mobility characteristics, current travel and sharing attitudes, current vehicle characteristics and contextual characteristics**. These results are generally consistent with each other for both years, except for the **shift observed in gender**, with females being more reluctant over time compared to men. The influence of **tech-savviness** in acceptance is the second factor leading to **controversial results**, with tech-savvy workers being initially interested in both full and partial automation while expressing their **hesitation in partial automation after two years, in 2017**. That may suggest their preference for full autonomy, which is considered to be more enjoyable and safe, but that is not proven from the results. As discussed earlier, the **number of working hours become significant only in 2017, while license ownership becomes statistically insignificant.** Moreover, the **positive influence of the total number of trips realised by workers on their intention to adopt AVs leads to statistically significant associations only in 2017**. We can assume that this change may arise from the fact that in the most recent survey, workers seem to travel more, as it can be observed from the two samples' descriptive statistics, presented in the methodology chapter. **Mobility characteristics, travel and sharing attitudes, mobility impairments, current vehicle characteristics and traffic situation also substantially affect acceptance in a similar way over time**, despite that not all variables capturing these factors lead to strong associations in terms of statistical significance in both years. For instance, the variable "importance of space" is significant only in 2017, possibly because of the enlarged influence of the continuous and overgrowing urbanisation. Finally, **workers' income level seems to have a direct relationship with acceptance, but not before 2017,** which could conceivably reflect the different income distribution observed between the two years and the slightly increased proportion of wealthy.

Finally, an additional analysis is conducted to investigate the top concerns regarding autonomous vehicles. For this purpose, we are making use of five more questions provided by the two datasets, asking in which extent the person would be concerned in using them, in terms of equipment and system safety, legal liability for drivers or owners, system and vehicle security, capability to react to the environment (other cars, bicyclists, pedestrians, etc.) and performance in poor weather or other unexpected conditions. The answers to these five questions are measured using a 5-point scale, ranging from "not at all concerned" to "very concerned". The statistical results for the workers and the full sample of both years are presented in Table 9.

Table 9: Concerns about potential dysfunctions on AVs performance

Study sample (workers)	Percentage (%) of respondents **concerned/very concerned**	
	2015	**2017**
Equipment and system safety	66,35%	70,94%
Legal liability for drivers or owners	67,21%	71,11%
System and vehicle security	60,72%	65,25%
Capability to react to the environment	*73,24%*	*77,23%*
Performance in unexpected conditions	*68,94%*	*74,85%*
Sample size	1278	1177
Full sample	Percentage (%) of respondents **concerned/very concerned**	
	2015	**2017**
Equipment and system safety	65,37%	69,60%
Legal liability for drivers or owners	64,82%	68,80%
System and vehicle security	59,49%	64,66%
Capability to react to the environment	*70,64%*	*75,29%*
Performance in unexpected conditions	*67,09%*	*72,51%*
Sample size	3604	4711

The results are consistent with the literature, showing that individuals tend to be more concerned about driverless cars, despite the fact that their interest in autonomy substantially increases. **The top concerns of people, based on the statistical results of both years are related to the expected capability of autonomous vehicles to efficiently interact with the environment (e.g. pedestrians, bicyclists, other conventional or automated cars), especially when poor weather or other unexpected conditions occur.** In order to examine which concerns significantly affect acceptance, we deploy an additional multinomial logistic model for public acceptance of fully autonomous vehicles, making use of the five abovementioned questions and additionally, the question referring to what extent workers are interested in riding a fully autonomous vehicle.

In this case, the probability that y (i.e. interest in riding a fully autonomous vehicle) is equal to one of the outcomes (e.g. m) can be written as follows:

$$\Pr(y_i = m|x) = \frac{\exp(\beta_m x_i)}{\sum_{j=1}^{J} \exp(\beta_j x_i)}$$

where $x = x_{Concerns}$. The category "somewhat/not at all interested in riding a fully autonomous vehicle" is assumed as a baseline, and the relative impacts of $\boldsymbol{x}$ on other answers (i.e., "Neutral", "Somewhat/Very interested) compared to the baseline category were examined.

The results are presented in Table 10 and reveal that, indeed, the top two concerns affected the stated level of interest of 2017 workers in an (at least) 10% significance level, making them more crucial factor than safety-related concerns. In 2015, **only the concern about AVs' capability to react to the environment is significant**, which is consistent with the literature. For instance, Shabanpour (2017), in his study points that the possibility of imperfect performance in response to unexpected traffic situations was the most critical concern of respondents, while Howard (2014) and Fraszczyk et al. (2015) report that enhanced safety was proven to be the most attractive feature of AVs to individuals. However, it doesn't significantly affect the interest in a positive way either.

Table 10: Multinomial Logistic Model for public acceptance of fully autonomous vehicles

	Neutral			Interested		
2015	Estimate	SE	Pr(>|t|)	Estimate	SE	Pr(>|t|)
(Intercept)	-1.37	0.18	0.00**	-0.51	0.14	0.00**
Equipment and system safety	0.24	0.34	0.47	-0.34	0.23	0.14
Legal liability for drivers or owners	0.38	0.30	0.20	0.28	0.21	0.19
System and vehicle security	-0.51	0.27	0.06	-0.20	0.20	0.32
Capability to react to the environment	-0.24	0.38	0.52	0.49	0.26	0.06†
Performance in unexpected conditions	0.10	0.35	0.78	-0.15	0.24	0.53
(Reference: Very/somewhat concerned)						
Sample size	1278					
2017						
(Intercept)	-0.45	0.20	0.00**	0.36	0.16	0.00**
Equipment and system safety	-0.33	0.29	0.17	-0.31	0.23	0.26
Legal liability for drivers or owners	-0.32	0.26	0.50	0.14	0.20	0.22
System and vehicle security	-0.10	0.25	0.77	-0.06	0.19	0.68
Capability to react to the environment	0.53	0.33	0.64	-0.12	0.25	0.10†
Performance in unexpected conditions	-0.63	0.30	0.37	-0.21	0.24	0.04*
(Reference: Very/somewhat concerned)						
Sample size	1177					

†significant at the 0.10 level, *significant at the 0.05 level, **significant ate the 0.01 level.

4.3 Models fit

All the models eventually deployed are multinomial logistic regression models, which are often considered as an attractive analysis, since they don't assume normality, linearity or homoscedasticity. However, multinomial logistic regression does have **assumptions**, such as the assumption of independence among the dependent variable choices. This assumption states that the choice of or membership in one category is not related to the choice or membership of another category (i.e., the dependent variable). The assumption of independence can be tested with the Hausman-McFadden test, but as stated by Starkweather and Moske (2011), large samples (e.g. N = 600) means that the data contain enough cases to satisfy the cases to variables assumption mentioned.

There are a few alternatives for assessing our models' **goodness of fit.** For this purpose, we initially use the deviance statistic and the log-likelihood function, which has a convenient statistical distribution (chi-squared) in large samples for testing the significance. The deviance is defined as $Deviance = -2\, x\, log - likelihood.$ For each model, we run nested models, which include all the selected variables, except for one variable per time. We then compare our original model against each nested model by carrying out **multiple likelihood ratio chi-square tests**. The original model had, in all cases, a smaller residual deviance, which indicates a better fit. That measurement complies with the result of the LR tests, for each one of which we obtained a P-value = 0 (or practically zero). Therefore, in all cases, we rejected the null hypothesis that the original model is not better than the new nested model at predicting the outcome. In other words, the chi-square was significant, so the excluded variable was considered to be a significant predictor in the equation. Thus we would prefer the initial full model (including all selected variables), which predicts significantly better or more accurately than the nested models.

An equivalent way to assess our models' goodness of fit is the pseudo R-Square (**McFadden R-square**), which is treated as a measure of effect size, similar to how R^2 is treated in standard multiple regression. However, these types of metrics do not represent the amount of variance in the outcome variable accounted for by the explanatory variables. Higher values indicate a better fit, but they should be interpreted with caution. Moreover, when the interest is in the relationship between variables, the

R-squared is less important, while an R-squared in the range of 0.10 to 0.15 is reasonable (Starkweather and Moske, 2011). According to Domencich and McFadden (1975), the log-likelihood function can be transformed into an index – also known as "likelihood-ratio index" – analogous to the multiple correlation coefficient by defining:

$$R^2_{McF} = 1 - \frac{L(\hat{\beta})}{L(\bar{\beta})}$$

where $\hat{\beta}$ is the maximum likelihood estimator and $\bar{\beta}$ is zero or is zero except for coefficients of alternative dummies. We suppose that $\bar{\beta}$ contains $\bar{k} \geq 0$ parameters and $\hat{\beta}$ contains $\hat{k}$ parameters, including the parameters that appear in $\bar{\beta}$. Then, in large samples, $[\hat{k}/(\hat{k} - \bar{k})]\ [\rho^2/(1-\rho^2)]$ is distributed approximately $F(\hat{k} - \bar{k}, \hat{k})$; this distribution can be used to test the hypothesis $\beta = \bar{\beta}$. The R^2_{McF} and R^2 indices both vary in the unit interval. The graph below summarises schematically a relatively stable empirical relationship between the indices.

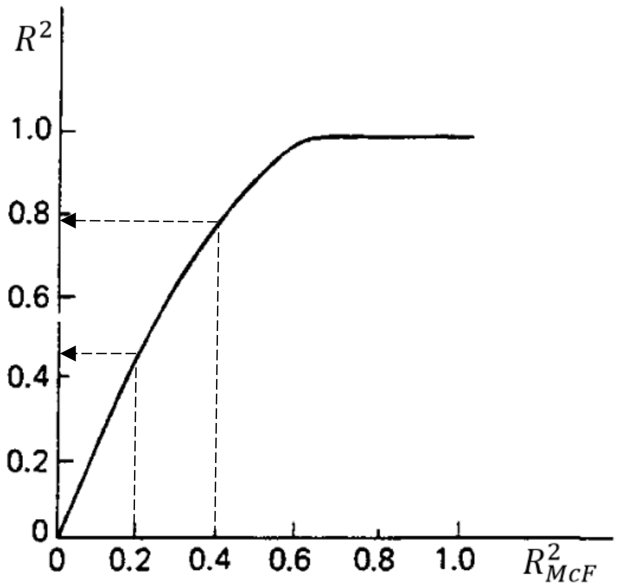

Figure 9: Empirical relationship between R^2 and R^2_{McF}

In terms of consistency and statistical properties, the McFadden R-square appears to provide a practical and theoretically sound index of the goodness of fit. Although there is no definitive answer to the question "what value of R^2_{McF} indicates a good fit", McFadden suggested values of between 0.20 and 0.40 should be taken to represent a very good fit, with up to approximately 80% of the variation in the data explained by the regression model (David A. Hensher and Peter R. Stopher, 1979; Lee, 2013). Our models' McFadden R-square range between 0.22 and 0.24, which indicates a very good fit, especially given the complexity of acceptance, which is a multilayered construct that is not directly measurable.

Finally, even if **multicollinearity** is not considered as a real assumption, high correlations between predictors can matter. The variance inflation factor (VIF) function is used to determine if the assumption of multicollinearity is met. The results show that the VIF for the variables ranges between 1.02 and 1.27 << 10, so there is little inter-correlation between the explanatory variables and the assumption of multicollinearity is met.

5 Conclusion, Limitations and Future Research

Autonomous vehicles have the potential to reshape modern transportation systems in numerous ways, depending on which of the potential implementation models will eventually dominate and how quickly they will become widespread. This, in turn, depends on the pace of adoption and how public perceptions will be configured over time, making the matter of explaining and predicting acceptance decidedly vital.

The exact prediction of an a priori acceptability of autonomous vehicles is objectively challenging, in view of the fact that autonomous vehicles' implementation is in its beginning stages, while full autonomy is not commercially available yet. The complexity of acceptance as a concept is confirmed by the large number of factors that influence it in a statistically significant way. Our findings reveal strong associations between AVs' acceptance and individuals' socio-demographics, mobility characteristics, travel attitudes, tech-savviness, current vehicle and contextual characteristics, while they indicate some interesting changes over time.

5.1 Key Findings

Concerning the ownership model of their preference, the results suggest that younger, higher educated male workers, residing in high-density urban areas, working beyond the average, currently having more active/green/sharing attitudes are more likely to embrace SAVs, while those currently driving relatively modern cars are more likely to become the early adopters of an ownership-oriented system of AVs. The results emerging from our automation level-oriented analysis suggest that male workers, working overtime, currently driving cars consuming renewable types of fuel are more inclined towards fully autonomous vehicles, on contrary to parents who express their hesitation on fully automation, while those realising a larger number of trips are more likely to embrace partially autonomy vehicles. Reasonably, the lack of driving license is negatively associated with acceptance of partial automation. Additional factors not specifically oriented are mobility impairments, tech-savviness, and income level.

The majority of the abovementioned factors stably affect acceptance in a similar way. The changes in the list of factors over time to be highlighted, except for the shift observed in gender is that the number of working hours, the total number of trips and the importance of space becomes positively significant only in 2017. That may reflect the growing urbanisation, which is considered to be one of the main challenges of transport planning in our century, along with the fact that people have the tendency to travel and commute more and the need to use this time more productively. Finally, tech-savviness also leads to an unclear conclusion, being negatively associated with public's interest in partial automation, possibly entailing that awareness of the technology and its potential dangers may lead to increased level of concern.

Our findings are not optimistic with respect to the idea that a shared-mobility transportation system will dominate in the future, since the slight shift of younger generations to an ownership-based model contradicts our initial discussion, but considering the current early stage of adoption, there are some positive insights, such as the increased use of ride-sharing services. As far as the trust levels regarding fully self-driving cars, the noticeable shift toward lower levels of automation may arise from the first fatal accident related to a highly automated driving feature in 2016, whose impact is also reflected in the increased levels of concern the following year. However, conversely with our initial expectations, a quite significant increase in the percentages of those interested in the new technology is observed (approximately 10%). Inevitably, a transformation of the current transportation system in order to be capable of addressing the rising transportation demands, including better connections, increased capacity, and optimisation of land use will eventually happen in a certain pace. Among the emerging transportation technologies, autonomous vehicles are a key and as shown by previous innovative technologies adoption rates, they may be adopted sooner than initially predicted, overcoming the technical challenges and the psychological barriers.

5.2 Limitations and Future Research

The present research has various limitations that must be considered when interpreting these findings, which in turn lead to some proposals for further research. In terms of this study, it is not plausible to control all the range of factors that impact on public acceptance towards AVs. A very frequent limitation occurring in almost every study, including the current one is related to the high proportions of missing data and methods used. Further limitations are related to the choice of the samples and their sizes, which have a remarkable effect on the accuracy of the estimations since bias in research can cause distorted results and wrong conclusions. In terms of this study, the total number of residents is impossible to be examined, therefore we choose subsets of the full samples, which have as little missing data as possible while being meaningful for our research.

The amount of the available datasets related to public acceptance of AVs is considerably restricted and their structure does not always allow an efficient set of variables to be taken into account. In respect to the availability, we made an effort to include representative variables for capturing a wide range of factors affecting the acceptance. However, the datasets and the corresponding questionnaires were lacking variables that could possibly capture psychological factors (i.e. locus of control, sensation seeking) but also factors related to lifestyle and preferences (i.e. passion for driving), found elsewhere in the literature as prominent for explaining acceptability. Thus, the conduction of a specified survey, including questions more focused on AVs acceptance would allow the extension of our proposed analytical models to explain and predict the pace of future adoption.

Further limitations occur in the nature of the existing variables, in terms of not being appropriate for extended manipulation (i.e. log transformations) or not providing enough information in the desired direction for our research, since none of these surveys exclusively aim to investigate acceptance. For instance, the crucial factor of tech-savviness is mainly captured by smartphone ownership and age, but it would be beneficial to know in what extent and for what purpose individuals use their smartphones and other technologies.

Finally, this study investigates the evolution of AVs’ acceptance over time, analysing repeated cross-sectional data of two time-points (2015 and 2017), providing useful insights and finding. However, in view of the fact that highly automated vehicles are currently in the early adopters’ critical phase and in light of the ongoing implementations and the numerous strides and setbacks occurred ever since 2017, further analysis is required when new data becomes available.

References

Abraham, H. *et al.* (2017) ‘Consumer Interest in Automation: Preliminary Observations Exploring a Year’s Change’, (May 25), p. 20.

Abraham, H. *et al.* (no date) ‘Consumer Interest in Automation: Preliminary Observations Exploring a Year’s Change’.

Anderson, J. M. *et al.* (2015) ‘Highway capacity benefits from using vehicle-to-vehicle communication and sensors for collision avoidance’, *Autonomes Fahren,* 83(1), pp. 2573–2587. doi: 10.1109/VETECF.2011.6093130.

Bagloee, S. A. *et al.* (2016) ‘Autonomous vehicles: challenges, opportunities, and future implications for transportation policies’, *Journal of Modern Transportation*. Springer Berlin Heidelberg, 24(4), pp. 284–303. doi: 10.1007/s40534-016-0117-3.

Banks, V. A. *et al.* (2018) ‘Is partially automated driving a bad idea? Observations from an on-road study’, *Applied Ergonomics*. Elsevier, 68(November 2017), pp. 138–145. doi: 10.1016/j.apergo.2017.11.010.

Bansal, P., Kockelman, K. M. and Singh, A. (2016) ‘Assessing public opinions of and interest in new vehicle technologies: An Austin perspective’, *Transportation Research Part C: Emerging Technologies*. Elsevier Ltd, 67, pp. 1–14. doi: 10.1016/j.trc.2016.01.019.

Buckley, L., Kaye, S. A. and Pradhan, A. K. (2018a) ‘Psychosocial factors associated with intended use of automated vehicles: A simulated driving study’, *Accident Analysis and Prevention*. Elsevier, 115(July 2017), pp. 202–208. doi: 10.1016/j.aap.2018.03.021.

Buckley, L., Kaye, S. A. and Pradhan, A. K. (2018b) ‘Psychosocial factors associated with intended use of automated vehicles: A simulated driving study’, *Accident Analysis and Prevention*. doi: 10.1016/j.aap.2018.03.021.

‘Car data: paving the way to value-creating mobility Perspectives on a new automotive business model’ (no date).

Choi, J. K. and Ji, Y. G. (2015) ‘Investigating the Importance of Trust on Adopting an Autonomous Vehicle’, *International Journal of Human-Computer Interaction*. Taylor & Francis, 31(10), pp. 692–702. doi: 10.1080/10447318.2015.1070549.

Cookson, G. and Pishue, B. (2017) ‘INRIX Global Traffic Scorecard’, *Inrix Global Traffic Scorecard*, (February), p. 44. Available at: https://media.bizj.us/view/img/10360454/inrix2016trafficscorecarden.pdf.

Correia, G. H. de A. and van Arem, B. (2016) ‘Solving the User Optimum Privately Owned

Automated Vehicles Assignment Problem (UO-POAVAP): A model to explore the impacts of self-driving vehicles on urban mobility', *Transportation Research Part B: Methodological*, 87, pp. 64–88. doi: 10.1016/j.trb.2016.03.002.

Davis, F. D. (1986) 'A technology acceptance model for empirically testing new end-user information systems: Theory and results', *Management*, Ph.D.(April), p. 291. doi: oclc/56932490.

Davis, F. D. (1989) 'Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology', *MIS Quarterly*, 13(3), p. 319. doi: 10.2307/249008.

Deloitte (2017) 'What's ahead for fully autonomous driving', (January), p. 16.

Domencich, T. and McFadden, D. (1975) 'Statistical Estimation of Choice Probability Functions', *Urban Travel Demand: A Behavioral Analysis*, pp. 101–25.

'Enhanced collision mitigation system' (2012), (April), pp. 1–4. Available at: http://www.jdpower.com/sites/default/files/2012049-uset.pdf.

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

For, R. and Of, E. (2015) 'M OTORISTS ' P REFERENCES FOR D IFFERENT L EVELS OF V EHICLE A UTOMATION', (July).

Fraszczyk, A., Brown, P. and Duan, S. (2015) 'Public Perception of Driverless Trains', *Urban Rail Transit*. Springer Berlin Heidelberg, 1(2), pp. 78–86. doi: 10.1007/s40864-015-0019-4.

Gora, P. and Rüb, I. (2016) 'Traffic Models for Self-driving Connected Cars', *Transportation Research Procedia*. Elsevier B.V., 14, pp. 2207–2216. doi: 10.1016/j.trpro.2016.05.236.

Gruel, W. and Stanford, J. M. (2016) 'Assessing the Long-term Effects of Autonomous Vehicles: A Speculative Approach', in *Transportation Research Procedia*. doi: 10.1016/j.trpro.2016.05.003.

Haboucha, C. J., Ishaq, R. and Shiftan, Y. (2017) 'User preferences regarding autonomous vehicles', *Transportation Research Part C: Emerging Technologies*, 78, pp. 37–49. doi: 10.1016/j.trc.2017.01.010.

Howard, D. (2014) 'Public Perceptions of Self-driving Cars: The Case of Berkeley, California', *MS Transportation Engineering*, 2014(1), p. 21.

Huijts, N. M. A., Molin, E. J. E. and Steg, L. (2012) 'Psychological factors influencing sustainable energy technology acceptance: A review-based comprehensive framework', *Renewable and Sustainable Energy Reviews*. Elsevier Ltd, 16(1), pp. 525–531. doi:

10.1016/j.rser.2011.08.018.

Hutchins, N. and Hook, L. (2017) 'Technology Acceptance Model for Safety Critical Autonomous Transportation Systems', *2017 IEEE/AIAA 36th Digital Avionics Systems Conference (DASC)*, pp. 1–5. doi: 10.1109/DASC.2017.8102010.

Im, I., Hong, S. and Kang, M. S. (2011) 'An international comparison of technology adoption: Testing the UTAUT model', *Information and Management*, 48(1), pp. 1–8. doi: 10.1016/j.im.2010.09.001.

Kohl, C. *et al.* (2017) 'Disruption of Individual Mobility Ahead? A Longitudinal Study of Risk and Benefit Perceptions of Self-Driving Cars on Twitter', *Proceedings der 13. Internationale Tagung Wirtschaftsinformatik (WI)*, pp. 1220–1234. Available at: http://www.wi2017.ch/de/proceedings.

KPMG (2015) 'Connected and Autonomous Vehicles – Opportunity'.

Krueger, R., Rashidi, T. H. and Rose, J. M. (2016) 'Preferences for shared autonomous vehicles', *Transportation Research Part C: Emerging Technologies*. Elsevier Ltd, 69, pp. 343–355. doi: 10.1016/j.trc.2016.06.015.

Kyriakidis, M., Happee, R. and De Winter, J. C. F. (2015) 'Public opinion on automated driving: Results of an international questionnaire among 5000 respondents', *Transportation Research Part F: Traffic Psychology and Behaviour*. Elsevier Ltd, 32, pp. 127–140. doi: 10.1016/j.trf.2015.04.014.

Van Der Laan, J. D., Heino, A. and De Waard, D. (1997) 'A simple procedure for the assessment of acceptance of advanced transport telematics', *Transportation Research Part C: Emerging Technologies*, 5(1), pp. 1–10. doi: 10.1016/S0968-090X(96)00025-3.

Lee, D. (2013) 'A comparison of choice-based landscape preference models between British and Korean visitors to National Parks', *Life Science Journal*, 10(2), pp. 2028–2036. doi: 10.1017/CBO9781107415324.004.

Lenz, B. (2015) 'Autonomes Fahren'. doi: 10.1007/978-3-662-45854-9.

Linden, A. and Fenn, J. (2003) 'Understanding Gartner's hype cycles', *Strategic Analysis Report N° R-20-1971. Gartner Research*, (May), p. 12. Available at: http://www.ask-force.org/web/Discourse/Linden-HypeCycle-2003.pdf.

Liu, W. (2018) 'An equilibrium analysis of commuter parking in the era of autonomous vehicles', *Transportation Research Part C: Emerging Technologies*. Elsevier, 92(April), pp. 191–207. doi: 10.1016/j.trc.2018.04.024.

Meyer, M. (2016) 'Global Automotive Executive Survey 2016', *KPMG International*, pp. 1–

52. doi: 132042.

Milakis, D., Van Arem, B. and Vanwee, B. (2017) ‘Policy and society related implications of automated driving: A review of literature and directions for future research’, *Journal of Intelligent Transportation Systems: Technology, Planning, and Operations*. Taylor & Francis, 21(4), pp. 324–348. doi: 10.1080/15472450.2017.1291351.

Di Minin, E. *et al.* (2017) ‘Integrating biodiversity, ecosystem services and socio-economic data to identify priority areas and landowners for conservation actions at the national scale’, *Biological Conservation*. The Authors, 206, pp. 56–64. doi: 10.1016/j.biocon.2016.11.037.

Nees, M. A. (2016) ‘Acceptance of Self-driving Cars’, *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, 60(1), pp. 1449–1453. doi: 10.1177/1541931213601332.

NHTSA (2016) ‘Federal Automated Vehicles Policy’, *International Energy Agency (IEA)*, (September), p. 116. doi: 12507-091216-v9.

Nordhoff, S., van Arem, B. and Happee, R. (2016) ‘Conceptual Model to Explain, Predict, and Improve User Acceptance of Driverless Podlike Vehicles’, *Transportation Research Record: Journal of the Transportation Research Board*, 2602(January), pp. 60–67. doi: 10.3141/2602-08.

Payre, W., Cestac, J. and Delhomme, P. (2014) ‘Intention to use a fully automated car: Attitudes and a priori acceptability’, *Transportation Research Part F: Traffic Psychology and Behaviour*. Elsevier Ltd, 27(PB), pp. 252–263. doi: 10.1016/j.trf.2014.04.009.

Piao, J. *et al.* (2016a) ‘Public Views towards Implementation of Automated Vehicles in Urban Areas’, *Transportation Research Procedia*. Elsevier B.V., 14(0), pp. 2168–2177. doi: 10.1016/j.trpro.2016.05.232.

Piao, J. *et al.* (2016b) ‘Public Views towards Implementation of Automated Vehicles in Urban Areas’, *Transportation Research Procedia*. Elsevier B.V., 14(0), pp. 2168–2177. doi: 10.1016/j.trpro.2016.05.232.

Rödel, C. *et al.* (2014) ‘Towards Autonomous Cars: The Effect of Autonomy Levels on Acceptance and User Experience’, *Proceedings of the 6th International Conference on Automotive User Interfaces and Interactive Vehicular Applications*, pp. 1–8. doi: 10.1145/2667317.2667330.

Rogers, E. M. (1995) *Diffusion of innovations, Macmillian Publishing Co.* doi: citeulike-article-id:126680.

Schaefers, T. (2013) ‘Exploring carsharing usage motives: A hierarchical means-end chain analysis', *Transportation Research Part A: Policy and Practice*. Elsevier Ltd, 47, pp. 69–77. doi: 10.1016/j.tra.2012.10.024.

Schoettle, B. and Sivak, M. (2014) 'A survey of public opinion about connected vehicles in the U.S., the U.K., and Australia', *2014 International Conference on Connected Vehicles and Expo, ICCVE 2014 - Proceedings*, (July), pp. 687–692. doi: 10.1109/ICCVE.2014.7297637.

Shabanpour, R. *et al.* (2017) 'Consumer preferences of electric and automated vehicles', *5th IEEE International Conference on Models and Technologies for Intelligent Transportation Systems, MT-ITS 2017 - Proceedings*, pp. 716–720. doi: 10.1109/MTITS.2017.8005606.

Sharma, R. and Mishra, R. (2014) 'A Review of Evolution of Theories and Models of Technology Adoption', 6(2), pp. 17–29. doi: 10.9790/487X-1810063748.

Silberg, G. *et al.* (2013) 'Self-Driving Cars: Are we Ready?', *Kpmg Llp*, pp. 1–36.

Spieser *et al.* (2014) 'Toward a Systematic Approach to the Design and Evaluation of Automated Mobility-on-Demand Systems : A Case Study in Singapore The MIT Faculty has made this article openly available . Please share Citation Accessed Citable Link Detailed Terms Toward a Syst', pp. 0–16.

Spulber, A. and Dennis, E. P. (2016) 'The impact of new mobility services on the automotive industry', *Center for Automotive Research*, (August), pp. 1–56.

Starkweather, J. and Moske, A. K. (2011) 'Multinomial logistic regression.', *Multinomial Logistic Regression*, 51(6), pp. 404–410. doi: 10.1097/00006199-200211000-00009.

Stephen, R. *et al.* (2016) 'Autonomous Vehicles'.

Venkatesh, V. *et al.* (2016) 'Unified Theory of Acceptance and Use of Technology: A Synthesis and the Road Ahead', *Jais*, 17(5), pp. 328–376.

Venkatesh, V. *et al.* (2018) 'Quarterly', 27(3), pp. 425–478.

Venkatesh, V. and Davis, F. (2000) 'Theoretical Extension of the Technology Acceptance Model: Four Longitudinal Field Studies', *Management science*, 46(2), pp. 186–204. Available at: http://scholar.google.com/scholar?hl=en&btnG=Search&q=intitle:Theoretical+Acceptance+Extension+Model+:+Field+Four+Studies+of+the+Technology+Longitudinal#4%5Cnhttp://pubsonline.informs.org/doi/abs/10.1287/mnsc.46.2.186.11926.

Wadud, Z. (2017) 'Fully automated vehicles: A cost of ownership analysis to inform early adoption', *Transportation Research Part A: Policy and Practice*. Elsevier Ltd, 101, pp. 163–176. doi: 10.1016/j.tra.2017.05.005.

Willumsen, L. G. and Kohli, S. (2016) 'Traffic forecasting and autonomous vehicles', *European Transport Conference*, pp. 1–14.

Zmud, J. P. and Sener, I. N. (2017) ‘Towards an Understanding of the Travel Behavior Impact of Autonomous Vehicles’, in *Transportation Research Procedia*. doi: 10.1016/j.trpro.2017.05.281.

Zmud, J., Sener, I. N. and Wagner, J. (2016) ‘Self-Driving Vehicles’, *Transportation Research Record: Journal of the Transportation Research Board*, 2565(January), pp. 57–64. doi: 10.3141/2565-07.