Master's Degree in

Marketing e Comunicazione

Curriculum Innovation and Marketing

Final Thesis

AUTONOMOUS DRIVING AND ITS FUTURE IMPACT ON MOBILITY:

An analysis of perception in EU

Supervisor
Prof. Pietro Lanzini

Graduand
Leonardo Bertoldi
867681

Academic Year
2018 / 2019

Title of the research:

Autonomous driving and its future impact on mobility: An analysis of perception in EU

Author:

Leonardo Bertoldi - 867681

ABSTRACT

The objective of this research is to investigate perception regarding autonomous vehicles in the European Union with a particular focus on travel time and perception. The core element of the study is a new concept called "*travel time benefit*", which was introduced by the author as an expansion of travel time perception literature. This represents the research core of the work with an additional focus on safety perception as a secondary matter. A complete overview of the automotive industry latest trends and upcoming changes is provided as an introduction. A series of hypotheses were formulated based on previous studies in literature and applied to the newly introduced concept of travel time benefit. A sample of European Union citizens was used to fulfil a survey through Amazon Mturk with the goal of gathering primary data on the matter, to be then analysed with SPSS. Results are to be read as the current perception of autonomous driving technology. The main consequences are investigated, with a focus on additional time made available, thanks to the fact of not having to drive, added safety of the occupants and so on. Findings of this research establish a useful market insight for the automotive industry huge upcoming autonomous vehicle revolution and add to the body of research on the topic in the European Union.

ACKNOWLEDGEMENTS

Dedicated to Giovanni Vantini.

First of all, I would like to thank *mamma Chiara e papà Tiziano*, for their endless support and advice. I love you with all the strength I have in my body.

Francesco for being brother of my own blood and on the same page for everything. We are stronger than ever, nothing will stop us having fun.

Matilde. Thank you for being my sweet half, complementary on so many level and equal on even more.

Mattia. Thank you for your endless source of ideas and comparisons. Out mutual feedback both on this thesis and on each and every aspect of life is so crucial for me.

Federico. Thank you for sticking around since we were 12 and for every adventure, game, film, change and life choices in between.

Brus. Ti ringrazio per aver portato la tua forza vulcanica ed entusiasmo, oltre ad un po' di sano dialetto veneto. Non bisogna mai dimenticarsi delle proprie origini.

Claudia. Thank you for being my go-to-same-personality-type-person from serious stuff to memes, touching the mystery of the Somerton man in between.

Rebecca. Thank you for teaching me how it feels to be in touch with my emotions all the time and for not feel ashamed about it.

I also want to acknowledge *La zalza*, *la compagnia del vinello*, my flatmates *Luca*, *Carmen*, *Sofia*, *Stefano* and all the good people at MARKETERs club.

Shout out to the beautiful city of Venice too, I grew so much in my appreciation of life and photography thanks to you. You will always be there as the most peaceful place.

TABLE OF CONTENTS

TABLE OF FIGURES

TABLES

I. INTRODUCTION

The purpose of this thesis is investigating consumer behaviour connection between travel time perception and mobility opportunities with a particular focus on autonomous driving perception and its consequences for the future of mobility.

The aim of this research is exploring consumer's travel time perception in relation to mobility choices. Literature here is present for traditional means of transportation, but it's missing the most updated perspective on the possible consequences of the most recent trend of autonomous driving which will be the objective of new findings for this research. On top of that the research considers ethic and security implications of letting an artificial intelligence drive a car and the consequences in consumers' perception.

The automotive sector is going through massive and rapid change in the past few years with a structural transformation from the status quo present for the past decades. Technology and behaviour changes will affect the market in the form of a multitude of services for different types of urban scenarios (McKinsey & Company, 2016).

The main four clusters of disruptive trends in the next 20 years will be: *electrification*, *shared* and *connected mobility* and *autonomous driving* (The Boston Consulting Group, 2018). EVs (electric vehicles) will gain a share of 30% by 2035 and by 2030 It will be more economically efficient to use on-demand mobility services than actually own a car for about 30% of European citizens. Self-driving cars will be one quarter of the total of new car registrations by 2030 (The Boston Consulting Group, 2018). These numbers speak volumes on how many changes will have to be done also from the urban point of view to accommodate them.

Customer interest on autonomous driving is rising especially in Asian countries (Roland Berger, 2018) and a future where self-driving "*robocabs*" can drive people around at a lower cost per trip of having a personal car is not that far off the line (Roland Berger, 2018). Technological improvement is key in this area, as these kinds of cars need a machine learning capable AI to be able to process in real time data from a suite of sensors and cameras.

The purpose of the research is giving market insights on the perception in the European Union of how self-driving cars would change the way we travel and how we can use gained time in other ways. This element hasn't been investigated enough until now in literature and it is one of the most promising novelties, especially for its managerial consequences. Since autonomous driving is a relatively new technology it is quite interesting to investigate these implications. Findings in this regard might open

new consumer behaviour opportunities for cross-sectional research in the future, when self-driving cars will become more mainstream in usage.

The Main research question will cover the "*perception of the effect of autonomous driving on travel time benefit for the consumer*". Travel time perception had already been investigated related to cars while travel time benefit is a concept introduced and explained by the author to further expand on the topic. The existence of a relationship is already proven, while what is missing is a perception perspective on the future spread of autonomous driving in our daily lives. Time spent driving could be used to relax, be productive, sleep, and improve lives of millions of people. Since this impact is relevant, the focus will be on finding market insights about it and investigating how this could affect consumer's choices about mobility in the near future.

A secondary focus of the research deals with the relation between autonomous driving cars and the security/ethical concerns related and to investigate about intention of adoption. This additional point is about the fact that we don't feel in control while giving autonomous driving capabilities to a vehicle. Every new means of transport in the past had been welcomed with scepticism and self-driving cars are the latest revolution in this sense. After addressing the current literature, the analysis will focus on the perception of safety of occupants and on the ethical concerns regarding the choices the AI has to made in real time in crucial situations like car accidents or even a pedestrian crossing the street. In the research this perspective will be included with one of the main factors of the multiple regression, while for intention of adoption an entire multiple regression will be used to explain it.

Automotive sector current situation and challenges are presented and from there a funnel-like structure is deployed. Context analysis starts from the general perspective of the automotive market then carries to the various trends of the future and ends on the focus of autonomous driving. This is to give the reader a correct and broad view of the actual state of the industry.

In the research both quantitative and qualitative data will be used; from primary data using a questionnaire made on a sample to secondary research gathered from publications, industry reports, papers and books. The main research question will focus will be addressed using two multiple regression analysis.

The main research question is addressed through a multiple regression on a designated sample of about 400 people from the European Union 28 countries. The motivation and criteria used for the selection of the sample itself will be explained in its entirety in the chapter about the measurement model. Test for reliability is carried on then to observe Cronbach alpha's of the model's scales. A qualitative approach is used for the secondary research focusing on ethics and perception of security

and being in control. The period of data collection and analysis was done between August and September 2019.

The research project is a 6-part script divided as follows.

The first ***introduction*** chapter serves as a global recap of the entire thesis project, stating main research purpose and questions that will have to be answered. Theoretical bases are discussed, and the structure of the thesis is explained and motivated.

Then the second section is about the ***current state of the automotive sector*** highlighting its present problems and all its future trends. It starts from a general point of view, giving a broad perspective on the industry and from there the analysis touches the most relevant upcoming novelties in the sector: electrification, connected car, mobility-as-a-service and autonomous driving. The latter will be the focus of the rest of the research project.

Following we can find part three which will be the ***literature review*** and here the topic of self-driving vehicles is introduced with a brief overview of the history of development, the technical foundations and theoretical foundations of the technology. In this section the literature background of research made in the automotive sector is connected with the travel time perception and safety concern literature. An additional brief description of business ethics regarding the topic of safety is present. The chapter ends with the hypotheses for the research.

Fourth part focuses on the empirical data analysis with a justification of the ***measurement model.*** The analysis will investigate the relationship between a series of factors and travel time benefit with a particular eye for self-driving cars implications and possible benefits. The entire measurement model is shown and explained, with the section ending with a reliability assessment of it.

The fifth chapter highlights ***findings and results of the empirical research*** focusing on the relation between travel time benefit and several factors explaining self-driving cars. The sample is described, and the analysis is carried through two multiple regressions and some additional statistical techniques like correlations and ANOVAs.

The last chapter is the ***conclusion*** where the final thoughts on results and managerial implications for the industry are discussed.

II. AUTOMOTIVE SECTOR CURRENT STATE

In this chapter the automotive industry as a whole is the focus of attention. It is important to give context to the research project and make clear what are the foundations of its development in the following sections. The industry will be described through its present situation and problems with a consequent brief analysis of the most interesting and relevant trends and solutions for the future.

2.1 Present situation: The Automotive sector in 2019

2.1.1 A moment of strategic change

The automotive industry in undergoing a crucial moment of strategic change in the market landscape, after a period of relative stability in the last 20 to 30 years. Such redefinition and fluidity had never been seen before and it is particularly linked to external forces driving the market which now is not anymore centred in western countries. Digitalization across the value chain and the always connected nature of our lives are heavily impacting the industry. Data shows how 82% of companies are *not* ready to this change with the consequence of not doing enough to keep up with newcomers in the industry (Ernst & Young, 2017). This is made obvious by the fast rise of giants like Uber and Lyft that were able to capitalize with the idea of creating a *ride-sharing* platform to connect demand and supply regarding mobility needs and this payed off making them billion-dollar giants.

The paradigm is changing, a new form and definition of mobility is needed. Following Wedeniwski's definition (Wedeniwski, 2016), modern mobility is seen as: "*a platform of integrated products or services available, with which spatial distances can be overcome in accordance with individual needs and billed for in a standardised way*". This definition explains perfectly the current trend going towards fulfilling individual preferences, by being able to offer a service that is both available when the user needs it and where the user is located in that specific moment. These challenges are driving innovation in the business models of various forms mobility involving from individuals to public bodies and firms.

In the last years new players in the market are more focused on their disruptive approach to innovation compared to established automotive sector OEMs very incremental one. While the latter already have control of the entire mobility value chain, the former are targeting attractive and profitable segments of the industry, posing a serious threat to established manufacturers (McKinsey & Company, 2016). New entrants are both firms and start-ups that have deeply rooted origins in the digital and software world since they have the technological know-how to deliver up to the expectations of the market (shared, autonomous and connected mobility) in this moment of instability (Ferràs-Hernández,

Tarrats-Pons, & Arimany-Serrat, 2017). China is the leader of the pack considering pure growth in the electric vehicles market. There the market rose by *70%* in 2017 compared to the previous year, followed by USA, Japan, Korea and Germany (Roland Berger, 2018). The automotive centre of gravity is inevitably Asia now and European historic brands need to step up their innovation potential with a lot of investments. The product itself is changing with a huge 30% value coming from software and 25% from electronics by 2030, both categories covering products where manufacturers are mainly using suppliers (McKinsey & Company , 2018).

Car manufacturers need to shift from the traditional formula of design-manufacture-sell of a vehicle to a new status quo, where consumers need ***mobility as a service*** and this means an offering that is *always ready*, *seamless* and *flexible to their needs* (The Boston Consulting Group, 2017). Owning a vehicle in this paradigm is *not* required, as the final user can utilize services for moving through the city virtually anytime/anywhere, even though some limitations are of course present. The topic has already been studied in literature and a model by Schade, Krail, & Kühn explains the three main components (Schade, Krail, & Kühn, 2014): *ticket and payment integration*, *mobility package* and *ICT integration*. They go from the first one which is for example a basic ticket that can work on multiple means of transportation to the third one which is at the core of services like DriveNow that use an online platform to meet users with available vehicles on the territory in real-time.

Workforce is another huge element of change for the industry as it will be seriously reduced by automation of production processes: by 2030 almost half of the employees will be cut in favour of robots mainly because of the different approach to manufacturing dictated by EVs (PwC, 2018). Moreover future hires will be very different from the ones of today as the automotive sector is a very male-centric (76% of employees are male as of 2018) and old (68% of employees are over 35 years old) sector (PwC, 2018). Working on diversity and inclusion in the workforce will for sure be a challenge as employees will have to have a wider skillset than in the past.

A serious re-writing of rules of the industry is on its way and the main cores of disruption are three: technological, social and regulations related.

2.1.2 The 3 cores of disruption

Breaking down the situation it is possible to divide the disruption that is going on in the sector in 3 major cores of influence, each one with its factors. These are labelled as a) technological, b) social and c) regulation core.

From a **technological** perspective a lot is going on lately and companies are spending billions on R&D to be the first to channel the latest and more profitable trend by making it wide available. The

last decade brought 3 main novelties in the field of automotive: autonomous driving, electrification and connectivity.

Autonomous driving was made possible by the huge increase of processing power of CPUs and GPUs for mobile real time applications. A thorough explanation of this technology and why it became available only now will be given in a dedicated chapter later in this thesis. Main factors are real time computation of data and machine learning because computers in the past weren't enough powerful to process data from both sensors and cameras on a car to make it behave in real time.

About *EVs* (*electric vehicles*), the technology to manufacture them was already there but the main problem were related to battery capacity and charging capability. It is only in the last years that batteries became enough big to guarantee a usable range and enough power to properly drive a car and by 2030 almost 50% of sold cars will be electric or hybrid (petrol and electrically assisted) (The Boston Consulting Group, 2018).

Connectivity is the third major technology core that will change the paradigm of mobility. Here data is at the centre of attention and the backbone of technology. Seamless connection between vehicles, IoT (internet of things) applications, smartphones and city infrastructures will enable real-time recommendations and decisions to optimize city's traffic and user's decisions (McKinsey & Company, 2017). This will be crucial to the effectiveness of future cities flow of mobility where AVs (autonomous vehicles) will be able to communicate with each other to prevent congestion and be safer being them aware of the position and speed of other cars.

From the **social** point of view, the way we look at mobility is changing in several ways including urbanization and the way cities are optimized for new technologies, thanks to the right infrastructures, and by a serious increase of new ways of working (like smart working) and sharing mobility services. 2/3 of the world population will live in urban areas by 2050, up from 54% in 2015 (The Boston Consulting Group, 2018).

Consumer behaviour in car usage is changing, as people buy less cars and either use company cars or alternative means of transport and services. Growth of car sales in china after 2025 is forecasted to slow down, as the biggest potential of growth in terms of sales is there since western countries are already at stall. By 2021 pure internal combustion engine (ICE) car sales revenue will reach an all-time maximum before decreasing in favour of electric mobility (The Boston Consulting Group, 2018).

Millennials are already now less likely to own a car than their parents, changing drastically the future of the industry that will be a lot more focused on the *fit-for-purpose paradigm* of car use which is an evolution of the current *all-purpose* model of car use (McKinsey & Company, 2016). Nowadays, cars

are used for basically every mobility need, being it going to work, doing shopping or going on vacation in a way that is independent from how many people are being carried or the destination. Especially younger generations will be a lot more reluctant to use their own car, and they will rely to more convenient on demand mobility services as they become widespread and more affordable. In the fit-for purpose paradigm people will use different services for different purposes and all from their smartphone. Cars will be detached from an entire century of personal property, with final customers being a lot less connected with brands, creating huge loyalty problems never seen before in the industry (Ernst & Young, 2017).

Car sales in the next two decades will stall as a consequence of the spreading of these kinds of solutions, with 10% of cars sold in 2030 will likely be shared vehicles. Moreover the percentage of young people (16-24) that have a driving license in declining (from 78% in 2000 to 71% in 2013) and this is another signal that millennials prefer flexibility and don't see having a personal car as appealing as in the past (McKinsey & Company, 2016). One of the consequences will be in value creation for automotive manufacturers because profits are shifting away from the actual purchase of the car itself to a growing mix of surrounding services around it. This is a huge factor that needs to be considered for strategic decisions for OEMs as data becomes the main currency and 37% of all data generated will become subject of analysis by 2020, a huge step up from 22% of 2013 (Ernst & Young, 2017).

Another major change will involve *dealers*. The existence of physical places as a place to buy cars will become obsolete, since less traditional private personal cars will be bought, and car-sharing services will thrive and compete in big cities. The trend is moving towards huge fleets of business cars and mobility services opposed to personal property (The Boston Consulting Group, 2017). The way people are looking for information for buying a car is also tremendously different from the past: 95% of people now spend at least four hours searching online for information before visiting a physical dealer (The Boston Consulting Group, 2018). People are already using much more online services and methods than before to compare products, while going to the actual dealer is just done for just checking out the final possible choices in the real world. In all of this, still only 5% of population would buy a car purely online without seeing it in person (The Boston Consulting Group, 2018) so dealers will become more and more *showrooms* just to see cars and not a place to seek information about the models like they were in the past.

About **regulations**, the automotive sector has to face a lot of restrictions in the latest years, especially by city regulations of urban mobility and by emission standards goals that are becoming stricter than ever. The next decade will be quite harsh on car makers during the transition to cleaner powertrains as regulations will pressure them to sell cars with a premium price because of the low maturity of the

technology and consumers still seem sceptical of the new solutions. In the period 2021-2025 meeting US and EU regulations as of present studies will be impossible, with 11.8 and 3.5 million additional cars that will have to be sold on top of the projections of demand (The Boston consulting group, 2018). In 2025 there will have to be 1/3 of sold vehicles in the US that are not pure ICE to reach the minimum requirements of regulations with hybrids with a similar prediction in Europe. In EU by 2025 EVs and hybrids will have a share of respectively 13% and 18% with diesel taking the biggest drop in percentage from today standards. All of these elements will create a transition period where prices for final customers are going to be higher while margins for automakers will be lower with the result of stalling sales after 2025 (The Boston consulting group, 2018).

Another core factor will be greenhouse emission regulations. Nowadays, cars alone create **12%** of the total CO2 emissions of the entire European Union (European Commission, 2019), which accounts for **10%** of the global greenhouse emissions (European Commission, 2019). In the last few years carbon emissions have been targeted with a lot of restrictive measures to improve on Europe 2020, 2030 and 2050 targets. The Paris agreement demands a strong effort of all industrial sectors to reduce their impact and automotive is part of the biggest producers of carbon oxide. The objective is minimizing the increase of temperature in the long-term (2050) to less than 2 degrees Celsius and that means reducing Europe 2009 standards of emission by 80-95% (European Commission, 2018). For the automotive industry only technical development of internal combustion engines is not enough to reach 2030 and 2050 emission goals, despite the recent trend of downsizing engines and hybrid powertrains. Diesel engines are in a moment of identity crysis after Volkswagen 2015 so called "*Dieselgate*" where the entire group cheated on its TDI engines NOx emissions for years (2006-2015) on American emission authorities (Fortune.com, 2016) getting fined 25 billion by US courts (Fortune.com, 2018). The solution to the emission problem seems obvious by now: introduce electric powertrains on a massive scale and invest on car sharing services. Complaints by car manufacturers were also quite present as on the present pace the EU set targets seems impossible to reach with current investments and technology (Guardian, 2018). The broader topic of sustainability will be analysed in depth a separate paragraph (2.1.4).

2.1.3 Change in revenue streams and R&D expenses

Such a moment of reshape of the sector will bring a severe **change in revenue streams**. Future growth is possible for the industry, but in areas that are *unconventional* for what was the status quo of the sector until now. AVs (autonomous vehicles) and EVs (electric vehicles) components, data manipulation and insight, connectivity and on-demand mobility services will be the most profitable new categories (The Boston Consulting Group, 2018). Core business margins will slow down, and

profitability will have to be searched elsewhere. At the same time the possible new expansion in other profitable areas means a lot of money to invest and competition by newcomers, that are a lot more focused on single elements of the market instead of the whole present value chain.

There is also a timing problem in the industry right now. New ways of mobility discussed in this chapter are the future of automotive and mobility, but the main concern is timing of their introduction. If a company focuses on bringing disruptive novelties to the market it could be too soon and as a consequence the firm could lose a lot of R&D money and profit from the core business if the tech is not mature or accepted by mainstream consideration. On the other hand, if a company waits too much the early adopters' margins of profit are gone and the brand and business as a whole would suffer from it (The Boston Consulting Group, 2017). This is particularly true in a sector like automotive, where suppliers are a key partner for development of new technologies and not having established standards will drive production costs higher than the past. Overall 2.4 trillion dollars must be invested in new growth areas by 2035 (The Boston Consuting Group, 2018).

These are some *key areas* where car brands need to invest right now:

- **Autonomous driving technology.** It will become in 10-15 years hugely important for its impact on the way people will travel, especially in large cities. A complete overview of the technology will be given in following chapter of this thesis.
- **Battery technology**. As the shift towards EVs will need a significantly higher number of them, companies will need to push R&D to develop more performing and durable units. Range has been one of the main limitations of EVs until now and battery technology is a key factor to unlock their potential. A lower cost per KWh of capacity needs to be achieved with the top player in the field being the Tesla-Panasonic partnership with $111/kWh, which is 37 dollars less than the main competitor (LG), but it's still a lot of money when the average battery alone (75KWh) is more than eight thousand dollars (Financial Times, 2018). According to J.P. Morgan estimates the cost per KWh for EVs to become mainstream is around 100 dollars/KWh which is probably one to two years aways for market leaders and two to four years for all the rest (J.P.Morgan, 2018).
- **Network of chargers on the territory**. This is crucial and here the responsibility of local administration is higher than ever. Cities can play a substantial role now in shaping the mobility infrastructure and landscape, making new technologies possible thanks to a great presence of fast chargers. Overall the transition to EVs will be slow because of the lack of an infrastructure of chargers. As of now for example for Tesla Model S actual recharging price

is 30 cents/KWh and with the battery ranging from 75 to 100 Kwh it means about 6 euros for 100km compared to about 8 euros for the average petrol competitor (Tesla Inc, 2019).

- **On-demand services like self-driving taxis and car sharing**. Brands like BMW with DriveNow and Mercedes with Car2Go are already on this path, but to be competitive in such a fast-evolving environment OEMs need to invest a lot more. At any time a new player could come in and disrupt the market like Uber did with taxis. These services potential profits will become a big as 76 billion by 2035, overcoming the forecast 60 billion for regular car sales of ICE and hybrid cars (The Boston Consulting Group, 2018). On demand platforms can overcome collaborating with traditional car manufacturers by working directly with suppliers and by using their massive amount of data. This enables them to do research like Uber and Lyft are doing right now for autonomous driving.
- **Partnerships/joint ventures with other firms**. In a moment of massive change even competitors join forces with the goal of creating flexible ecosystems with OEMs and suppliers (McKinsey & Company, 2016). The goal is of course reducing costs of both technology development and network infrastructures, while retaining the individual identity against competitors. Moreover, creating these conglomerates could also make easier for governments to develop the right legislation. A recent example of a huge partnership in the field of mobility is *ShareNow* (ShareNow, 2019) a car sharing service born from the joint effort of *BMW Group* and *Daimler AG* (Mercedes) to create a unified network for the future of mobility. With more than 20.000 cars worldwide at the time of writing (3200 of them being electric) and a network of 100.000 chargers in 25 markets called ChargeNow, this service lets people access a car anytime anywhere following the fit for purpose paradigm, making travelling by car flexible and hassle-free.

2.1.4 Sustainability aspect and concerns

CSR (*corporate social responsibility*) is now more than ever a requirement for increasing conscious final customers that are aware and capable of creating huge PR problems on the internet, from just a not perfect marketing campaign of a product. Thanks to internet and social media each marketing message the company communicates could involve unexpected backlash and terrible consequences on stock prices and sales. A clear example here is the Volkswagen emission scandal, that made the stock fall by *37* points in the days after the reveal to the public (Fortune.com, 2018).

Sustainability is one of the most contemporary topics in management. The challenges that it creates for a company are multi-dimensional and range from *economic* to *social* and *environmental* concerns. A sustainable company is able to deliver in a sustainable way on all those three elements, which

together are called the *triple bottom line* (Hart & Milstein, 2003). This concept came out in the mid-1990s as a way to include social and environmental dimensions to the evaluation of a business activity and by now it has been accepted as a framework that evaluates three Ps: *people*, *planet* and *profits* (Slaper & Hall, 2017).

The automotive industry is no different from other sectors and its sustainability needs to be taken into consideration. The concept of "*smart mobility*" is particularly close to the scope of our analysis, as it represents a balance between expanding and optimising mobility in urban areas taking in consideration factors like society and environment (Zawieska & Pieriegud, 2018). Reducing carbon emissions is one of the main priorities for the industry at the moment, and this needs to be achieved through policies in cities, despite the huge expansion of markets like China. The United Nations (UN) Sustainable Development Goals are seventeen objectives that were put together to guide development towards a better future for humanity; 2030 is the target year to achieve them in every industry (United Nations, 2019). Their focus is quite wide in its overall scope, but precise in each of the seventeen aspects. In automotive the focus is on value chain optimization: manufacturing and shipping parts is crucial for the just-in-time paradigm used in the industry (SMMT, 2018). Out of the total seventeen, for obvious reasons of space, only the three most relevant for the automotive sector will be covered in this thesis. These are number seven, nine and twelve which are "Affordable and clean energy", "Industry innovation and infrastructure" and "Responsible consumption and production" respectively.

Affordable and clean energy (number seven) is all about reducing the carbon footprint in the automotive sector, by transitioning to more efficient forms of propulsion engines. Stakeholder's focus now is on EVs, as direct emissions are strongly reduced by using alternative to internal combustion engines, on top of that electricity can be created by renewable sources. Government incentives and regulations are also important to make people consider the advantages for the environment of these kinds of cars over the pure economical evaluation. Consequences of CO2 emissions might become dire if all industries respond with massive action and as discussed previously EU for example is pushing manufacturers to comply with strict regulation on greenhouse emissions.

Up next number nine is another relevant pillar in this industry: ***Industry, innovation and infrastructure***. The focus in this one is on R&D and its implications for society's progress, which in this moment coincide with electric cars and autonomous driving. A huge challenge for automotive will be creating a network of fast charging stations on the territory, to lower running costs under those of ICE cars and make charging available for everyone. Furthermore, battery technology needs to improve and most importantly improve efficiency and range of vehicles as electric trucks are also a

probable outcome when the tech is ready. Only then EVs will thrive and adoption rate will grow out of a small niche.

Third element is the 12th UNSDG: ***Responsible consumption and production***. The aim here is "*doing more and better with less*" and the focus is on consumers education on sustainable lifestyle and on a 360 degrees approach on supply chain during the entire product lifecycle (United Nations, 2019). Third party bodies' certifications are important to increase awareness of consequences of waste and incorrect practices. Innovations like car-sharing and ridesharing are already changing mobility and with the broader propagation of EVs the situation will further improve.

2.2 Industry changes: the 4 pillars of the future of automotive

2.2.1 Electrification

The first main pillar is electrification. In 2018 car manufacturers had planned an R&D expense of 90 billion dollars only for developing electric power trains (Ernst & Young, 2018). Once reached technological requirements, like mass produced batteries and a widespread network of fast chargers available, EVs adoption will start increasing with the share of sales by 2030 being in the range of 10-50% depending on the area. The author lies on the more conservative side of the range in its judgement, but such a wide interval is explained by the fact that embracing this technology is highly dependent on the urban context. In bigger cities EVs will have higher rates because of smaller distances, higher income of people that are willing to pay for them, emission regulations with stops for older models and most importantly charge stations availability (McKinsey & Company, 2016). The next few years will see a transition from a only internal combustion engine market to a mixed situation by 2030 where hybrids (in all of its forms) will gain about 35% share, while EVs slowly enter in the conversation with about 15% of overall sales (The Boston consulting group, 2018).

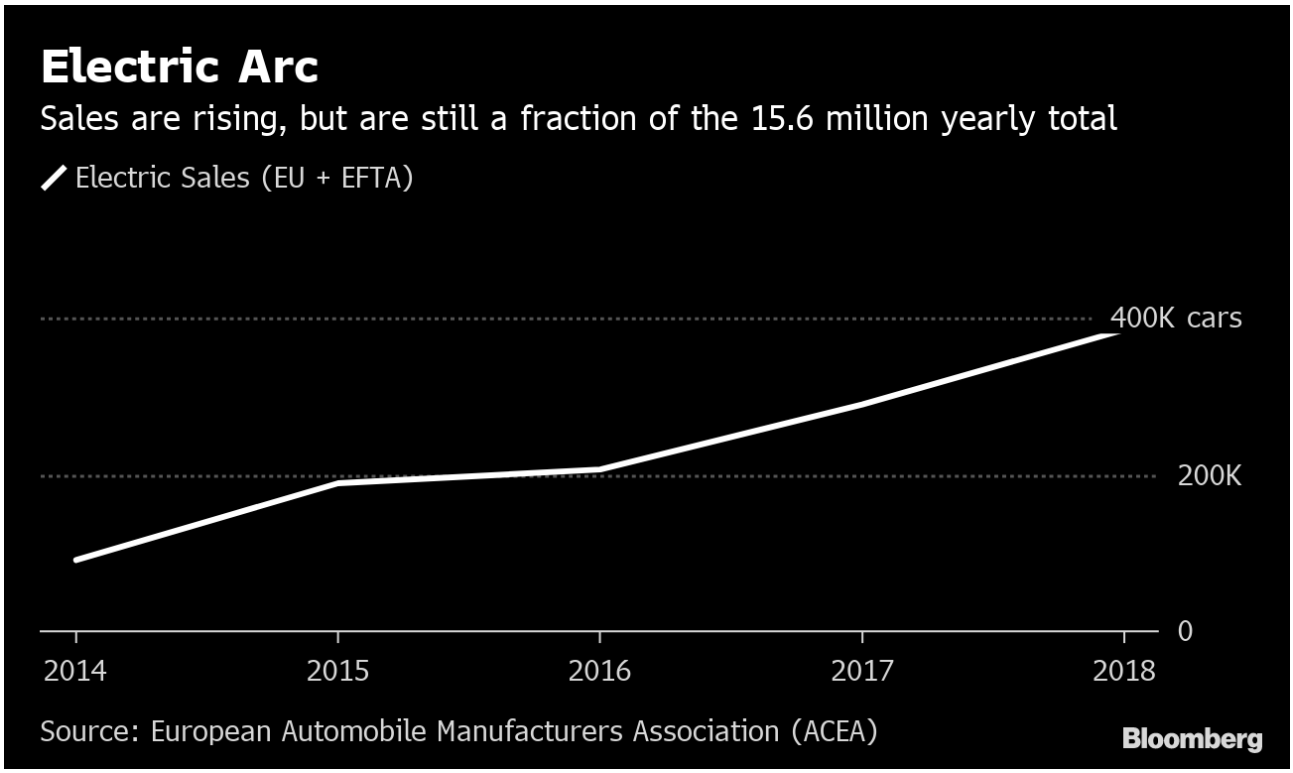


Figure 1 - EV sales 2014-2018
Source: Bloomberg

2.2.1.1 Overview of the changes in the industry

Looking at the overview of the industry, 2025 will be the turning point with almost 30% of sales being EVs (7%) or HEVs (hybrid electric vehicles), with hybrids accounting for 23% of the market (J.P.Morgan, 2018). This means that pure internal combustion engine vehicles will drop from 98% of market share to a mere 41% by in just 15 years between 2015 and 2030 (J.P.Morgan, 2018). In 2040 55% of new cars will be EVs and by that time the share of electric vehicles on the total cars on the road will be about 1/3 of the total (Bloomberg New Energy Finance, 2018).

From a geographical point of view, as said before China is one of the most promising and attractive countries for EVs: already by 2025 55% of the global share of electric cars sales will be in China, making it the uncontested n1 market. The obvious reasons are a huge infrastructure of chargers, costs of batteries going down by almost 20% on a yearly basis and government pushing towards electrification. This is a consequence of a huge role of the Chinese government with its investment in infrastructures and R&D funds (Bartnik, Wilhelm, & Fujimoto, 2018). As a matter of a fact Chinese car manufacturers were still lagging behind in their own domestic market with a mere 20% of share until 2015 (Murphy, 2015), but now that a disruption is happening, their catch-up took a serious acceleration, especially for EV technology. As mentioned earlier, the estimation for battery costs to

be available on entry level cars is maximum 100 dollars for KWh, a milestone that will be probably achieved in 2019. Materials' cost will also have to be taken into consideration in the following years since demand for lithium, nickel and copper will increase, with Lithium for example requested a noticeable 20% more in the next 5 years (J.P.Morgan, 2018).

Charging infrastructure is a determinant factor for EVs mainstream adoption in the near future. Tesla alone is present with 1441 supercharging stations for a total of 12.888 charging spots globally (Tesla Inc, 2019). For number of stations by country though China is once again number one in investments with State Council itself demanding by 2020 12.000 new stations and 4 million charging spots (J.P.Morgan, 2018). At the beginning of 2018 about 600.000 public charging points were installed globally (Bloomberg New Energy Finance, 2018). Charging electric vehicles itself is done in multiple ways, at different speeds and at different prices. The main division is on three AC levels:

- **Level 1** is the one that every owner of an electric car can use at home using the regular electricity of their home to charge. It is usually used at night in the same way we charge our mobile phone every day.
- **Level 2** is the base level for road non-fast-charging stations and home fast charging solutions. It is least expensive than fast charging and it can charge on at least a 24KWh battery in 4 hours (J.P.Morgan, 2018). For reference a BMW i3 has a battery of 42,2 kWh and can be charged to 80% in 3 hours with BMW own home fast charger which is faster than regular non-fast-charging columns (BMW, 2019). These are used to top batteries for example when the owner drives to work and leaves the car in the parking lot for the day before commuting back home in the evening.
- **Level 3** where the aforementioned Tesla's superchargers fall into. These are able to charge 120 kW or more and can charge up to 80% a regular Tesla Model X in 30 to 40 minutes (Tesla Inc, 2019). These are used as a quick on the go fill up during longer trips and are quite expensive. For example, for a 600km trip charging a Tesla on superchargers would cost about 33 euros compared to 50 euros of petrol for a regular ICE car (Tesla Inc, 2019).

Figure 2 - ABB Terra series of future ready EV chargers can reach up to 350 kW
Source: abb.com/ev-charging

On top of this classification of "old school" wired charging, which is the industry standard as of now, two more alternatives are being tested: *battery swapping* and *wireless charging*. The former is about a totally different approach to charging itself as the entire development of the car needs to take into consideration removable batteries. Instead of waiting for the battery to charge, a potential client would just have to drive into swapping stations and change its vehicle battery with a charged one. The limitations of this approach are many and don't resolve the main problem of lack of availability of charging points, but Tesla is currently piloting it in some of its supercharging stations. The latter approach to charging is using induction in a way that is similar to how wireless charging works in recent smartphone. It is still under development and it could be a great solution for slow chargers like for example at home or at the office (Amstrdam Roundtable Foundation, 2014).

2.2.1.2 EVs market attractiveness

EVs sales are slowly but steadily growing but sales vary a lot between markets and urban vs rural areas. For example, in 2015 in China only 0.7% of cars sold were electric powered in contrast with 26% of Norway (Accenture, 2016). To better understand why it is possible to see such fluctuations based on the context an indicator can be used: **EV market attractiveness**. It represents "*the degree to which-from a customer perspective-the purchase of an EV instead of a conventional vehicle is a more attractive option, in both monetary and non-monetary terms*" (Accenture, 2016). It is dependent

on both market related and non-market related factors which affect the entire industry scenario. Focusing on the market related, the elements here are nine and divided in three categories: *political factors* (like monetary government grants for buying zero emission vehicles and charging infrastructure), *economic factors* (like the cost of charging and the cost of the car itself) and *technological factors* (like range of cars) (Accenture, 2016). This figure gives us an idea of the multitude of factors that comes into consideration in the EV market.

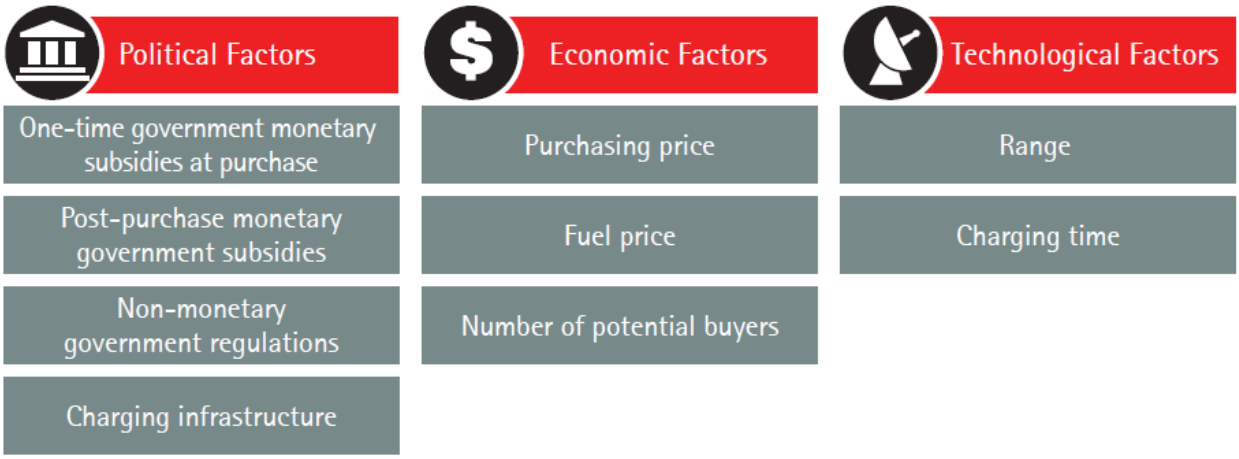


Figure 3 - Adoption Factors
Source: Accenture (2016)

Taking a look at the segmentation of countries in regard to market attractiveness of countries based on 2 variables: EV market size and EV market growth. This creates four categories of players in the market and can be represented in a matrix. In both high- market growth and market size we find China and the US as the two countries where EV is currently a thriving phenomenon, giving it the label of *Best-in-class*. In the two opposite mid situation where one of the two variable is big and the other is small we can find *high potential* states and *pensioners*: the former is the destination of most European countries and it represents high future market growth even for a quite small market, while the latter it is a category that is still not present since the sector is quite new and high market size-low market growth is not a present scenario in the industry. This case would be a country where the market is already overfilled with electric vehicles. Fourth and last category is *Hesitators* that represents countries like Russia or India where the infrastructure is not present and R&D expenditure is low and as a consequence the EV market is nonexistent (Accenture, 2016). As an example of High potential state, we can take France. Electric car sales in November 2018 recorded +111% compared to the same month of 2017, with 3541 EVs were sold and France is reinforcing its position as one of the top EU

countries for electric vehicles market attractiveness mainly thanks to government regulations and tax reliefs (electrive.com, 2018). Italy as of mid-2019 remains below average with a quite high cost of charging per mile compared to other countries as seen in the figure below (Il Sole 24 ore, 2019), with the example of charging a Tesla Model S resulting at 9,27 euros for 160 km. This cost is comparable to other countries like Germany and Denmark with a very well-developed charging infrastructures, but it is pricier considering the average income of people living in Italy is lower.

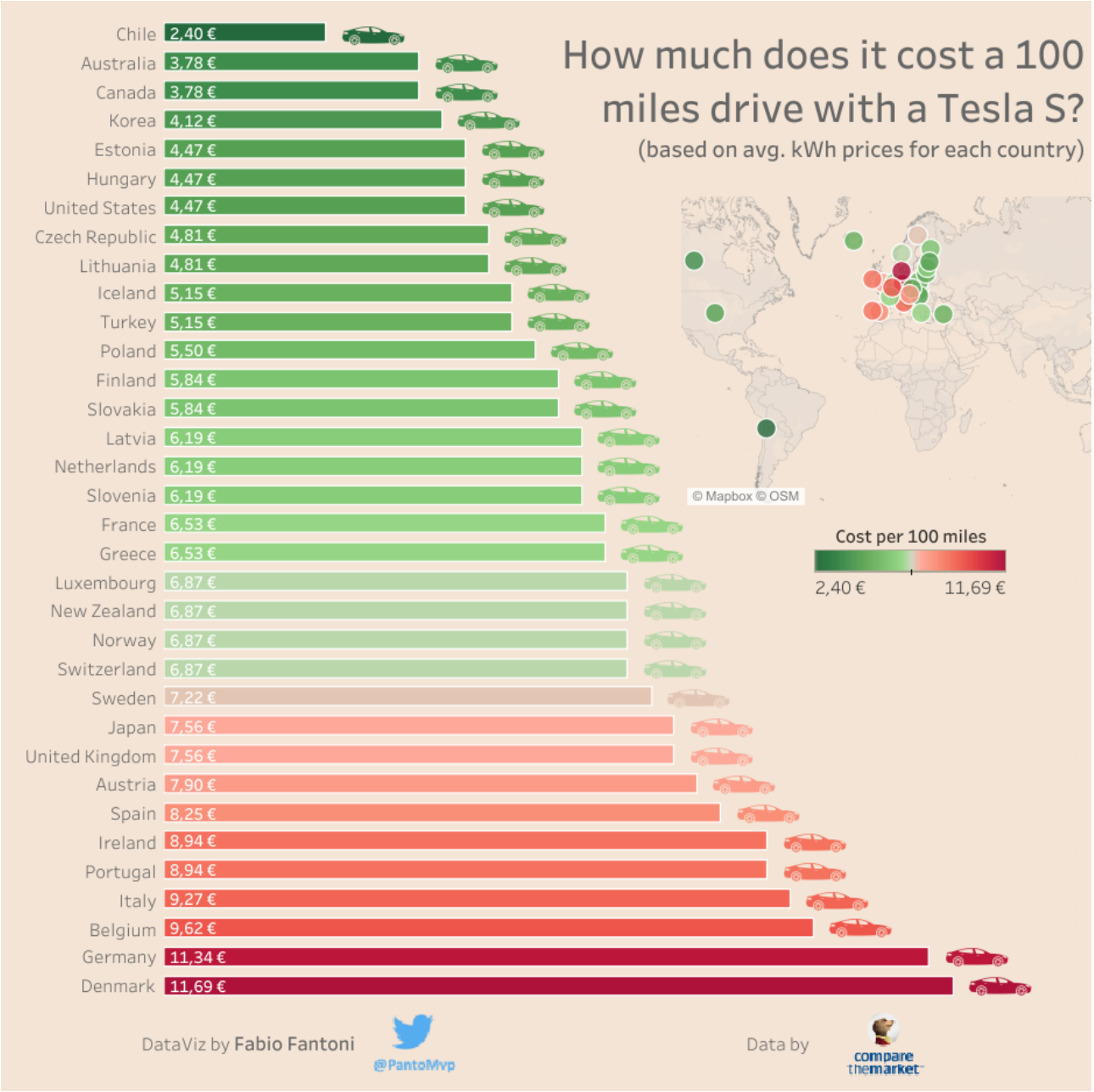


Figure 4 - Cost of a 100 miles drive with a Tesla Model S in different countries

Source: ilsole24ore.com

2.2.1.3 EVs adoption factors

Now that the conditions of adoption in the market have been analyzed, It is time to focus on what can governments do to improve on them. It seems like policy support is the strongest influencing factor to make citizens buy EVs, followed by environmental factors like average income and spread of charging stations. The pure number of policy tools and the price of charging instead are two elements that have a weak effect on purchase (Yong & Park, 2017). The most effective measures to boost adoption of electric vehicles for a certain government is to invest and promoting a charging infrastructure and at the same time introduce tax exemptions and subsidies. It has been proven how even a high GDP-per-capita country can be outrun in EVs adoption by poorer countries just by the fact that the government is not pushing policies or incentives (Yong & Park, 2017). Furthermore, studies (Gebauer, Vilimek, Keinath, & Carbon, 2016) found out that people after experiencing fast charging technology improved by a significant margin their EV consideration and perception. After trying themselves how fast the charge can be their attitude towards use changes. The implication for governments about this are for sure connected to the investments needed, since installing a network of fast chargers is once again proved to be the main solution to boost awareness about EVs and their adoption.

In EU the determining factors from the consumer point of view are still related to price, especially price of purchase as the main element of choice, with fuel costs and maintenance as the second highest priority for people. It is also interesting how half of the interviewed people bought a second-hand car, and this is another factor to keep in mind as it can slow down EVs mainstream adoption (European Commission, 2017). From a longitudinal point of view between 2012 and 2017 people still consider price as the main problem for EVs adoption, but the percentage of people that thinks the technology is expensive decreased. This is a good sign as people are aware that both prices of cars and batteries decreased massively over the period (European Commission, 2017). Looking at Italy the main factors that make the country not an ideal place for electric mobility as of now are high price, low driving range and number of charging stations. Moreover, the actual preferred powertrain by Italian customers now are HEVs (hybrid electric vehicles) and environmental concerns awareness is not strong enough to be a among the top three elements during car choice (Ciarapica, 2013). Environmental concern is indeed present though and it is more present in women and older drivers and in both cases highly educated. Still people don't view EVs as an effective way to combat greenhouse emissions and they are not far from the truth since the impact on the environment of electric cars is not that different, especially if electricity is produced with non-renewable energy sources (Dimitropoulos, 2014).

In Italy the present situation is not great considering the 2030 deadline for reaching sustainability goals. The country remains a personal car-dominated market with the second highest number of cars per capita of the European Union (ACEA, 2018). A lot of work needs to be done on the infrastructure and awareness for an effective shift to electrification in the next few years. Looking at the E-mobility index for 2018 Italy is in the last place for both industry and technology among the top 7 automotive world markets (figure 2), with France leading for technology and USA and China for industry (Roland Berger, 2018). It is quite clear how the Italian EVs market is very late and this issue is also expressed by the lack of R&D e-mobility funding by the government (figure 3).

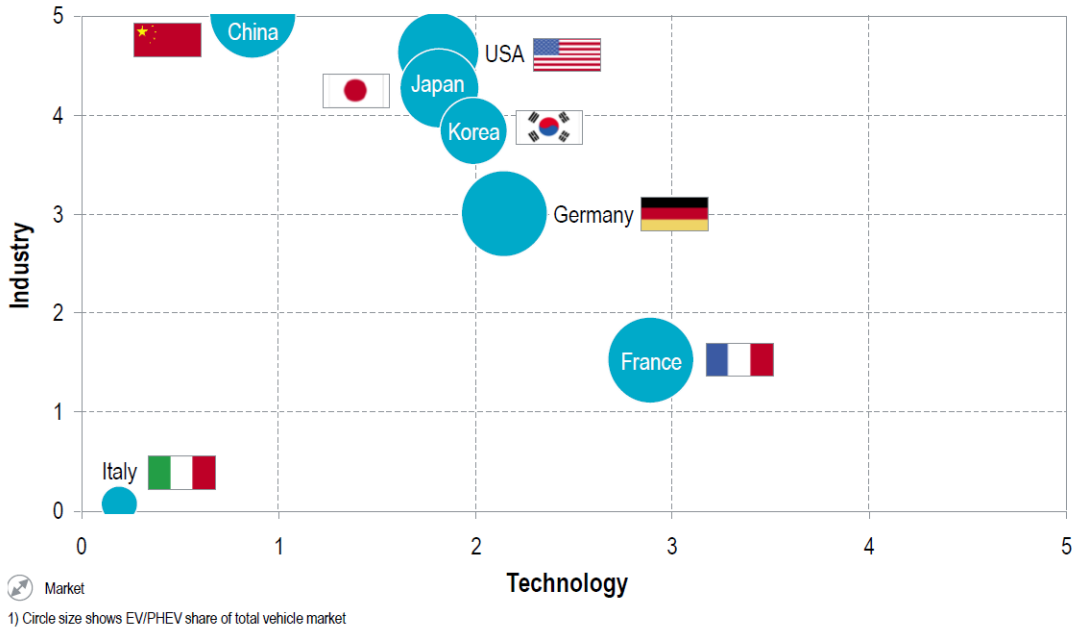


Figure 5 - E-Mobility index 2018

Source: fka, Roland Berger

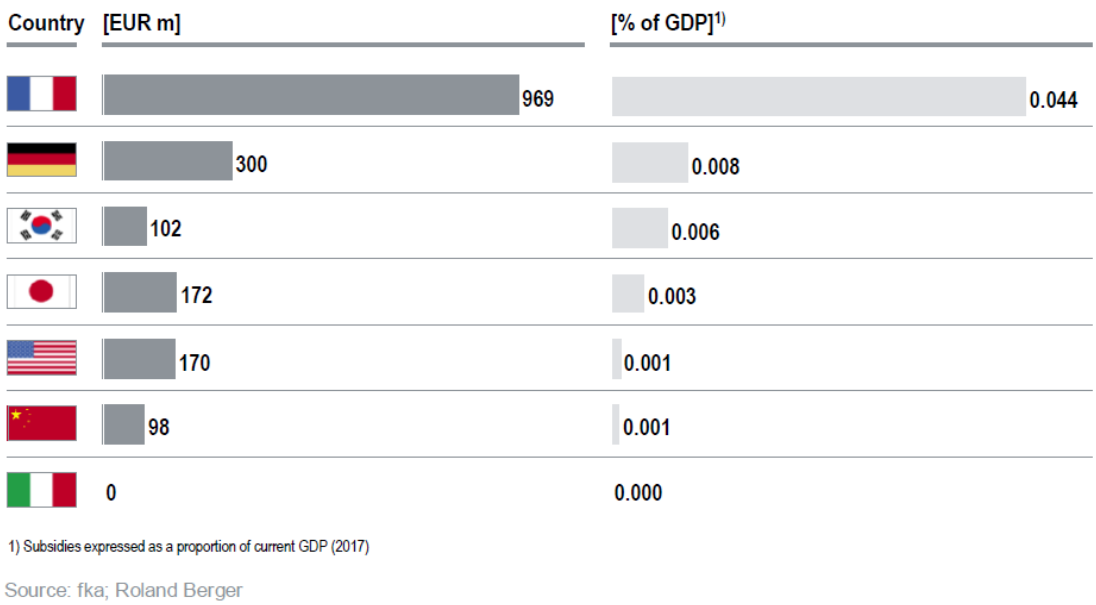


Figure 6 - State R&D funding for e-mobility
Source: fka, Roland Berger

2.2.2 Shared mobility

The second pillar is shared mobility. The term itself describes a transportation service that is shared among its users. It includes different concepts: the case when a car (like car2go) or a bike is shared between people subscribed to the service, the case of public transport, taxis, car-pooling done by individuals with their car, the case when a ride on a vehicle is shared with other occupants (like Lyft) (Sprei, 2018). This mode is growing so much that the concept itself of owning a car will be challenged in the next decade and automakers will have to reinvent themselves as mobility service providers, on top of being producers of vehicles (PwC, 2018). How cities deal with mobility and transportation will be affected too with shared mobility services that could reach 30% of the travels in Europe by 2030 (PwC, 2018).

2.2.2.1 Change in ownership of the car

Owning a private car and pay for all of its expenses is becoming less convenient in the last few years as the market and society are changing at a pace that is faster than what we saw before. New technologies like EVs and autonomous driving are being developed relentlessly, urbanization is on the rise with 66% of world population forecasted to live in cities by 2050. Governments and regulations struggle to keep up with this moment of disruption (The Boston Consuting Group, 2018). It is highly probable that the market will gradually shift to mobility-on-demand services in the next few years with a serious consequence on how cars are even designed as the experience itself is moving

from driving to being passengers (Roland Berger, 2018). Taxis are a clear example of vehicles that benefit a lot for being hybrid electric since being able to drive on electric power alone at low speeds is particularly effective in large towns where the time spent in traffic is high. This is why HEVs will increase massively their sales figures, being the most efficient way to travel in city and waiting for large scale availability of EVs. NYC taxis are already 60% hybrid and all the autonomous driving services of the near future will follow this route as the initial premium in price is easily recovered by savings on fuel (The Boston consulting group, 2018). China will be the main catalyst of the change with a massive 60% of the global market for mobility services already by 2020 (which is more than the rest of the world combined) making it an incredible attractive market for the automotive industry future (Roland Berger, 2018).

2.2.2.2 Urbanization and city congestion

City congestion of cars is huge factor that needs to be taken into consideration. The impact on the overall economy of congestion can be calculated to an approximate of 2-4% of the city GDP (McKinsey & Company, 2017). Transportation network companies (TNC) like Lyft and Uber are exploding around the world and they are contributing to add more cars in cities that travel around without passengers for 20 to 50% of the time and increase travel demand taking people away from public transportation (PwC, 2019). These services are more convenient especially for short range trips (usually under about 10 km) as their cost per kilometre exceeds the one of a private vehicle and in the case of being with other people, sharing the ride and the cost and making shared TNC rides more convenient for longer trips. In all of this still public transportation costs are about one third to one quarter in the cases cited above (and become even lower with longer trips) with zero impact on cities congestion (PwC, 2019). Another huge factor of traffic creation in towns are e-commerce and on-demand services delivery trucks. With platforms like Amazon offering shipping the same day in many countries it is not difficult to understand the huge logistic structure that needs to be put in place to offer such convenience and speed. Furthermore, the higher the economies of scale, the lower cost online retailers can experience for the service. This seemed like a benefit because from a mobility point of view since citizens could simply order online and stay away from roads. The problem is more complex though. People buy a lot online increasing a lot the number of trips required, on top of that delivery can be 10 to 30% of the cases a missed delivery since people missed the courier and this adds even more to the number of hours trucks need to travel around towns (PwC, 2019). Autonomous vehicles are said to be a solution for some of these road conditions, but still the future is uncertain. Slow rate of adoption of the new tech, restrain of people at sharing rides, bad regulations and urban design changes are all factors to consider.

Another very important topic is the one related to commercial vehicles (CVs) in town and the problems they can cause. By 2030 studies forecast how one billion people will move to cities with all the consequences on transport of goods and food going as far as +40% in volume to keep up with population increase (McKinsey & Company, 2017). These CVs pollute more than traditional cars due to their diesel engines that are notorious for their NOx emissions and higher fuel consumption due to high utilization. Just by looking at e-commerce sales there will be a forecasted +85% increase between 2015 and 2020 (McKinsey & Company, 2017). Urban mobility will have to take into consideration solutions to keep traffic in check. The possible outcomes in the near future (2030) could be essentially three: business as usual urbanization, unconstrained mobility and seamless mobility (McKinsley & Company, 2019). These 3 scenarios range from basically no change from now in the first case, with longer times and lower quality of life for citizens, to the third case, where the 4 pillars of the future of automotive (connectivity, autonomy, sharing and electrification that will be discussed in 2.2) will be achieved to create the best-case scenario for cities. The third paradigm would improve across the board mobility in cities with lower costs, shorter delays and higher availability of options, especially with autonomous vehicles taking over. To reach this third stage the main points are: increasing the offer of options and use in the best way the present infrastructure, improving how passengers use public transport and third, work on sustainability aspects of the system (McKinsley & Company, 2019).

At the Italian level, as outlined by Morandi and Vagnoni (Moradi & Vagnoni, 2018) "stakeholders mainly paid attentions to the operational and strategic aspects of political and economic factors" with the result of a serious bias in mobility towards individual car usage, the so called "automobility". This led the system to serious traffic problems, but even more serious emission problems with cities trying to cope ineffectively with this situation with stops for older vehicles touching even euro 5 cars in some extreme cases (Ansa, 2019). At the moment only major cities like Milan are seeing a serous planning for a renewal of the transport system with the latest car-sharing and smart mobility solutions. As personal cars are still the most used means of transport, this opens the possibility for EVs and shared mobility to grow a lot in Italy since they are a more privacy conscious way of mobility.

2.2.2.3 Subscription models

In the moment of change that is undergoing in the automotive industry many services are proliferating in an effort to find alternative revenue streams and opportunities to leverage on sales. Renting, leasing and subscription are the most used in the automotive industry and It is important to distinguish between them since they differ from a juridical point of view. The definition from the Oxford English Dictionary states how on one hand **renting** is "to pay rent for (land, buildings, etc.); to take possession

of, hold, occupy, or use, by payment of rent" (Oxford English Dictionary, 2019). On the other, **leasing** is "a contract between parties, by which the one conveys lands or tenements to the other for life, for years, or at will, usually in consideration of rent or other periodical compensation" (Oxford English Dictionary, 2019). The two most interesting differences between the two in the case of automotive are: time and possibility of ownership. Renting a car is usually quite limited in time and there is no implication to buy that car at the end of the period, whereas in leasing the length tends to be significantly longer with the possibility at the end of the lease to buy the car at a certain price (Torrente & Schlesinger, 2011). For example, the company Hertz offers both models: leasing is more convenient for long term business fleet cars, while renting is for using your car during a 5 days holiday trip.

A different model of contract that became quite popular lately thanks for its use in internet services (like Netflix, Spotify, Amazon Prime and many others) is the **subscription model**. It is defined as "Regular payment for access to a commercially provided service" (Oxford English Dictionary, 2019). In the past its most common used application were magazines: subscribing for that year granted a discount compared to getting all the individual issues of that publication. This kind of contract gives the buyer "the right of consuming these units repeatedly over time on a regular or irregular basis" (Gabszewicz & Sonnac, 1999). Other than spending less, the most striking advantage this contract gives compared to other solutions is competitive positioning both against competitors and potential threats or new entrants in the market. A consumer subscribed to a service is less sensitive to competitor's discounts or sales promotion since going out of a contract with the present service requires effort and the relationship itself becomes stronger overtime as habits create (Cook & Garver, 2002).

Figure 7 - Care by Volvo launched in 2018 with the XC40

Source: volvocars.com

This model has been adapted lately by car manufacturers like Volvo in its Care by Volvo subscription service (Volvo cars, 2019). The implementation for automotive is offering a car with the payment of a monthly fee and with all the possible additional services, insurance, maintenance, winter tires and flexibility in case of problems included. Volvo is not the only one launching this kind of service; Access by BMW, Mercedes-Benz Collection, Porsche Passport and Ford's Canvas are only some of the businesses started by major players (Edmunds.com, 2018) The motivation of the choice of these manufacturers is similar to the one used by magazines and online services: improve customer loyalty and improve brand perception. Another element that makes this route particularly interesting is convenience of utilizing the car. As previously discussed, newer generations are less prone to buy cars and might enjoy having this additional option to use vehicles and being able to end the contract at any moment. Data show how millennials are already moving away from ownership with an increase in leasing from 21% to 33% in their market segment in the 2011-2016 proving the importance of services like this in the long-term (Edmunds, 2017). The main motivation for this increase is of course money since leasing makes possible owning a higher tier car to people like millennials whose income is not high enough to own one. This increase in the trend of not owning a car could potentially further increase thanks to mainstream access to subscription car services. But not all services have the same target, purpose and resulting price tag.

Literature on this division in terms of typology is quite recent since these services themselves are far from established. From research there are two main approaches that represent the current market of automotive subscription services: convenience-driven and experience-driven subscriptions (Zago, 2018). CDVSS (convenience-driven vehicle subscription) are those services where focus is on price and convenience for the end user. The value proposition here is all about not having to worry about any aspect of the car through a service with a basic package and fair price. The main player as of now in this category is Ford with its Canvas service. On the other hand, EDVSS (experience-driven vehicle subscription services) are for a more premium experience like Passport by Porsche where people have access at the entire range of models and can change car between them (Zago, 2018). Another classification for subscriptions is: *flip services* (these make possible to change car during the subscription period), *one-car services* (these are very similar to leasing since you have access to one car) and *stay awhile services* (which are the most affordable solution and are convenient for long period of time) (Lachnit, 2018).

2.2.2.4 Co-creation and new ways of innovating

In this moment of massive change in the industry innovation is crucial to beat competition and companies spend billion in R&D to always have the latest ideas and products. In the last years though the paradigm of how successful a product is and how it is accepted by the public shifted a lot and the main reason was internet. Social networks where people are free to create videos, images, tutorials, reviews, blog post (all so-called user generated content) and crowd-funding sites like Kickstarter made possible to anyone with an internet connection to create something, bridging the gap between creation and audiences. The integration of online communities in the creation of products is a concept that is being considered more and more with tools like: virtual customer integration, netnography and toolkits (Fuller, Hutter, & Faullant, 2011). Participation is the key word here and the bridge between companies and creatives. Customers now can engage with companies on so many levels on product design and delivery, furthermore value is created together with final users as a way to improve the identification of their needs and feedbacks to improve on the product (Payne, Storbacka, & Frow, 2008). Surpassing the pre-90s goods-dominant perspective, now brands are becoming experiences and this is particularly true for automotive, where the customer is a coo-creator of value (Payne A. , Storbacka, K., Frow, & Knox, 2009). In the automotive industry an example of this approach is the BMW Group Co-Creation Lab, which in 2010 gathered 8600 evaluations and 5000 comments on 300 ideas created by the members of the 6 weeks long online community (Bartl, Jawecki, & & Wiegandt, 2010). This approach for innovation though is still used as a one-time solution instead of a systematic way and for this reason companies should establish it as a permanent parallel integrated way to improve on their products.

2.2.3 Connected mobility

In the present age data are becoming the main currency for digital services and the automotive industry is undergoing a serious change from this point of view. The third pillar is connected mobility and it will disrupt the way a car can be integrated in the ecosystem of people's lives thanks to data. The main use of vehicles figures and statistics will be for three purposes: generate revenues, reduce costs and improve driving safety (Baroncello, Husain, & Moller, 2018). Connected cars are defined as "vehicles in which the driver and passengers can access, consume and share information through vehicular communication systems, such as vehicle-to-vehicle or vehicle-to-infrastructure communications" (Hong, Shin, & Lee, 2016). Both drivers and passengers will be much more connected to the car with a more customized experience. In future iterations of its implementation artificial intelligence will be present to better integrate data from the car and inputs from passengers all in the cloud and connected with the passenger's other services (Nkenyereye & Jang, 2016).

As a way to better understand the actual and future integration between man and machine is the McKinsey Connected Car Customer Experience framework (Baroncello, Husain, & Moller, 2018). The model uses a 5-level structure from basic to full connectivity. It is organized as it follows:

1. **General hardware connectivity**: it is the basic level of cars before being able to connect a smartphone to them
2. **Individual connectivity**: this is the level as of right now where drivers can use Apple Car Play or Android Auto on their vehicles.
3. **Preference-based**: entails a targeted experience not only for the driver but also for all the other passengers being able to use an individual infotainment and controls
4. **Multimodal live dialogue**: all passengers can connect their services with the car and get personal recommendations and ads
5. **Virtual chauffeur**: a vehicle AI can interact with all the passengers and do complex tasks

This framework is useful to fully understand the potential for new business models in the many possibilities that a level 5 car could offer. Apple Car Play and Android Auto are the first step to this merging, going all the way up to AI capable to predict passenger's needs, take their commands, target them with additional recommendations using data from their social media or work profiles. This opens up so many possibilities for adding additional advanced actions from being able to reply to predict open parking spots, to place an order on amazon to make a reservation at your favorite restaurant all from the connected car and all seamlessly integrated (Yang, Lim, & Agrawal, 2008). Communication between vehicles could also massively prevent incidents since cars have an awareness of the surrounding vehicles. Implications for house control are quite relevant too since the rise of IoT integration of smart houses with various internet connected devices. Players in various sectors are now connected creating value through applications that put users at the center of control.

2.2.4 Autonomous driving

Autonomous vehicles is the fourth and last pillar. This section will provide a short overview of the trend while the literature review will go much deeper in the history of development, different frameworks and research done about it and it will shed a light on the main research questions of this thesis.

2.2.4.1 Embracing driverless cars

The technology behind autonomous vehicles just started to develop but data tells us how "15% of new cars sold in 2030 will be at least level 4 on the autonomous driving scale which means they will be able to drive 100% by themselves" (McKinsey & Company, 2016) and SAEVs (shared

autonomous electric vehicles) will bring down costs per mile by a significant margin compared to actually owning a car. The average person that owns a car and uses it for 10.000 miles a year will experience a 1.22 dollar per mile cost in a large city because of a series of expenses like parking, gasoline, taxes and fees. That same person if instead didn't own a car and used SAEVs services would benefit to a lowered cost of about 50%, leaving all other variables the same (The Boston Consulting Group, 2017). Other benefits would be more time to be productive during travel time and less worries about parking or staying on track with payments of insurance for example. The reduction in costs is possible by the longer time of operation of an autonomous car (up to 15-20 hours a day) compared to a human counterpart: the number of miles per year will be higher too so costs can be amortized faster (The Boston Consulting Group, 2017). From the point of view of companies running ride-sharing services this technology will make possible cutting off the main operating cost: human drivers. These points prove how in less than 2 decades in large cities it will be more convenient to not own a car at all and just use ride sharing and public transport (which have an even lower price per mile even today). The ideal scenario for a SAEV user would be a commuter that lives in peripheral areas of a big city, that needs to drive to daily and its job is located in the center. This person with its own car contributes to emissions and creation of congestion, while using a ride-sharing service would reduce its footprint on the city and spend less money. Regarding parking, these services would free up a lot of space, up to 150.000 slots in huge cities, and would significantly improve public spaces that can be re-purposed for other objectives like green areas (The Boston Consulting Group, 2017).

Figure 8 - Waymo (owned by Google) ordered 20.000 Jaguar I-Pace for its fleet
Source: waymo.com/whats-next

2.2.4.2 Adoption rate and consequences

The rise of this technology could mean a significant reduction in human error but on the other side people are uncertain about the consequences of this future where they are not driving (Ernst & Young, 2018). Looking at adoption rate from demographic research it is quite obvious that the adoption of such a disruptive tech would appeal more younger generations (than the older part of the population) and people that live in metropolitan areas (compared to rural areas). In fact 56% of people 18-24 years old would have no problem using such mobility services while the percentage goes down to 37% of people 45-54 years old. Considering territory areas: 2/3 of people living in rural areas as of now would experience serious problems to use a ride-sharing service while the number goes down to 49% in large cities (The Boston Consulting Group, 2017). This is the situation as of now and in the future these numbers will change as people get better along with the technology after its introduction.

2.2.5 The transformation of an industry

These four pillars explain how much this industry is changing and going through a radical reshape of its basic technology after decades of incremental innovation. With EVs the entire knowledge of and know how of ICEs about high performance engine is thrown out of the window with start-ups being able to outclass a modern Ferrari acceleration with an electric motor. In the next chapter the focus will shift to the protagonist of this research: autonomous driving. In the literature review the author will analyse the history of the tech from its beginning to its latest the current state and then move to the analysis of research done about it.

III. LITERATURE REVIEW

3.1 Autonomous driving as the future of automotive

In the previous chapter the analysis was on a general level, looking at the automotive sector and the disruptive changes that it is going through. The areas of major development were also discussed looking at the most crucial R&D areas where car manufacturers need to invest. In the second part of the chapter, the analysis moved to the sector 4 main trends: *electrification*, *shared mobility*, *connected mobility* and *autonomous driving*. In this literature review the focus will be on the 4th element, which is the focal point of this dissertation: autonomous driving and its perception. In the following paragraphs the analysis will go from the definition of the topic, to a brief development perspective, to understanding the consequences for commuting and looking at the hypotheses for the 2 main research questions.

3.1.1 Self driving car definition and the 5 autonomous driving stages

Autonomous driving is one of the most discussed topics in the automotive industry as of now and the focus of this dissertation. Since this entire chapter will focus on that it is important to give a proper definition to the term. To do the SAE International definition will be used. SAE stands for Society of Automotive Engineers, which is an engineer's organization founded about 100 years ago with the mission of creating standards and share knowledge about automotive and other sectors like aerospace (SAE International, 2019). We'll be mainly using the *J3016 – Surface Vehicle Recommended Practice* document to define the main concepts of this section, which will be very important to understand the research itself.

First of all the definition of a **Driving Automation System**: "*The hardware and software that are collectively capable of performing part or all of the dynamic driving task (DDT)*" (SAE International, 2018). This is a general explanation of the condition that enables a vehicle to be able to drive itself, but it is quite generic, not giving precise information to the degree of that control and ability of the system itself. There are in fact **5 levels of driving automation**, plus a level zero that stands for no automation at all, which means that the driver is 100% in charge of the control of the car. Before seeing the 5 levels in detail there are 2 definitions that specify a sort of division in a lower and higher tier of automation: *Active safety system* and *Automated driving systems (ADS)*.

On the one hand **Active Safety Systems** are "*...systems that sense and monitor conditions inside and outside the vehicle for the purpose of identifying perceived present and potential dangers to the vehicle, occupants and/or other road users, and automatically intervene to help avoid or mitigate*

potential collisions with various methods…" (SAE International, 2018). This explanation is true for the more basic levels of automation, namely levels 1 and 2. On the other hand **Automated driving system** (**ADS**) are more of a higher level on the scale being 3-4-5, so it is located upwards in the territory of the car having full control on the vehicle. They are described as "*The hardware and software that are collectively capable of performing the entire dynamic driving task (DDT) on a sustained basis, regardless of whether it is limited to a specific operational design domain (ODD)"* (SAE International, 2018).

As shown in the figure below the division between these 2 main clusters of driving automation is made clear by different colors: *blue* for driving automation system and *green* for automated driving systems. As mentioned before, there are five levels of increasing automation to be discussed following the official SAE International classification (SAE International, 2018).

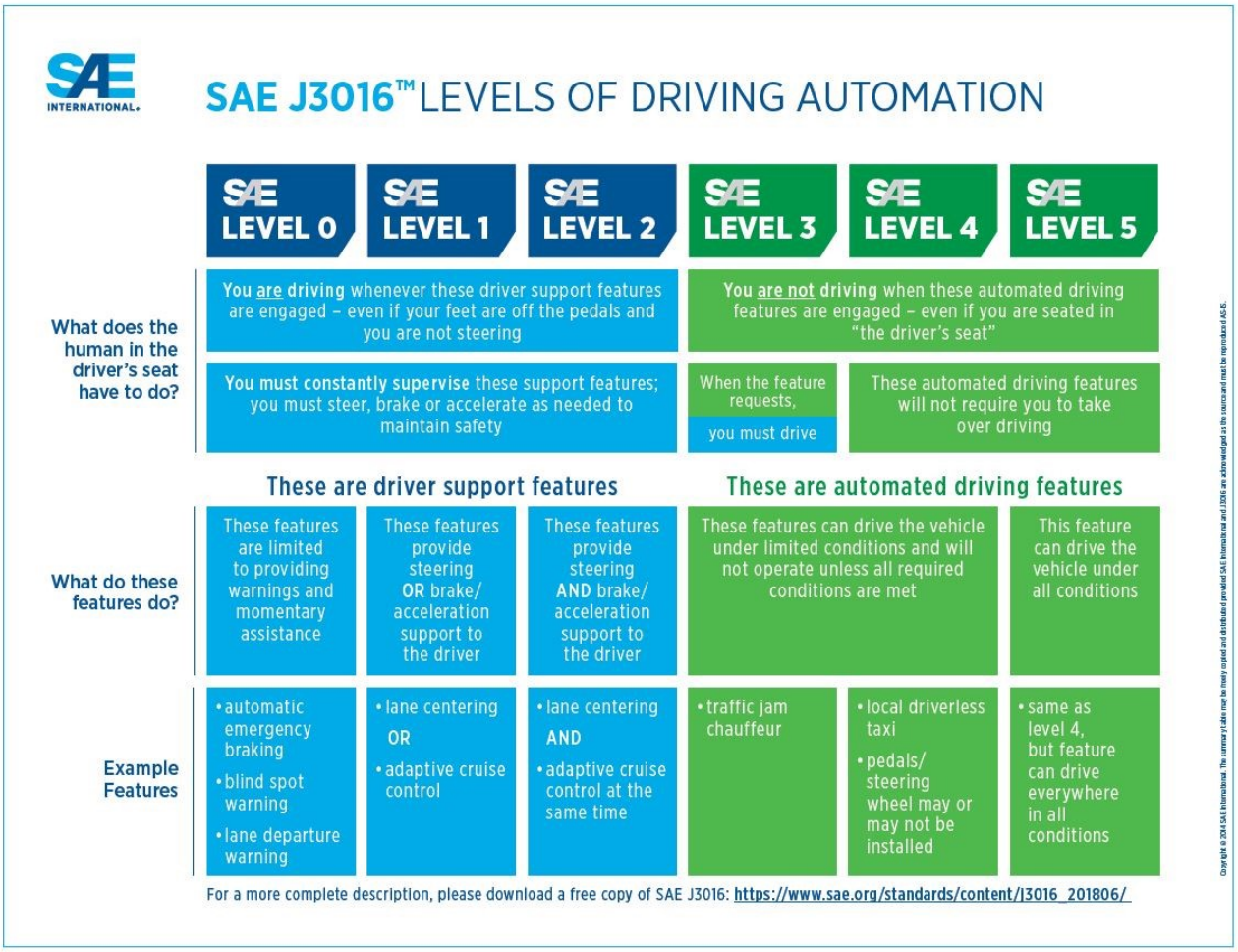


Figure 9 - Levels of Driving automation

Source: SAE International, 2018

SAE Level 0 – No Driving Automation: at this level we are not really talking about automation as the driver is the only one involved in any kind of driving inputs. This is the current level of basically all modern cars sold in 2019 as there are still some safety features included in level 0 like auto emergency breaking or lane departure/blind spot warnings which are found even on entry level cars as an optional. The driver must do 100% of the dynamic driving task and it is not helped by any systems whatsoever in doing so. The systems can provide warnings, for example when the driver is changing lane on the motorway without a turning signal on but not , and the only case where they can override the actual driver input is the case of emergency breaking with a pedestrian crossing or a car breaking in front.

SAE level 1 – Driver Assistance: at level 1 there is a step up in the car helping capabilities with either longitudinal ***or*** lateral motion assist made by the car systems. Adaptive cruise control and automatic lane keeping/centering are the two possible assists: the former means that the car can accelerate, lower its speed and keep safe distance from the car in front while travelling and the former stands for the ability of the car to stay in lane on the motorway. They are not allowed to be active at the same time. Moreover, the driver has to keep his/her hands on the steering wheel all the time obviously. The systems give support and help in either after mentioned situations.

SAE Level 2 – Partial Driving Automation: level 2 is basically a level 1 where both the driving aids are active at the same time with no restriction. So, the car will both accelerate, brake, keep distance from the car in front and keep the lane by itself steering itself. This is currently the maximum permitted level in EU regulations as the driver has to keep its hands on the steering wheel or the system will have to disengage after the repeat of a warning signal and make the car slow down safely to a stop (European Commission, 2018). This is the last level which presents only a driver support, from the third level and upper the automation is in charge of the main driving task. For this reason, it is the last level of Active Safety systems.

SAE Level 3 – Conditional Driving Automation: third level means that the driver is *secondary* compared to the system. The *entire* dynamic driving task is sustained by the car itself and the human driver will have to be ready to regain control in certain situations that are not supported by the system. From level three and upward we are in the proper **ADS** (automated driving systems) and it is not required for the driver to have his/her hands on the steering wheel at all time, but he/she will have to be ready to take over. Cars with this level of autonomous driving will be on the market in 2020-2021 by manufacturers like Volvo (Volvo, 2019) and Tesla (Tesla, 2019), even with software updates on cars sold today, since it is just a matter of software not having the restrictions of level 2.

SAE Level 4 – High Driving Automation: the fourth level is all about no driver control needed in basically all conditions. The steering wheel is still there, and the passengers can regain control of the car at any time if they want to do so. Human intervention is not required though and that's the main difference with level 3: the vehicle is *completely independent* is its DDT.

SAE Level 5 – Full Driving Automation: the fifth and last level of automation is total and the steering wheel is even *optional,* as there is no such thing as human driver and the passengers cannot regain manual control of the vehicle. This is what self-driving taxis will be and that is exactly what many companies like Waymo are spending millions to test their software as many miles possible and in the most different scenarios to get to this level of reliability (Waymo, 2019). The main downside as of now for level 5 self-driving taxis is the fact that cars need to travel in a highly mapped path with data already present from hundreds or even thousands of previous runs. That is why before releasing a final form of the service to the public self-driving taxis companies like Waymo (which is owned by Google) will have to train their AI for a long period of time, because this tech relies on machine learning and inputs have to be in real time after all.

3.1.2 History of development and machine learning

It is now time to look back at the process in time that brought to market this technology in the past years. Unsurprisingly for decades there was a sort of intention to make them drive by themselves, but the idea never came to place because of technical limitations. It was mainly a technological progress related thing. It wasn't possible even 20 years ago in the way it is done now and with such a lower cost.

Retracing back the steps that let to modern self-driving vehicles leads us to the beginning of the last decade, precisely in 2005. The setting is the Mojave Desert near Las Vegas (USA), while the protagonist is *Stanley*, the autonomous vehicle that won the challenge. The goal of the challenge created by DARPA (Defense Advanced Research Projects Agency) was for an autonomous vehicle to travel in a pre-mapped 142 miles route in the desert, without the intervention of any kind of external help (Thrun, et al., 2006). The winner, Stanley, was a 2004 Volkswagen Touareg TDI modified with a series of sensors, cameras and 6 on-board computers to process information and make driving decisions. It was developed by a team made by Stanford University, Volkswagen, Intel and others. Stanley took *6 hours and 53 minutes* to reach the finish line ahead of the competition.

The structure of the system was powerful enough to process its surrounding at 100Hz and make steering decisions at 20Hz, which means that it could correct its evaluations and make decisions respectively 100 times and 20 times per second. The car also interestingly drove for about 5% of the

time with a 60cm error from the path, which means that probably in a normal street those could have been incidents with other cars. The car also had more than one case where it tried to avoid obstacles in the middle of the road where there was absolutely nothing, it did it in a safe enough way and managed to arrive to the finish line with a 19.1 mph average speed(about 30 km/h). It is fascinating to look back at the huge effort from different stakeholders that took them to achieve such a result not even 20 years ago: a car driving in a pre-determined path in the desert at an average speed of 30 km/h without other cars or obstacles in the way. Saying that this scenario is simple compared to everyday roads is an understatement: there were no other cars, there were no obstacles, the road was pre-determined and the speed was a lot lower than normal conditions (Thrun, et al., 2006).

Figure 10 - Stanley, the car that won the 2005 DARPA Challenge
Source: stanford.edu

In 2007 DARPA created another challenge: the "*DARPA Urban Challenge*" which took place in a mock city environment, created in a controlled urban area. This time the challenge was mainly based on a more real-world scenario, with interactions with other vehicles taking part of the challenge possible and road signs and rules to follow. *Junior* was the entry from the makers of Stanley (which then basically went working with google after the challenge), and It arrived 2nd. The car used was a Volkswagen Passat wagon with an updated system from Stanley being able to process more information in real time using probabilistic models to predict what other moving vehicles would do and react as a consequence in its route planning (Montemerlo, et al., 2008).

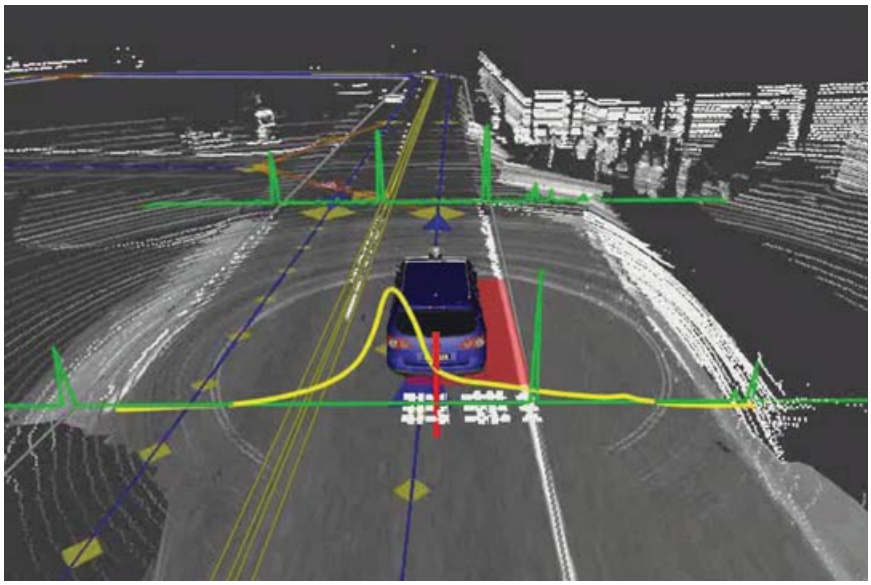


Figure 11 - How Junior saw the road in the DARPA Urban Challenge
Source: Stanford University

Nowadays, the technology behind the functioning of autonomous cars is a lot more established. Following (Hinduja, Thanekar, Valecha, & Gujar, 2018), (McKinsey&Company, 2017) and (Gruyer, et al., 2017) at the moment the established combination of sensors is the complementarity of LiDAR, RADAR and cameras around the car. The three have respectively functions of: object recognition at short to medium range for *LiDARs* (Light Detection And Raging System), long range obstacle detection for *RADARs* and lastly *cameras*.

Cameras work in 2D by giving a vision representation of the surrounding environment focusing mostly on object recognition and classification via a trained AI. LiDARs and RADARs work in 3D with the lidar using laser and radar using certain radio frequencies both used to map distances using the reception time of those different emissions. All these data are then processed together by the on-board computer to create the optimal route. Additional very important element is the GPS of the car to of course localize it, but alone it is not enough since its accuracy is some meters, so it is used in relation to the other systems. On the front of the car there are also IR (infra-red sensors) to be used at night and in adverse condition to have proper readings of road signs. On top of that there are Dedicated short-range communication devices that make the car able to connect to the internet and in the future to talk with other vehicles in real time. Last but not least live maps of the world are synchronized with the cloud to have the most updated road and information about traffic, incidents or deviations. In all of this hardware seems quite ready, the main problem remains the software. The

three biggest challenges in that regard remain: *object analysis*, *proper decision making* and a *fail-safe mechanism* to recover from fails and bad decision of the car (McKinsey&Company, 2017).

One of the main players in the autonomous driving space right now is **Nvidia**, the GPU (graphics processing unit) manufacturer for computers that is expanding in healthcare and mobility applications. Its example will be used to explain how self-driving tech works at the hardware-software level at today's standards. By using technology normally used for graphical applications like videogames Nvidia built the know-how to apply that knowledge to autonomous vehicles. They are very important for the future of autonomous driving because GPUs are particularly well designed for doing a huge parallel number of operations driven by different specialized parts of the chip. This is exactly what *Nvidia DRIVE AGX* is, an SoC (system-on-a-chip) made with 6 different types of processors that at the same time run data processing from sensors through an AI to drive the car at a level 5 of the SAE scale (Nvidia, 2019).

Data from the car surroundings are interpreted in real-time and interpolated with cloud information for that area like mapping, traffic, accidents and other warnings given by other vehicles. All of this is used to generate the best possible route for the vehicle. These systems on cars will have to be all time connected to the cloud where AI Supercomputers will offset part of the processing through 5G ultra-fast and low latency connections (more on that later). They also make possible to run simulations of real-world cases to see how the AI would respond. Images are used to train the AI in data centers so that objects can be classified in a more precise way while data from Radar and LiDAR are used for a continuous refresh of the mapping of roads so that other vehicles can use that data to make better driving choices (Nvidia, 2018).

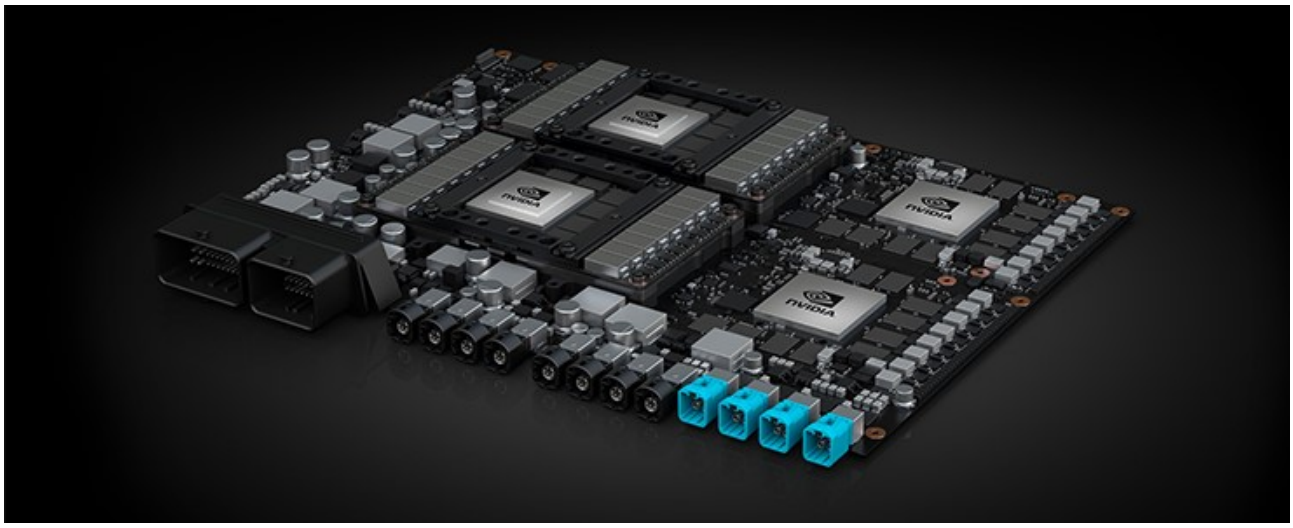


Figure 12 - Nvidia DRIVE AGX

Source: Nvidia.com

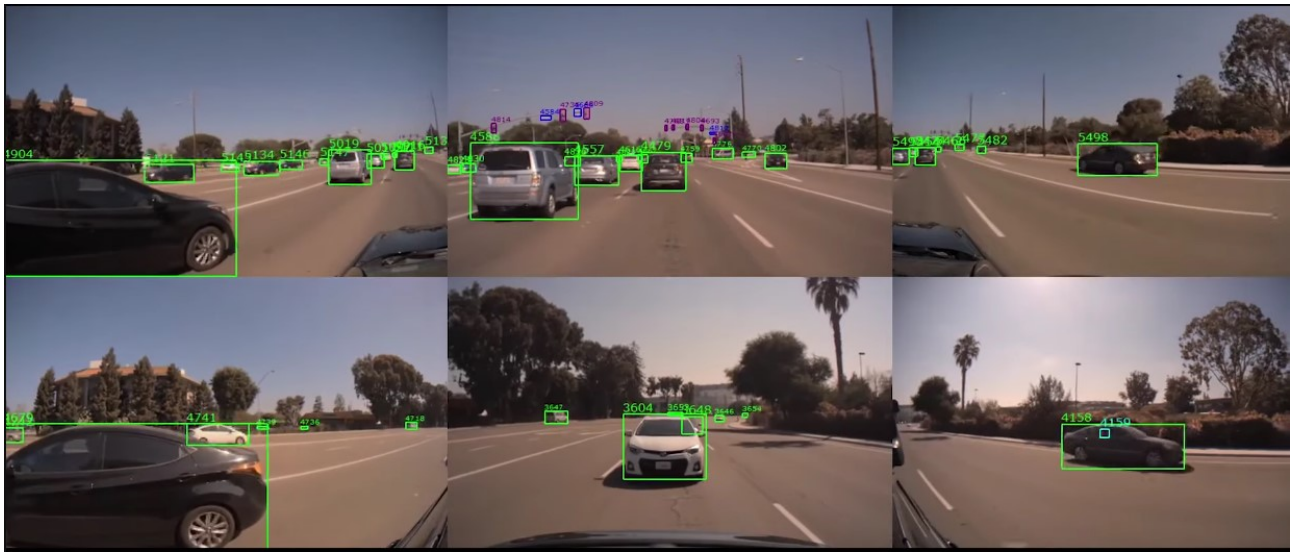


Figure 13 - How Nvidia DRIVE AGX processes data from cameras
Source: Nvidia.com

As seen in the figure the cameras alone can calculate distances from other cars and assign an ID to the single vehicles so they can be tracked accurately over time. Lines on the ground and signals are tracked too and identified by AI.

3.1.3 Moving towards level 5 autonomous vehicles: present and future challenges

Now that the levels were analyzed and defined It is clear that in a future not too distant there will be level 5 autonomous cars and taxis travelling on normal roads. The agreed time to market is about 10 to 15 years following latest reports (McKinsley & Company, 2019) (Deloitte, 2019). Time could be too soon, but the electrification revolution **is happening** much in force because of EU regulations, making it a huge problem for automakers. As of mid-2019 in fact the industry is *"…facing up to an estimated **34 billion euros** in penalties as well as **eroding profits** from selling more electric cars*" (Bloomberg, 2019). The strict regulations imposed by the European Union on the 2020-2030 CO2 emissions possible for a brand fleet impose the goal of a lowering by 23% emissions in 2030 compared to 2005 and a limit of 95 grams of CO2/km (European Commission, 2019). These limitations are costing millions on R&D to release as many EVs and Hybrid cars possible to meet them avoid expensive fines from the EU. In spite of this present and short-term critical situation (the regulations will become active from the 1st of January 2020) the problem is very present in the strategic plans of car makers, that are now trying to sell as many low emission cars possible and in a short period of time (The Wall Street Journal, 2019). Level 5 Autonomous driving is a more classifiable under mid-term horizon (10+ years), but there are both pros and cons to the technology.

Now the analysis will look at both sides of the coin in the perspective towards rising levels of automation for cars keeping this present situation in mind.

It is sure that "*the disruptive nature of driverless technology will necessarily reconstruct the modes of consumption and systems of use in private mobility*" as Skeete concludes (Skeete, 2018) while looking at the consequences of level 5 automation. He keeps going stating that policymakers will be at the center of this change, since the demand-side change won't be strong enough to make this tech mainstream. The author of this thesis has to partly disagree with this statement since it is such a change in the paradigm that enables people to rethink about what it means to travel by car. The second part of this thesis will be all ab out finding out what is the actual perception of autonomous driving so more reflections on that later. As it will be discussed further later *ICT* (information and communication technology) and *ITS* (intelligent transport systems) technology will be crucial foundations of this radical change.

Another corner stone will be how people think about their cars as it is expected that people will be less attached to their private vehicle than before and it has been years that this idea of **MaaS** (*mobility-as-a-service*) is present in literature with the main idea of "*selling mobility instead of cars*" (Firnkorn & Müller, 2011). A change towards a more shared way of thinking our cars seems very strange, since driving is one of the most habit related things people do in their commutes. An interest point to add on this element is made about the difference with another contemporary huge innovation in automotive: electric vehicles (EVs). Electrification is a modular innovation where the technology is changed, but the use is basically the same: being the engine of the car (Skeete, 2018). While on the other hand, self-driving vehicles will have such a wider impact on both the automotive sector and the everyday lives of people. The author agrees that the consequences of the technology will have a much larger scope than what is expected especially since the sector sees players like Apple and Google which are tech giants coming in and seeing the opportunity.

Expanding on this it is possible to define a **mobility system** following (Rotmans, Kemp, & Van Asselt, 2001) with the concept of: "*set of connected changes, which reinforce each other but take place in several different area, such a technology and belief systems*". In the automotive technological change, we are looking at not only a variation of people habits but also a more profound variation of their relationship with mobility. As a matter of a fact the car will swift from an object of desire and status symbol to a more detached mean of transport. This change will reflect in people's everyday lives (Docherty, Marsden, & Anable, 2018). But how will governance deal with this change? For sure there is a pattern going on, with a change of roles between the service providers and the local administration that now are more on the same level than before. Coordination is important as the

amount of 3rd party mobility offers that are spreading in big cities is at an all-time high and at the same time the rate of their introduction and exit in and from the market is increased.

All of this leaves city administrations to deal with a much more variable situation than the last decades where all the means of transportation were provided by the city government and in general by public entities. As a matter of a fact now all sorts of private providers like Lime are flooding the market with electric scooters (Lime, 2019) and other mobility-as-a-service offerings. This "*smart mobility*" paradigm has as its value base flexibility. This new approach needs to be balanced in a way that optimizes the coverage of the urban fabric while at the same time do this while being compliant with the local administration and the international regulations about emissions, which are becoming more and more stringent (Docherty, Marsden, & Anable, 2018). To sum up this crucial challenge the author adds that the most important element will be balance. All these acts of interactions between the local city government and private companies will have to be regulated, as the space available for additional mobility offerings is limited. Now it is an un-organized attack of this possible revenue space in the market.

Looking at things from the more practical perspective of deployment of level 5 automation the analysis reflects a couple of good points which are still not totally developed: **object definition** which is quite easy to develop and **edge cases decision making** that is a lot more complex (McKinsey&Company, 2017). Both are quite interesting.

Looking at the first one the term "object" relates to a huge quantity and variability of things that vehicle sensors will have to recognize and categorize reacting in a different way to the probability of outcomes deriving from those different scenarios. It is indeed very long and difficult to program all those lines of code to be able to have a pattern of reaction to different things. Other massive obstacles are weather and time of the day which add even more variability. The main challenge is for this centralized and connected AI to have seen all kinds of conditions and possible scenarios and this is improved on only by working on more complex algorithms and by having your fleet do more testing kilometers. That's why the main players have been testing for years with prototypes before having the ability to bring something to the market.

The most difficult problem to overcome are still *edge cases*. This means that for an AI to deal with 95% of cases is relatively easy to achieve, while from there diminishing returns become so pronounced compared to time elapsed/miles driven. A human driver's average miles driven without a car accident are 165000, but to get to that level of safety an autonomous vehicle AI not only will have to be trained so much more miles, but edge cases will have to be addressed (McKinsey&Company, 2017). Those are all the different scenarios out of the ordinary and that

driving a lot of miles can only partly solve; the only solution is to work on software-based predictors which is a totally different story and skill level than machine learning. Some even believe that It will never be possible to reach the level of a human ability to deal with unusual situations for this reason and some sort of 3rd party certification will have to be set up to certify cars.

Another interesting and unthinkable threat never seen before is the **risk of cyberattacks related to connected vehicles**. As discussed by D-STOP (Yeh, Choi, Prelcic, Bhat, & Heath, 2018) cars are increasingly focusing on radio frequency tech to operate driverless keys, radars and lidars, Wi-Fi to offer hotspots to occupants and 4G (and soon 5G) internet connection to use all the services on board. All these technologies weren't available even 5-10 years ago. By adopting them the cyber-attack risks related to them rose to a quite serious level that will have to be addressed before mass production of autonomous vehicles.

Related to radars there can be 3 types of attacks: *jamming*, *spoofing* and *interference*. The first one is about disabling radar functionality with the creation of a jamming signal to disrupt the car ability to use its radar to map its surrounding distances disabling the functionality of the sensors. Spoofing instead is about giving false information to radar sensors to trick them to think distances are different than what they are in reality, with all the consequences of the case. This is for example the way cars are stolen by cloning the keyless id of the key to open the car with a transmitter. The third and last one is interference, which is similar to jamming since the system experiences a loss in its functionality, but the action is done by external environmental causes like the presence of crowded radar wavelengths. The same 3 threats are also applicable to vehicle to vehicle communication using Wi-Fi technology (Yeh, Choi, Prelcic, Bhat, & Heath, 2018).

Production costs for components is another factor that needs to be take into consideration while talking about innovations that are so based on pure technology. 10 years ago at the time of the DARPA challenges costs were very high for an entire system while now, similarly to cost of batteries previously discussed, the trend is down spiraling. The main cost for autonomous driving technology as of mid-2019 remains the LiDAR system, costing as much as 75000 dollars per car (Wired.com, 2019) which makes it impossible to use in consumer cars as of now. Elon Musk over at Tesla in fact is one of the main critics o the technology as it is still to expensive and obtrusive to make its way in production cars. On the other side of the argument Waymo (Google basically) decided to develop their own lidars to cut costs and they will be mounted on its fleet of self-driving taxis (Wired.com, 2019). Another player betting on Lidar technology is Uber as seen by its implementation to its current Volvo XC90 prototypes (Uber, 2019) as seen in the figure below.

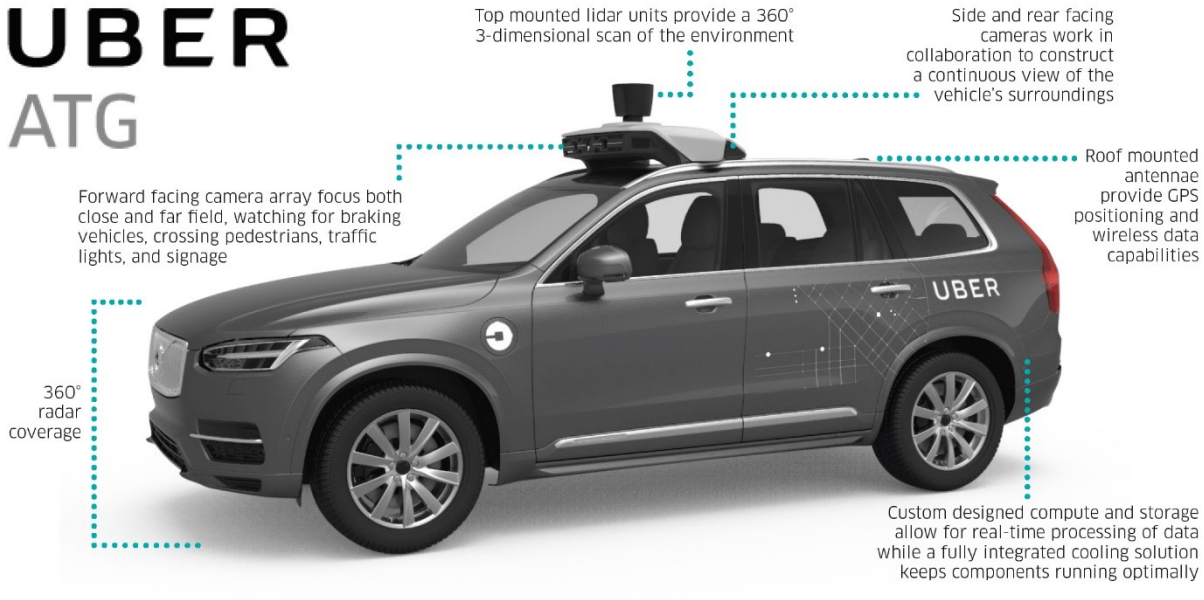


Figure 14 - Uber uses Lidar technology on its fleet of Volvo XC90
Source: Uber.com/it/it/atg

A fundamental element for connected mobility and the ***ability of cars to be in consistent communication between each other*** and with the profusion of services that they will provide is a solid network connection. The future of mobile internet and data connection is **5G**. With all the data that autonomous cars will need, this technology and its spread will be crucial for a fast adoption of the new mobility paradigm (Forbes, 2018). This is the case because 4G connection, which is the actual standard, are not fast enough by design to have the bandwidth to send/receive, in real time, the amount of information that autonomous driving vehicles will need to be able to act and adapt to the most different situations at all time while still being connected to all the services that we need from them like IoT (Internet of Things) connections with the future *Iot-ready* furniture in homes of similar application. This combined with processing power increase thanks to the huge amount of R&D going into this direction will enable cars to be supercomputers on wheels compared to today's standards of automotive infotainments.

Many publications (Andrews, et al., 2014) (Palattella, et al., 2016) give a great overview of the technical specs of the technology that will be a serious step up from the current 4G. Just to have an idea of the potential aggregate data rate will be *1000 times faster* and the edge rate (which is the worst-case scenario speed) will be *100 times higher* with 5G compared to the present. Just these numbers show how much future smartphones, connected cars, wearables, IoT applications and other devices that will crowd much more the single network cells than in the past. 5G also brings energy

efficiency and latency improvements over the current tech, two factors that are very relevant to cars as EVs will be a lot more widespread. The main challenge on top of the cost of building the infrastructure, will be being able to offer everywhere the *coverage* that enable a car to operate at 100% if its potential, and most importantly, safety. *Latency* is another huge problem as these cars will have to process and make decisions on a huge amount of data, both from physical sensors on the vehicle and other information synced in real time with the cloud. Last but not list another huge question mark will be the network that cars will use to send information with each other: how will it work while travelling through different countries? Will each car manufacturer have its own network, or will there be a unified protocol? The definition of these points is undergoing, and it poses a great deal of disruption effects once again on the automotive sector.

Another multifaceted present challenge regards the so-called **ITS**, acronym for "**Intelligent Transport Systems**" which is a broad definition of a group of technologies that make vehicles *smart* about the decision they can make in a systemic view. The typical scenario here is already present on current cars, when on the infotainment screen we can see traffic data in real time or speed detectors on the road ahead. Possible environmental benefits are talked about in literature (Grant-Muller & Usher, 2014) making it possible for an ecosystem of vehicles to be more efficient in their way of travelling and using resources if they can communicate and adapt in the ecosystem. These improvements are possible thanks to ICT (Information Communication Technology and ITS is just a name for the ICT paradigm applied to automotive) that enables thanks to an internet and other sensors connections to deliver services to cars. A relevant increase in efficiency for the system overall is a very likely outcome, with enhanced traffic management, less congestion and influences in the way people make choices. About climate benefit though it is not totally clear as other technologies like EVs and environmental policies are a lot more effective in reducing the carbon footprint for example.

Expanding on this urban mobility policy implications on of the crucial challenges, it is the so-called "**last-mile problem**" which represent the gap between a certain person house or office with the closest public transportation. It particularly present for people living in less dense and central areas of cities, where the network of means of transportation is more spread out (The Boston Consulting Group, 2016). This is the perfect case, in the opinion of the author, to invest on mobility-as-a-service platforms like electric scooters, car-sharing services and robo-taxis since they require an effective upgrade for the city mobility without the need of a huge investment by the local governance. As said before these services provide many advantages, but they are still not cheap and for example an entire fleet of autonomous taxis requires a huge investment by private companies, that will of course focus their efforts in the biggest cities first where the ROI in faster. In general the spread of autonomous

vehicles is seen positively for a number of reasons, like for example a better use of the car since the single individual car stays parked most of its time, while a self-driving taxi could improve by a lot its usage rate, with positive consequences on the parking space and traffic that now are more optimized. Moreover, having more mobility choices for citizens is for sure an improvement in their daily life, giving them more options to navigate the urban areas. On the flip side though, there could be negatives too like the reduction of income from indirect taxes for cities: the example here are parking tickets and fuel taxes which will have to be replaced with some other fee (The Boston Consulting Group, 2016), with an impact on some other sector and the closest solution would be offsetting that to EV charging stations. It is inevitable that autonomous vehicles taxis services will need years to be profitable since as of now firstcomers are only the huge tech corporations mentioned above like Uber and Waymo.

Safety which is another very interesting topic as a concept will be discussed in the next paragraphs and It is an area where, to the knowledge of the author, actual laws and regulations are not able to stay on track with the fast-paced innovation. As mentioned before, Tesla for example already has the hardware to push higher levels of autonomous driving than level 2, but regulations are there to stop it. The problem is that it is still not clear how the law situation will adapt to further levels of automation where the biggest part of the problems could surface. Some sort of independent certification will have to be created: EURO NCAP already does a lot for crash testing and some basic advanced safety technology like *auto emergency breaking*, *lane support* and *speed assist systems* (EURO NCAP, 2019).

3.2 Understanding the consequences of autonomous driving

In the previous sub-chapter, the focus of the analysis were autonomous vehicles in general as a way to create a framework to understand the technology. From now on the attention shifts to a precise case scenario: the implication of this technology for travel time and safety perception. In this section the analysis will be on the present literature and methods regarding the two main focuses of this thesis.

3.2.1 Main research core - Travel time perception and the concept of travel time benefit

In this paragraph the focus will be on travel time perception, its influences and its perception errors. A definition of the concept of travel time benefit will follow, as it will be the main core of the measurement model of this thesis.

3.2.1.1 Travel time perception: evidence from literature

Travelling has been considered for the longest time as a sort of wasted time that a certain person has to spend moving between two locations. This assumption was so widespread in general culture that created a sort of misconception that moving, especially by car, didn't have any utility as an act compared to the utility of reaching the destination. It is true that people travel because they want to reach a certain location of course, but at the same time this is *not enough to explain why people travel*.

Proper understanding of the demand for travel is investigated by (Mokhtarian, Salomon, & Redmond, 2001) as something which is ***valued for its own sake***. The act of travelling itself is part of the point of why we travel. Mandatory travel seems less heavy and the act of driving gains a utility that could come from many reasons from being free, to being able to have alone time to think or to transition between situations too. There are many reasons why people do it, but the underlying conclusion is that *people extract some value from it as a stand-alone act*. This concept is further expanded by other publications (Handy, Weston, & Mokhtarian, 2005) (Mokhtarian & Salomon, 2001) with implications for urban travelling by car: people drive "...by choice rather than necessity".

Our daily travels are of course influenced by the major decisions of our lives, but the more practical side of it is a lot more based on micro-decision we make for example to avoid traffic or to indulge on our personal time some more minutes. The concept of ***excess travel*** is introduced as "*travelling not for the utility of thee destination itself*" and the most quoted reasons why people indulge in it are exploring new places and see beautiful scenery following empirical studies quoted above. For some people some activities that they do while travelling, like listening to music, would be impossible to fit into their life schedule so that time become valuable too. This concept is closely related to personality types and people's attitudes and will also be analyzed in the research part of this thesis.

Until the 1970s another assumption was still very present: "the assumption of stable trip rates given certain household characteristics (Mokhtarian & Chen, 2004). An interesting concept brought up in the 80s as a way go over this obsolete idea was the so-called ***Travel Time Budget*** (TTB). This idea consists of a c*ertain amount of time that in our mind we tend to allocate travelling during our daily lives*. This amount of time which is usually around 1 hour to 1 hour and a half per day (Schafer & Victor, 2000) and this portion of time depends on many factors that (Mokhtarian & Chen, 2004) explained in a very competent way in their literature review about this particular concept. For the purpose of this section, they will be briefly covered since the choices of time allocation to travel are very relevant to the main research question of this thesis. Since the definition talks about time, it is quite reasonable since travelling a higher distance in the same amount of time is beneficial for people's travel utility.

Research started to be based on observing people's behavior, more and more and questions started to be asked in a different way that straight talking to people and interviewing them. Our decisions and perceptions are very flawed by our biases and mental heuristics (Thaler & Sunstein, 2009) that can make people's answers inconsistent at best and totally not representative of what was their past behavior.

At the beginning of the research endeavors on the topic of travel time, the focus was on asking people to report their perception and calculate the distortion compared to the effective length of the trip (Clark, 1982). The concept is the same now, but today the norm is a more structured self-reporting techniques or GPS based devices for methods of travel time analysis. These studies focus on the *gap* between people's perceived travel time compared to the real time elapsed, representing often how our perception of time is *relative* to many factors. Pe***ople tend to overestimate elapsed time in the case of self-reporting*** according to most studies (Curl, 2018) and that is because we are *not* analytical in our way of processing time. (Kelly, Krenn, Titze, Stopher, & Foster, 2013) saw an average of + 2.2 to +13.5 minutes in excess while people self-reported their commute compared to analytical GPS data.

Our brain not only has a *biased* perception, but we also tend to *manipulate* our answers to make us look in a certain way or to portray an image of ourselves that we like. Other reasons are demographic characteristics, familiarity and our degree of pleasantness of the trip; because if the trip was not comfortable, of course people will rate it as much longer that it actually was and the other way around. Another way of gathering data is by smartphones (Toole, Colak, Alhasoun, Evsukoff, & Gonzalez, 2014) which generate a huge amount of data (for example positional information thanks to GPS) and make it possible to process insights at a broader level.

Data nowadays comes as we said from smartphones, but also from census data, road networks and survey and model comparisons made by 3rd party agencies and companies like Nielsen for example. Big data is the analytical and general level, while surveys, focus groups and interviews remain the more qualitative and personal method of looking at perception of certain phenomena. The interest behind understanding people's behavior is of course massive for health and public policies like urban decisions, since these have many effects and *spillovers*, which are not always visible from the beginning.

At the socioeconomic level studies demonstrated an effect of age on time travelled with the conclusion that people between 17 and 24 spend the most time travelling out of all the age groups (Gunn, 1981). Having a car surprisingly is not a conclusive factor and the same can be said for gender and income as they don't have an effect on the amount of time travelled. In general though

(Mokhtarian & Salomon, 2001) explain how we saw earlier that ***travel is valued for its own sake*** and because of that each person preference is different in regards to the amount of time spent travelling. Therefore, people will try to adjust their daily commute time for example to reflect the amount of time they need or want to spend travelling considering it an activity that brings them pleasure and enjoyment for many cases. To sum up the conclusions of literature are varied as there isn't a general rule to determine a certain travel time since it can vary a lot in the socioeconomic, household characteristics, urban areas where people live and type of travel they do since the utility of travel is very subjective.

In addition another study which is related to this concept of *utility of travel* is made by Diana (Diana, 2008) and it uses a measurement model to evaluate the primary utility of travel. This is another case where travelling is seen as an *act generating utility by itself*, independently to what they do at the destination. Part of the measurement model used in this paper will be adapted to fit in the measurement model of this thesis.

Another interesting element is the connection between *value of time, age and marital status* as older people or with children will be willing to pay more for their time compared to younger people without children. All of this is expected in the opinion of the author. (Krueger, Rashidi, & Rose, 2016) came across the conclusion that *acceptance* of autonomous driving was higher in the case of young people and for people that already used mobility services in the past. While on the other hand, something which was not expected by the author was the fact that people willingness to pay for a dynamic ride sharing service was higher than a regular car sharing due to the fact of less waiting time involved.

Introducing the application of travel time to autonomous driving the analysis steps in a much *less* analyzed territory literature-wise. Studies are still in early stage since the technology is very recent and limited in its mainstream utilization by people. Data is not present at all, since automakers and companies investing billions in this tech and it is interesting to understand if these findings remain true. When making travel decisions people choose which mean of transport to take using several criteria based mainly on *time*, *convenience*, *preference*, *money*.

Considering *time*, It is relevant to introduce the concept of ***value of time*** (*VoT*) (Kolarova, Steck, Cyganski, & Trommer, 2018) which is based on the assumption that *allocation of our daily limited time is the main element of choice for our actions*. Defining it, value of time is "*the price people are willing to pay to acquire an additional unit of time*" (Athira, Muneera, Krishnamurthy, & Anjaneyulu, 2016). This relates strictly with the choice of means of transportation, thinking about them as a cost opportunity of time calculated as a trade-off between time and cost. Moreover, the concept is used in

many other studies like this one by Hensher (Hensher, 2011) where a ***rating*** is assigned to the different travel options alternatives compared in pairs, with a "*saved time*" parameter in the equation.

A variable with significant effect on this concept is for sure *income* which makes people with more money more likely to value more their time and to pay more for a faster mean of travel (Athira, Muneera, Krishnamurthy, & Anjaneyulu, 2016). This will be interesting to find if it's also true in the research of this thesis.

It turns out that people's perception of travelling in a self-driving vehicle is similar to the one of ***public transportation*** (Hensher, 2011) with the benefit of a more positive perception compared to driving one's car. The feeling of not having to drive *brings relief* to the driver and *makes people more inclined to experience the positive effects of travelling for its own sake* that were discussed before. On the flip side waiting times for public transport was perceived negatively, compared to the freedom of a personal car. These two findings together might hint that a self-driving vehicle could be the *best of both worlds*, but we have to take in consideration a very important variable that is overlooked in these studies: trip purpose. Destination of people's trips are very influential to how humans perceive travel time as mentioned before and it is quite difficult to have an estimation of its effect.

3.2.1.2 Influencers of time travel perception and time perception errors

Journey perception is one of the core elements of research. On the topic the literature review by (Kelly, Krenn, Titze, Stopher, & Foster, 2013) is an excellent meta-analysis of what has been done on the matter. Again, they stress the importance of the two main methods of gathering data: *self-reported travel behavior* and *GPS based devices* like smartphones. Defining the term journey duration most studies used a one-day period with the longest period being one week for some. Data analysis from the meta-analysis paints a picture which goes in two main directions: matched and unmatched trips.

The former uses an interlinked method where only trips which are validated by both self-reporting and GPS methods are used in the analysis. Then the global discrepancy between self-report and gps is the average of the single journey's difference in time, calculated trip-per-trip. The latter instead, compares the overall self-report average with the overall GPS average to find out the difference between the two methods. On average in the studies used for the meta-analysis for both methods of comparison self- reported times were longer than "real" times validated by GPS data with the un-matched method showing slightly bigger gaps in the range of +9% to +75%.

Furthermore a critical element remains reducing as much as possible the burden for the respondent to give an answer and this is one of the reasons why people having less of a hassle with the GPS method

make it feasible to use it for a more long-term study (Auld, Williams, Mohammadian, & Nelson, 2009). Designing survey questions in the best way possible is another element that could have consequences on how people reply. Moreover an additional reason why people tend to overestimate their travel time as noted by (Kelly, et al., 2011) is the fact that travel related activities, like preparing for travel itself, are considered by people as part of travel time while of course they actually aren't.

Other factors that come into place are people's tendency to manipulate and approximate responses and in the perception of the travel itself. In fact, it is easier to overestimate a certain travel time if the destination or the travel itself is not pleasant for a huge range of reasons. Just evaluating commuting will have a very different result than taking into consideration people travelling during holidays for the very different perception in the destination and context. These make a *considerable* difference, travel time is experienced and estimated through perception leading to a subjective travel time for people.

A different point of view on the matter is related to **habits** which surfaced in recent years as a very significant element that needs to be considered in consumer behavior becoming the basis for many models. They are a form of goal driven behavior which means that their objective is to reach a determined objective with least possible effort. The main problem is that the majority of our actions are made as a habit since they are mentally represented as associations between goals and actions (Aarts & Dijksterhuis, 2000). They are defined as "*repeated behaviors that have become automatic responses in recurrent and stable contexts*" (Verplanken, 2012) and the main distinctive element of their action is ***automaticity***.

This means that our brain doesn't have to *fully process* what to do in that well-known situation, it just replicates the past behavior making our lives a lot easier since a large part of what we do is always the same. This helps human's brains to save energy to process what is really important. The downside of this mechanism is that during such autopilot behaviors our aware cognitive decisional process is shut down and we don't pay attention to our actions. Until we step out of the usual frame we are in we don't even consider alternatives and this can have massive implications especially for introduction of new technologies or behaviors like in the case of autonomous driving (Lanzini, 2017).

3.2.1.3 Travel time benefit theoretical definition

It is now time to define the modeling of travel time perception as until now were seen only the different perspectives in literature on the topic. Before constructing a measurement model, there's a need for a theoretical definition of the concept focus of this thesis. The concept needs to be narrowed

down to a slightly different point of view, which instead of focusing on the *distortion* of time perceived during travelling, focuses on its *value*. With travel time benefit the author defines:

"***The benefit of added time available thanks to not having to drive while riding in an autonomous vehicle***"

This definition follows the growing body of research about the intrinsic utility of travel (Mokhtarian & Chen, 2004) (Kolarova, Steck, Cyganski, & Trommer, 2018) with the application of the horizon theme of autonomous driving. The focus is not on time saved compared to the overall travel time (Kelly, et al., 2011), nor on the difference in perception between clock-time and perceived time (Clark, 1982).

This idea is more connected to the value that we give to our time and to how we spend it, and it's more connected with the specific case of not having to drive. It was made as an educated definition after a quite extensive literature review of the topic at the center of the analysis and will be analyzed with a measurement model. Instead of being a general definition, this one is very precise in its case scenario connected with autonomous driving and hopefully it will be followed by other studies in the future.

3.2.2 Secondary research core - Commuting and safety concerns

In this paragraph the focus will be on the topic of safety in the automotive sector and the discussion will of course include the consequences of new technologies like autonomous driving on people's behaviors and lives. The discussion will first of all see evidence from literature, focusing then on the more business ethics point of view of the topic. This is meant to be a secondary point of view on the perception of this technology. It will be included in the measurement model with a

3.2.2.1 Safety perception: evidence from literature and

A ***human centered approach to this kind of innovation*** following (Kyriakidis, et al., 2019) could arrive to three different scenarios: a) *not replacing the driver*, b) *make drivers regain control in certain situations* or c) *took humans out of the equation*. Let's look at each one of these possibilities one by one.

First of all a), the situation which is closer to present time, developing **systems which are only a support to the driver** without putting them in 100% control of the car. This level is compatible with a level 2 of automation which falls into the *Active Safety Systems* paradigm. We are here now and this scenario would imply that from here laws totally ban further improvements in self-driving capabilities of vehicles. This is highly unlikely to the knowledge of the author because the entire industry is

investing billions on research and the overall accepted probable future is automated to a degree which is certainly superior to the present one.

Second scenario b) is compatible to the **3rd level of automation** that states how the car is able to do basically everything on its own, but the driver has to be able to regain control at any time during operation to deal with certain edge situations. Now we are in the automated driving systems (ADS) territory and is the car which is driving. This will be the next big thing for autonomous driving, and it will be possible when the law will permit to leave the steering wheel. The horizon for this event might be just 5 years away.

The third c) and last scenario is the most complete and the most disruptive. At **level 4 and 5 cars won't require human intervention** in anything they do. This will be reality in 10+ years putting things in perspective and being realistic, it could be even less for the more premium segment of cars.

Which of the 3 scenarios will be the new standard is not clear, for sure the balance will be between the second and the third where systems become the main actor in control of the vehicle. It is clear that all stakeholders will have to work closely together to create some sort of certification like the one that Federal Aviation Administration (FAA) releases for aircraft piloting software (FAA, 2019). Thanks to a well-defined certification and test procedure cars would be tested for some typical use scenarios like aircraft are verified right now. As already mentioned, Euro NCAP and similar 3rd party entities will have to independently certify autonomous driving capabilities of cars to draw a line to what is possible to introduce to the market and what is not. Moreover, *Iso standard 26262* is the actual ISO standard for safety in the automotive industry (ISO - International Organization for Standardization, 2018) and it is applicable for autonomous driving. The most interesting parts are especially 5-6 which are hardware and software related and part 9 which represent the analysis of safety of the car systems.

At the moment, the most advanced flagship cars have 3 main systems working together: *control systems*, *telematics systems* and *advanced driver assistance systems* (den Hartog & Zannone, 2018). The first is all about managing the vehicle physical functions and passive safety functions, the second is all about connectivity with internet (with in the future the possibility of connection vehicle to vehicle and vehicle to infrastructure) and the third one is the system responsible for autonomous driving. As we already saw at the hardware level cars already have the technology, right now the main focus is on ***software*** through machine learning, with the main challenge being that autonomous vehicles systems can misbehave even in absence of hardware or software problems since they can react in less than ideal ways in certain situations just because of a limitation of their ability to judge what is appropriate to do. This is a huge challenge because it is difficult to define 100% of the possible

cases that can happen, there is not a number of hours that the system has to be trained to be 100% perfect especially for borderline cases.

Figure 15 - A Tesla Model 3 during a Euro NCAP autonomous emergency breaking (AEB) test
Source: youtube.com/euroncap

Deloitte Italy gives a quite recent picture of the actual safety perception of self-driving technology among the main world's nations citizens (Deloitte, 2019). The results for 2019 for both Italy and globally show a quite unexpected slowdown in the trend of acceptance of the tech. In Italy 29% of interviewed people stated that cars are not safe enough to travel in public roads, a number which is basically the same as 2018 with its 30%. Looking at the big picture, again the situation is exactly the same as 2018 with every major country having the same perception after a steep positive change between 2017 and 2018.

The reason why is probably connected with public breakout of news regarding their safety, with half of Italy's respondents saying that latest news about accidents in the field had a great role in their perception of the technology. Now that manufacturers are starting to invest a lot in real world testing and at the same time the level of complexity of the driving aids that cars give is increasing it is to be expected that more accidents would happen. One of the latest example is the one that killed a pedestrian in Arizona in March 2018 involving a Uber self-driving test vehicle (The Verge, 2018). In this case the car didn't avoid the crash with a woman crossing and the explanation of the company was that in these kinds of cases not a single human could have avoided such situation and that the car misunderstood the woman as a false positive. But the media echo of such an event is so huge

compared to the thousands of people that die on road. From the relative limited tests that Uber and other companies did in recent years it is already quite clear how the technology and sensors behind this technology will make it a lot more secure than human drivers after proper testing. Such thing is already visible as highlighted by this article by Wired (Wired.com, 2018) as most of 49 crashes in the first 10 months of 2018 in California, 28 were the self-driving car being rear ended, with the second most occurred accident being again the autonomous vehicle being sideswiped. So overall the responsibility of those accidents was hardly of the autonomous vehicle but because of availability bias (Thaler & Sunstein, 2009).

Another trend visible in Deloitte data is the increasing trust in *non-traditional* car manufacturers (Deloitte, 2019) with in 2019 only 1/3 of Italians thinking that OEMs have the edge over tech companies like Uber, Google and others. This is another striking element in the opinion of the author since it seems like 100+ years of history behind a brand are overlooked once again by the average consumer in the case of a disrupting technology. This is nothing new as it happened in the past with Nokia and the newcomer smartphone creation by Apple: the iPhone. As seen in the previous chapters in this thesis we already saw how Tesla tech is superior in batteries and in miles driven to more traditional competitors.

In addition, more *driver-centric* considerations need to be made, since humans at the wheel are not going away any time soon. They will have a role for decades, at least as a *supervisor* or as a *last chance in case of failures* or in situations where the systems can't handle the driving task. Technology and sensors are not 100% accurate and people could disengage the systems to perform unsafe behaviours too, so the spectrum of things is wide. As the authors of this publication perfectly summarize (Noy, Shinar, & Horrey, 2018) "reducing or even eliminating driver errors does not necessarily eliminate vehicle, road or environmental factors or other users from contributing to crashes". The overall rate of improvement for overall road safety will be present but it may be over-hyped by many publications so that is a factor that needs to be taken into consideration.

Moreover there's the concept of the "*ironies of automation*" (Noy, Shinar, & Horrey, 2018) which is strictly related to the Fitts list of function allocation between man and machines (de Winter & Dodou, 2014) and that is quite interesting in its application to autonomous driving. By considering the first 4 levels of automation (from level 0 to level 3) where humans still must be able to drive and take over, there are some major challenges born in the same moment a human has to monitor a machine. First of all, *task allocation* is a crucial decision since machines are good at automating repetitive decisions which are also those that are easier to do, leaving humans only the difficult ones where he could use some help. *Deskilling*, which represents the degradation of driving skill, represents another point: if

humans had to intervene in difficult situations but they are not driving for the majority of time, that intervention won't be effective. People would not be vigilant and in the moment they had to take control the consequences would be subpar which leads to the point: *liability*. Responsibility still remains in the hands of the driver and a whole doctrine will have to be created from scratch to deal with accidents and similar cases where a self-driving vehicle was one of the parties involved (Noy, Shinar, & Horrey, 2018).

The topic of safety has been analysed until now mentioning ISO certification, studies and examples for the automotive sector. A different but very related theme is the one of ***security***, whose semantical meaning is "*protection of a person, building, organization, or country against threats such as crime or attacks…*" (Cambridge Dictionary, 2019). This needs to be mentioned in this thesis because of the crucial element of ***cyber-security***. A connected car presents so many more possible breaches and openings compared to the past were every vehicle was an isolated entity from the system.

Confidentiality is the first concern as now everyone links their phone to car infotainment systems and this action exposes personal information like contacts, calls, data because they are shared with the car. Another concern is *integrity* that in this case means from source-to-receiver certification of the software running on cars as possible backdoors could be easily created by 3rd party applications improperly installed. Possible thieves and shady people should not be able to get information about the ID privacy neither the location of the vehicle by hacking into the vehicle systems. (den Hartog & Zannone, 2018).

Having mentioned the main security problems of a connected car and now we add how (Macher, Armengaud, Brenner, & Kreiner, 2016) provide an example of using the SAHARA approach (Safety-aware Hazard Analysis and Risk Assessment) to assess the security of a car. Expanding once again on the safety literature in strict correlation with ISO 26262 (Mauborgne, et al., 2017) propose the definition of Functional Safety Requirements which are defined as "specification of implementation-independent safety behaviour or implementation-independent safety measure, including its safety related attributes". This assessment is based on fault tree analysis using a logical model. All of this is for sure important for the state of literature, but not particularly connected to the scope of the analysis of this thesis because not much has been done on real world scenarios until now and case studies are lacking unfortunately. It will be very interesting to the application of these on mainstream data.

3.2.2.2 Business ethics and social responsibility point of view

The business ethics point of view apparently might be not useful to fully understand this new technology and its implications. The author of this thesis disagrees and intends to briefly bring up the

famous *trolley problem* that was over analyzed in the psychology field literature in the last decades and see why it is very important for self-driving cars.

This reasoning relates to normative ethical theories and the "beliefs about what is morally right and wrong" (Cambridge Dictonary, 2019). The case is the well-known trolley problem brought to attention by Philippa Foot, an English philosopher of the 20th century, even though her version of the problem was about a surgeon having to decide between the death of different patients. There are many versions of this famous trolley case and this analysis will follow the most quoted one as found in this publication by Thompson (Thomson, 1984). The story is divided in different scenarios and for the lack of space here we will focus on the first and most well know scenario.

In the ***first scenario*** there is a trolley going on its rails with no problems until the moment the driver realizes that there are five people on the tracks. He wants to brake and stop the trolley to save those people that will never have the time to get out of the way, but the brakes are broken, and he cannot stop the inevitable killing of those five people. There is a possibility to save them though: a switch to make the trolley go a secondary course. On that secondary course there is again someone on the way, but in this case It's just one man. What is the driver supposed to do?

There is also a variation of this case where the maker of the choice is a "***bystander***" that can activate the switch for the trolley to go into each direction. Is it considered the same *killing people* or *letting people die* because it is inevitable? And what is the weight of this decision? This case raised a huge debate on what has to be done and what should be done. In this two variations of the same case for example the driver has the responsibility to protect people on the trolley and it is doing his job, while the bystander is just a regular person that is looking at this situation: he can let five people die failing to save them or he can kill a person by using the switch.

There's an additional variation too which is called the "***fat man***". In this scenario the bystander is on a bridge that crosses the rails with a fat guy. He sees that there are five people on the rails and that the trolley won't be able to stop in time. He thinks that if the pushes the fat man from the bridge and into the rails, his weight could stop the trolley saving the five people but killing him. What the author of the research says is that "It is not enough to justify killing a person that if we do so five others will be saved" and in the case of the bystander "he minimizes the number of deaths which get caused by something that already threatens people and that will cause deaths whatever the bystander does", while in the case of the fat man "shoving a person is an infringing of a right of his, even if doing it does not cause his death" (Thomson, 1984). So, for the bystander it is morally right to flip the switch and save a net count of four people because the two outcomes are inevitable by nature of the situation and there is no infringement of anyone's rights. While for the person that shoves the fat man it is not

right to do it, because doing so is putting *him* into danger and an infringement of *his* rights (he wasn't on the rails at all, while the one man in the first case was indeed!).

A more recent study (Swann Jr, Gómez, Dovidio, Hart, & Jetten, 2010) also analyzed this case scenario with groups, just to see if people would behave differently if the people that needed to be saved were part of their group or not. The result was that *people that identify more with their group were more prone to sacrifice their life to save some other members in the same group* which in the study were people of the same nationality.

All of this was the general base of the business ethics problem, but why is it *relevant* for this thesis? The answer is that **self-driving cars might be faced with similar scenarios in real life**. To investigate what behavior would be ethical and moral to do the *MIT - Massachusetts Institute of Technology* set up a website called "*Moral Machine*" where people could take a sort of moral quiz deciding what an autonomous vehicle would have to do in certain situations. As seen in the image below in every scenario someone will have to die and the viewer must decide the course of action (MIT , 2019). The results of this experiment were included in this study (Awad, et al., 2018) with about 40 million people doing the test.

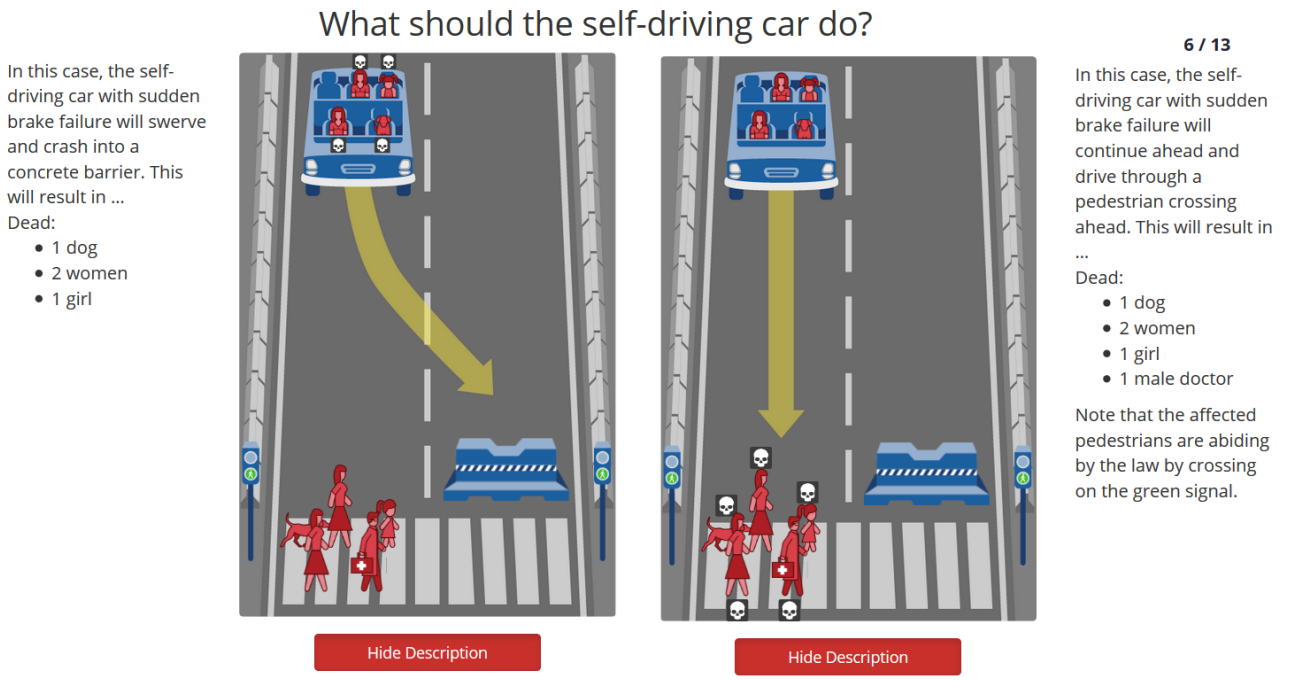


Figure 16 - MIT Moral machine

Source: http://moralmachine.mit.edu/

The general trends out of this huge sample were *saving humans over animals*, *saving more human lives as possible*, *saving young people over older people* and *saving people that are following traffic laws*. It was also found that there is a *correlation between preferences and cultural/economic variations between countries* with three clusters evident with three slightly different behaviours: western countries (USA, Italy, UK), eastern countries (China, Japan, Saudi Arabia) and southern countries (mainly South America). All of this matter because with autonomous vehicles we are giving a machine the ***will to decide what to do*** in that split second that its AI can still react to a certain dangerous situation, which could even kill someone. Of course, no human could be able to make that decision, because we would react by instinct or not react at all because we can't compete with the array of sensors that the AI can use to decide how to react. This area will require a lot of research to establish what is morally right and wrong in those situations (Awad, et al., 2018), with real word tests being done systematically to find an answer.

3.3 Hypotheses of the research

After a quite solid overview of the autonomous driving landscape, the pros and cons of this technology and the two main areas of research's literature, it is time to formulate the *hypotheses for the analysis*. In this paragraph the analysis will go through the questionnaire constructs, giving the possible hypotheses and expectations of the author about the results of the survey. The main goal of the research remains travel time benefit and the perception of it connected with autonomous driving technology, but there are also other elements that need to be taken into consideration from litarature. The total constructs used were six and they will be explained in this chapter and in the measurement model chapter.

3.3.1 Theory of Planned Behavior and Travel time benefit

"*Travel time benefit*" and "*Theory of planned behavior*" are the two constructs that were used as dependent variable in the two main multiple regression in the analysis. For this reason, no hypotheses were formulated about them since they will be the variable that needs to be explained. A quick overview of the theory of Planned behavior will be given though, as a way to introduce the construct.

One of the most important theories in consumer behavior in the latest decades is the **Theory of planned behavior** by Ajzen (Ajzen I. , 1991). It falls in the *prescriptive* side of the *cognitive consumer behavior models* which means that it is a model that gives insights about what can be done on top of learning how consumer behavior is structured (Lanzini, 2017). This model is an extension of the theory of reasoned action and it incorporates one more antecedent of behavioral intention for a total of three. They are attitudes, subjective norms and perceived behavioral control.

The first one is based on behavioral beliefs of the subject like predisposition towards a specific way of doing something, so It is about our beliefs.

The second one is all about the context in which we are and what we believe others expect from us. The third and last antecedent is about the perceived difficulty of doing the target activity and it is the addition on top of the theory of reasoned action (Ajzen I. , 1991). These three elements create in our mind the behavioral intention of doing the target behavior. This is still in our head though; the actual behavior comes after that and requires an additional step.

In the case of this construct, the target be behavior is: "***Using in the future an autonomous driving vehicle for my journeys***". Looking ad Ajzen guide on how to integrate a theory of planned behavior in a survey, the advised number of items goes is 5-6 for each factor that represent the 3 antecedents of intention (Ajzen I. , 2006). In this thesis' measurement model were used five items for the "attitude towards behavior" factor, four items for the "subjective norm" factor and five for the "Perceived behavioral control" factor. A representation of the model can be seen in the image below while the single used items will be displayed in the measurement model chapter.

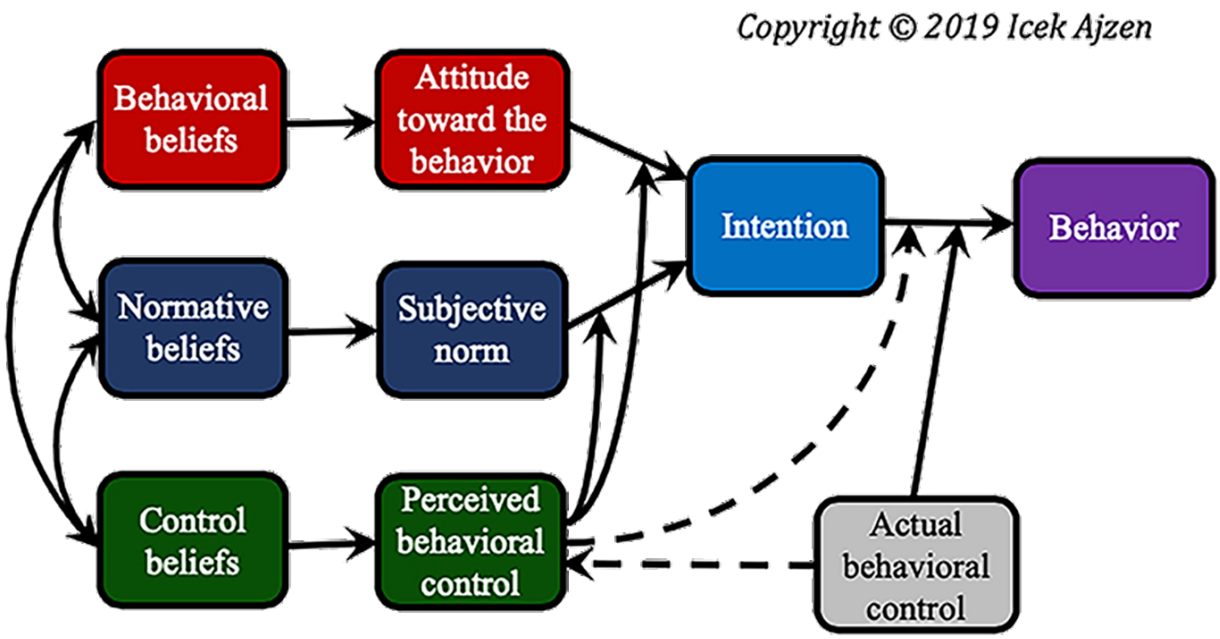


Figure 17 - Theory of Planned behaviour Model
Source: https://people.umass.edu/aizen

On one hand there's the "***theory of planned behavior***" construct, which now makes sense after this brief explanation of the theory at the foundation of the construct. The intention of undertaking the behavior of using an autonomous vehicle is what this construct explains. It will be used in the second multiple regression where "*travel time benefit*" will be the independent variable, with the three antecedents of intention as its respective factors.

On the other hand, the "***travel time benefit***" construct is the dependent variable of the first multiple regression used to assess the main research question of this thesis, and for this reason hypotheses were formulated based on the inclusion as independent variables of its three factors which are: "*multitasking during travel*", "*convenient efficiency*" and "*time saving*". The hypotheses formulated are:

H1a: "*A high multitasking during travel score will have a positive effect on theory of planned behavior*"

H1b: "*A convenient efficiency score will have a positive effect on theory of planned behavior*"

H1c: "*A high time saving score will have a positive effect on theory of planned behavior*"

3.3.2 Hypotheses for the "Technology acceptance" construct

In this construct there are three factors used to explain people's approval of this new technology mainly adapted from (Nielsen & Haustein, 2018) which was a study specifically done to test the expectations towards autonomous driving technology. In the study three clusters were used to identify people: *enthusiasts* for the technology, *indifferent* people and *sceptics*. The average enthusiast is male, young and lives in metropolitan areas so these findings will reflect probably in this study too and in these three factors.

The first factor is *expected advantage of fully self-driving cars*. It explains the perceived added value of fully level 5 self-driving car over a normal car. The possible hypothesis for this one is:

H2a: "*A high expected advantage score will have a positive effect on travel time benefit*"

As seen in many studies like (Liu, Zhang, & He, 2019) (Nielsen & Haustein, 2018) a first expectation will be that age will be a factor for the acceptance of this technology. In many cases older people struggle to accept newer technologies and the case of autonomous driving is no different. More mature people require a higher level of safety too and this will be compared also visible in the second part of this chapter when the literature analysis will cover the second focus of this thesis. So we can give the following hypothesis for the entire "technology acceptance" construct:

H2b: "*Older people will be less open-minded about the acceptance of autonomous driving technology*"

This is interesting because OEMs and car makers will have to take into consideration that right now the people that have the most money to buy cars *and* the people that might need this tech more, the elders, are the *less interested* in it. This will have to be taken into account while designing marketing campaigns to sell and justify higher prices for this tech. Young adopters on the other hand will be the first adopters like they basically always are when it comes to newer products on the market and this leads us to the second hypothesis:

Regarding the *new technologies fan* factor as by the author based on studies like (Neoh, Chipulu, Marshall, & Tewkesbury, 2018) mostly because average users of these services are again quite young and open minded about their mobility needs.

H2c: "*The new technology fan factor will have a positive effect on travel time benefit*"

The third factor which is *interest in use-case* which is quite similar to the first factor of this construct. It explains the overall interest in use scenarios like taxis, buses, shuttles or for work related.

H2d: "*People already using services like ride-sharing will be more open to trying this new technology*"

H2e: "*The interest in use case factor will have a positive effect on travel time benefit*"

H2f "*It is to be expected that the item regarding shuttle usage for self-driving cars will be the one with the higher positive score towards this factor"*

It has been found in the past that shuttle use cases are more likely to be accepted by people. For instance, bringing people from the airport to the train station or from the city center to big malls (Neoh, Chipulu, Marshall, & Tewkesbury, 2018). The author expects the same thing here with the item about it scoring higher than the other three.

3.3.3 Hypotheses for the "Car perception" construct

These constructs explain people's deep perception, motives and reasons about using their car. It is based on a Steg study (Steg, 2005) on people's motives about car usage, with the goal of understanding how to tailor better policy measures on travel demand. She used the theory of planned behavior too to determine the instrumental motives. The division was made in three clusters: *instrumental*, *symbolic* and *affective*. Let's see the hypothesis for the ***instrumental*** factor:

H3a: "*The instrumental factor will have a positive effect on travel time benefit*"

This first factor is strictly connected with the concept of efficiency and effectiveness in usage. People that fall in this category see cars as instruments to get their tasks done or to move from A to B with absolutely no focus on the pleasure of driving or to enjoying that time (Steg, 2005). People want to be efficient in their use of time and this factor will have a massive positive effect on travel time perception for self-driving vehicles, since people will be able to do other things that matter to them instead of "*wasting time*" driving. The extra time that they will gain will be perceived as a huge benefit and they will be interested in the technology.

Moving to the ***symbolic*** factor things are quite different. This factor is more connected to the ego and social sphere of people, as it represents how much people see their car a status symbol and as a way to stand out from others o to represent themselves. It is the factor that focuses more on the social side of humans, covering the "other people's judgements of my car" side of owning a vehicle. As a consequence especially in the first years of introduction of this new technology it could have a positive effect on how people feel about themselves (Steg, 2005). Autonomous vehicles will be considered as a status symbol, being able to do other things while the car is driving could inflate many people's need for social superiority and for this reason the following hypothesis was formulated:

H3b: "*The symbolic factor will have a positive effect on travel time benefit*"

On the opposite end of the spectrum compared to the first one there's the ***affective*** factor. This one is hugely connected with the passion of driving and with all the feelings, emotions and sensations it created in people's mind. People scoring high in this factor are true car enthusiast using their car because they love it and that probably go for a drive just for the sake of it. (Steg, 2005) They consider a car much more than an object to reach a destination or to show off, they are true car lovers hence the following hypothesis:

H3c: "*The affective factor will have a negative effect on travel time benefit*"

This is the easiest educated guess inside this construct in the opinion of the author, since people that score high in this factor will be the least open to a self-driving car in the first place. That is because they love driving and probably indulge in excess travel just for the pleasure of using their car. They won't be touched the plus of additional usable time of self-driving cars.

3.3.4 Hypotheses for the "Commute benefit" construct

This construct is the biggest so far with five factors. It is based on different literature references. Factors here are: *implicit trip motivations*, *motivation for car use*, *ride sharing*, *car sharing* and *utility of travel*.

The first one is *Implicit trip motivation* and it explains how much people tend to travel for the sake of it and for pleasure. It is adapted from this study by Diana (Diana, 2008) about the utility of travel already mentioned in the literature review segment. The first hypothesis regarding this construct is the following:

H4a: "*Implicit trip motivation will have a negative effect on travel time benefit*"

This will probably be true because this factor describes those people that love to roam and explore with their cars, having fun while driving and sometimes doing it without a specific purpose. As a natural consequence, they won't care about having additional time to enjoying other things while driving, since the act of driving itself is the main event.

Following we have the *motivation for car use factor* which is all about using a personal car instead of public transportation for the everyday commute. These items were adapted from (Neoh, Chipulu, Marshall, & Tewkesbury, 2018) study on commuters trip motivation and explain how much people prefer using their private car over public transportation for commuting. Its effect on travel time benefit is somehow mixed, since there wasn't evidence in the literature from where the scale was taken. Since the factor describes preferring car over other means, the author assumes that someone scoring high in this factor will have a significant travel time benefit by using an autonomous driving vehicle.

H4b: "*Motivation for car use will have a positive effect on travel time benefit*"

Then there are two factors which are basically identical in their structure and kind of questions, with the only difference of the focus: one is about *ridesharing* and the other about *car sharing* services. These two were included to test the correlation of respondent's present utilization of these platforms with their commuting. Again these were adapted from (Neoh, Chipulu, Marshall, & Tewkesbury, 2018) and these two explain how much people feel positive about those kind of services and their effect on travel time benefit is to be expected as following:

H4c: "*The ride sharing factor will have a positive effect on travel time benefit*"

H4d: "*The car-sharing factor will have a positive effect on travel time benefit*"

The last factor of this construct relates to the concept of *utility of travel*, which was one of the main concepts of the literature review on travel time. The source is (Mokhtarian & Salomon, 2001) and the factor explains how much people value travel time as something by itself in their commute, for example as a useful transition between work and home. This is an additional factor useful to describe the effect on travel time benefit:

H4e: "*The utility of travel factor will have positive effect on travel time benefit*"

This is the case since people that already highly value that transition time of their commute will be able to use it in an even more prolific way in the case of autonomous cars.

3.3.6 Hypotheses for the "Safety concern" construct

As found by (Liu, Zhang, & He, 2019) elders are a lot less risk averse than younger generations and as a consequence they require a level of safety which is double compared to the more adventurous youngsters. In general, it is quite normal to find that propensity for risk taking decreases with age of the participant and this translates to a safer driving by older drivers. This is the base of our first hypothesis:

H6a: "*Older people require a higher level of security for self-driving cars than younger generations*"

With this hypothesis the literature chapter comes to an end. In the next two chapters the measurement model and analysis will be described respectively, bringing to life the research.

IV. MEASUREMENT MODEL

4.1 Quantitative research design

After the context and literature review chapters and after looking at the possible hypotheses for the research, it is now time to dig deep into the core part of this thesis: the measurement model used to analyse the main and the secondary research questions.

The philosophy behind the research is *positivism* as hypotheses were made based on literature and results are to be seen as a business insight on the automotive sector (Saunders, Lewis, & Thornhill, 2016). The analysis is *conclusive* since it is aimed at describing certain phenomena (Malhotra & Birks, 2007) like in this case the "travel time benefit for self-driving cars" concept introduced previously and the effect of various constructs on it. A second and less important core of analysis will be related to perceived safety regarding autonomous vehicles. The approach used is *quantitative* through a *structured questionnaire*, mainly with likert scales which are an *itemized* and *non-comparative scaling* technique. The used sample of respondents was from the European Union, reached using the Amazon Mturk platform. Respondents were paid from 0.15 euros per HIT (which is Mturk word for completed job, in this case the completed questionnaire) and since this research wasn't financed by anyone but the author, the number of respondents was just above the minimum theoretical for a correct representation of the population size.

4.1.1 Measurement model development

In the literature review and hypothesis's chapters most of the general underlining reasoning about the constructs and factors were explained, as well as the academic studies behind them. In this chapter we will see again all the references and the focus will go even deeper looking at the single items used for the measurement model, especially for those factors omitted in the hypothesis chapter. The questionnaire is structured in nine stages:

1. *Initial description*
2. *Control questions*
3. *"Theory of planned behaviour" construct*
4. *"Technology acceptance" construct*
5. *"Car perception" construct*
6. *"Commute benefit" construct*
7. *"Travel time benefit" construct*
8. *"Safety concern" construct*

9. *Demographic questions*

Out of these nine, only stages three to eight represent constructs. Each construct is made of two to five factors and each factor is a group of items (questions). In the construct pages the respondents replied with **likert scales** with 7-point scales (from strongly disagree to strongly agree). In the other pages, answers are mixed multiple choice. The survey was made available to the public through the Amazon Mturk service. The questionnaire itself was made using Qualtrics and made available through a link on Mturk. 0.15 to 0.20 euros were paid to each person fulfilling the HIT thanks to a random code generated at the end of the survey that needed to be copy pasted into a Mturk field.

First of all, at stage 1 before starting the survey, a short description gave an overview of the topic with the definition of a autonomous vehicles as follows:

"Thank you for agreeing to take part in this project! This survey is the core part of an academic research thesis measuring people's perception towards automotive autonomous driving technology in the EU. The definition of autonomous driving that needs to be taken into consideration during this survey is:

"The hardware and software that are collectively capable of performing part or all of the dynamic driving tasks (DDT) of a vehicle on a sustained basis" *(SAE definition)*

This survey should take about 8 minutes to complete based on previous pilot surveys. I am asking you to be honest and sincere while responding. All the answers you will provide will be kept confidential and only analyzed as aggregated data. Thank you!"

Here the respondent is able to start the survey and the following page is welcomed with a group of four multiple choice questions used as "control questions" for some concepts.

1. *My current knowledge about autonomous driving is:*
2. *In the last 3 months how many times you've used car-sharing services (DriveNow, Car2Go, Enjoy or similar) for your mobility?*
3. *In the last 3 months how many times you've used a ride sharing service (Uber, BlaBlacar, Lyft or similar) for your mobility?*
4. *I am an EU citizen:*

The first three were used as control questions to see if respondents were giving random answers during the survey and for correlation analysis, while the fourth one was a discriminant for people since only EU citizens were part of the sample. If someone didn't respond with yes, the questionnaire would have automatically ended.

At stage three the first construct is based on the *Theory of Planned Behaviour* by Ajzen (Ajzen I. , 1991) (Ajzen I. , 2006). It was used in this case to assess the target behaviour of "*Using in the future an autonomous driving vehicle for my journeys*" as explained in the hypothesis section. Here the three main factors represent the three antecedents of intention in the theory and four to five items are used for each factor. A good deal of personal elaboration was introduced following Ajzen guidelines to write a scale for its theory inside a measurement model. This construct will be at the center of attention during the second multiple regression analysis, explaining intention of adoption.

Construct	Factor	Item	Reference
Theory of Planned Behaviour	**Attitude towards Behaviour**	1. My commute is a real hassle 2. My commute trip is a useful transition between home and work 3. The travelling that I need to do interferes with doing other things I like 4. Travelling is generally tiring for me because I have to drive 5. Using an autonomous driving vehicle for my journeys might improve how I use my time	adapted from (Ajzen, 2006) & (Mokhtarian, Remond, Salomon, 2010)
	Subjective Norm	1. I would consider owning a self-driving car as status symbol or because people would approve of my behaviour 2. I will think about using this technology if my friends/relative recommended it 3. I would consider owning a self-driving car to show off/status symbol 4. Using this technology would show how my personality is	adapted from (Ajzen, 2006) & Personal elaboration
	Perceived behavioural control	1. I feel like I am more in control when I am driving compared to someone else driving for me 2. I feel like I am a better driver than the average driver on the road 3. I feel like self-driving tech will never be as good as an average human driver 4. I feel like It would be easy for me to give control to an autonomous vehicle 5. I would require having the ability to regain control on my car at any time if my car was self-driving	adapted from Ajzen (2006) & Personal elaboration

Table 1 - Theory of Planned Behaviour construct
Source: Personal elaboration of literature

The second construct used at stage four is *technology acceptance*. Here the factors are three, describing acceptance's perception of self-driving technology. These factors are widely based on (Nielsen & Haustein, 2018) research about the expectations of this technology and were additionally

adapted by the author. The *expected advantage of fully self-driving cars* factor deals with the perceived added value of an autonomous vehicle over a standard car. The following factor, *new technologies fan*, explains people's open mindedness to new technologies on the market and the last one scores people's overall interest in using scenarios (like taxi, buses, shuttles, etc)

Construct	Factor	Item	Reference
Technology acceptance	**Expected advantage of fully self-driving cars (sae level 5)**	1. I would be able to do other activities while driving a fully autonomous vehicle 2. I would be relieved from paying attention to traffic 3. I would not have to park the car myself 4. It would be possible to drive under the influence of alcohol or medication	Adapted from (Nielsen & Haustein, 2018)
	New technologies fan	1. I like trying new technologies when they are still under development 2. I try out new technologies when the majority has already tested them 3. I do not feel the need to try out new technologies	Adapted from (Nielsen & Haustein, 2018)
	Interest in use-case	1. I wouldn't mind travelling in a self-driving taxi without driver 2. I wouldn't mind travelling to a place of work, education or similar in a self-driving car 3. I wouldn't mind travelling for short shuttle rides (like from the airport to the city) 4. I wouldn't mind riding in a self-driving bus without driver	Adapted from (Nielsen & Haustein, 2018)

Table 2 - Technology acceptance construct

Source: Personal elaboration of literature

In the following construct the respondent is asked to evaluate three factors explaining its *car perception*. Steg is the author of this scale which was left totally unchanged from his research trying to create clusters based on driver's perception of their ride (Steg, 2005). The factors are three and describe three clusters based on people's way of experiencing divided in *instrumental*, *symbolic* and *affective*.

Construct	Factor	Item	Reference
Car perception	**Instrumental**	1. For me, the car has instrumental functions only 2. It does not matter to me which type of car I drive 3. If I did not need a car, I would dispose of it immediately	Adapted from (Steg, 2005)
	Symbolic	1. A car provides status and prestige 2. My car shows who I am 3. I may be jealous of someone with a nice car	Adapted from (Steg, 2005)
	Affective	1. I love driving 2. I know of a dream car that I would love to possess 3. I like to drive just for the fun	Adapted from (Steg, 2005)

Table 3 - Car Perception construct

Source: Personal elaboration of literature

Commute benefit is the fourth construct and it is made of five factors, with different origins in literature. The first factor is *implicit trip motivations* and it's adapted from Diana's work about the utility of travel (Diana, 2008). It explains how much people tend to travel for the sake of it and for pleasure. The second factor is called *motivation for car use* and it explains how much people prefer using a car for their daily commute, compared to other means of transportation. It is sourced from (Neoh, Chipulu, Marshall, & Tewkesbury, 2018) and the same can be said for the third and fourth factors: *ride sharing* and *car sharing*. They are personal elaborations of the literature with the goal of describing people's willingness to commute with such mobility services. The fifth and last factor is *utility of travel*, adapted from (Mokhtarian & Salomon, 2001). It focuses on travel time utility during commuting by car.

Construct	Factor	Item	Reference
Commute benefit	**Implicit trip motivations**	1. Travelling means exploring new places 2. I tend to take an unusual itinerary to reach a known destination 3. I love travelling just for relax 4. Sometimes I take a trip without a well-defined purpose 5. I tend to travel for fun	Adapted from (Diana, 2008)
	Motivation for car use (and	1. Public transportation requires too many changes between means of transportation 2. No public transport goes to my workplace	Adapted from (Neoh, Chipulu,

	incentives to switch for commuting)	3. I use the car after work for personal reasons (for example shopping) 4. No incentive can persuade me to give up driving and switch to other means of transportation 5. I would give up driving if other travel modes can save me time compared to my car	Marshall, Tewkesbury, 2018)
	Ride sharing (Uber, BlaBlaCar)	1. I would share a self-driving taxi (like Uber) to work with colleagues 2. I would consider commuting in a self driving taxi as my first choice of transportation to work 3. I look forward to using a self-driving ride-sharing service to work in the future 4. I would use a ride sharing service if my employer provides me with benefits like a company membership to one of these services	Adapted from (Neoh, Chipulu, Marshall, Tewkesbury, 2018)
	Car-sharing (DriveNow, Car2GO)	1. I would use a car sharing service (like DriveNow, Car2Go) to work with colleagues 2. I would consider commuting using a car sharing service as my first choice of transportation to work 3. I would use a car sharing service if my employer provides me with benefits like a company membership to one of these services	Adapted from (Neoh, Chipulu, Marshall, Tewkesbury, 2018)
	Utility of travel	1. Travel time during my commute is generally wasted time 2. My commute is a useful home-work transition 3. I currently use my commute time productively	Adapted from (Mokhtarian, Salomon, 2001)

Table 4 - Commute benefit construct

Source: Personal elaboration of literature

At the 7th stage there's *Travel time benefit* which is the construct that represents the Y in the multiple regression and for this reason no hypotheses were made on it in the previous chapter. It is based on three factors used to explain in mathematical terms the travel time benefit concept defined by the author in the literature review chapter. Those three factors are: *multitasking during travel*, *convenient efficiency* and *time saving*.

Starting from the first one, the item's sources were two different literature publications. The first two items of the factor were taken from this publication (Nielsen & Haustein, 2018) about interest in self-driving cars. The methodology for assessing behavioral responses are not well established so here were considered general expectations. These were taken from the "expected advantage of fully self-driving cars" literature factor. The remaining three items of this factor were taken from the "rationale for intent to use" section of this paper (Zmud, Sener, & Wagner, 2016), addressing the why individuals decide to use self-driving vehicles. The research was based on interviews and these items

were among the most common replies in the category "ability to be productive while travelling in a car". The second factor is *Convenient Efficiency* and the main source of its content is (Zmud, Sener, & Wagner, 2016) for the same reason of the previous one, these items were present as responses in that research. The last factor of the construct is called *Time saving* and once again was retrieved from (Zmud, Sener, & Wagner, 2016) in the same way.

Construct	Factor	Item	Reference
Travel time benefit	**Multitasking during travel**	1. I would do other activities while travelling if i didn't have to drive 2. I expect I would be more productive since my travel time would become usable time for other activities 3. It would be easier to conduct business while the car is driving itself compared to when I am driving 4. It would be easier to spend personal time with people while the car is driving itself compared to when I am driving	Adapted from (Nielsen, Haustein, 2018) Adapted from (Zmud, Sener, Wagner, 2016)
	Convenient Efficiency	1. I would arrive relaxed at my destination if I didn't have to drive 2. I would waste less working hours If I didn't have to drive 3. I would let the car drive itself in boring travels on highways 4. I would still disengage the technology and normally drive my car when I feel like driving	Adapted from (Zmud, Sener, Wagner, 2016
	Time saving	1. I wouldn't have to stop to rest on long journeys if the car could drive me to destination 2. I would get done personal matters while commuting so I could have more free time when home 3. I would feel like I am using public transportation but without wasting time to between means of transportation	Adapted from (Zmud, Sener, Wagner, 2016)

Table 5 - Travel Time benefit construct

Source: Personal elaboration of literature

The last construct of the measurement model is named *Safety concern*. The approach for this one was quite different since it is the secondary research focus of this thesis. The author decided to structure it in two factors: *objective safety performance* and *perceived technology safety* with the former explaining the objective technological safety and the latter people subjective perceptions of it. This division was made trying to provide a complete point of view on the matter. The first factor comes from the concept of "intrinsic utility of travel" that explains how there is an utility component intrinsic to the fact of travelling. A great part of this factor is personal elaboration of (Diana, 2008) like in

other factors of this measurement model. The *perceived technology safety* factor is taken from a paper about interest in self-driving cars (Nielsen & Haustein, 2018). The factor used in the research was "attitude towards self-driving cars" and was adapted to explain subjective perceived safety by the author.

Construct	Factor	Item	Reference
Safety concern	**Objective safety performance**	1. Safety is an important factor for cars 2. I highly value 3rd party safety certifications like EuroNCAP when I buy a car 3. I like the latest implementations of auto emergency breaking and safety features in cars 4. I highly value safety of the occupants concerning accidents 5. I think that computers and sensors will be safer than a human being at the wheel when the technology will be developed	Adapted from (Diana, 2007)
	Perceived technology safety	1. I am worried that I will lose my driving skills by using an autonomous vehicle 2. I am worried about the legal responsibility in the case of an accident involving self driving vehicles 3. I am worried that a self-driving vehicle will make me feel less in control 4. I am worried about software hacking/vulnerabilities 5. I would feel safe driving in a fully self-driving car without a steering wheel	Adapted from (Nielsen, Haustein, 2018)

Table 6 - Safety Concern construct

Source: Personal elaboration of literature

The last group of questions were multiple choice and related to *Demographics*:

1. *Gender*
2. *Age*
3. *Highest qualification*
4. *Employment status*
5. *Family status (married or not) children or not*
6. *How I consider my family income*
7. *How big is your city?*
8. *Country*
9. *Owning a car*

For question 7 about city's populations, the OECD definition was used (European Commission, 2012). The range goes from S (small) for cities between 50000 and 100000 people to Global City status for urban areas of more than 5 million inhabitants. This is the official framework of the European Commission that is used to define city size in Europe. All the other questions followed the standard *Qualtrics* division in possible answers.

4.1.2 Pilot testing

Before sending the final survey on Amazon Mturk for the final data gathering the author decided to do two stages of pilot testing to refine the questionnaire and learn all the analysis instruments properly. Qualtrics, MTurk, Excel and SPSS were the three main instruments used in the analysis of data in this thesis and some testing was definitely required before starting right away with the huge sample of data.

After prof. Lanzini approval of the questionnaire a first version of the survey was dispensed in July to 5 close friends and fellow marketing students to gather their very important feedback, especially on clarity, understandability and overall flow of the questionnaire. No data analysis was done on this step.

The first pilot was done on a sample of 20 anonymous European citizens reached through Amazon Mturk to get acquainted with the platform and see if there were problems in how people responded. The average response time of this survey was 6 minutes and 7 seconds, so more factors and refinements were introduced. More questions were changed or rearranger during or after the first pilot analysis.

A second pilot of 20 respondents was made with the final version of the questionnaire and the results were analyzed being a correct representation of the analysis process that just will have to be repeated on the final sample. The author had the opportunity to get confident with the use of MTurk and its payment method for workers and at the same time SPSS books and tutorials were consulted to learn the software and plan the best possible analysis route. After these two pilot tests, It was time to dispense the final survey to the actual sample through Mturk. In the following sub-chapter, the author will describe the sample.

4.1.3 Sample used for the research

The target population of the survey was *European Union* since the beginning of the ideation of this thesis. It is a market that hasn't been tested as much as the US in literature and this alone was the main reason of interest in doing the analysis on EU citizens. Of course, this could somehow make

less meaningful all the scales already used in literature for analyzing US populations, but the interest in bringing something new to the table outweighed the possible risk of lower significance.

The European population currently sits at 513.491.691 people according to Eurostat data for January 1st 2019 (Eurostat, 2019). The sample size to be representative for this population was calculated following Qualtrics guidelines (Qualtrics, 2019) for a 95% confidence level, a 5% margin of error and a population of the size of the EU to be **385** respondents. This will be achieved through Amazon Mturk workers, which has showed in the past positive results compared to standard online surveys (Buhrmester, Kwang, & Gosling, 2011) and it proved to be a quite handy way to gather data in a relatively short time.

With the goal of representing in the best possible way the EU28 population, some age groups were excluded from the sample. Children under 15 years of age were excluded since Amazon Mturk workers must be at least 18 or older. People aged 70 or more were excluded too since they are too old to be reached effectively via Mturk and at the same time they probably won't see the benefits of self-driving vehicles on themselves, since they will probably be widespread in a couple of decades.

4.2 Reliability and validity of the model

4.4.1 Reliability

Reliability refers to "*the extent to which a scale produces consistent results in case repeated measurements are made*" (Malhotra & Birks, 2007). It means that the same answer should be given by repeating the measure, so it's all about *consistency*. It refers to the degree to which the items that make up the scale "hang together" (Pallant, 2011). It is "the average of all possible split-half coefficients resulting from different ways of splitting the scale items" (Malhotra & Birks, 2007). *Cronbach's Alpha* coefficient will be used to assess the measurement's model reliability. Each construct is made out of a group of factors and each factor consists of a series of items. Each item is an individual likert question on a 7-point scale (from "Strongly disagree" to "Strongly disagree") with an indifferent option made available. To be considered satisfactory, this coefficient should be at least 0.6 or even better 0.7 on a single scale (factor). There is not a fixed number because depending on the research a value of 0.85 could be considered unsatisfactory, while in another explorative research a value of 0,65 is just fine, and this is the case of this thesis. Another property of this coefficient is that its value increases when the number of items in the scale increase (Malhotra & Birks, 2007).

Each factor was checked and assessed with this method. Summary results can be found in the following tables, while in the appendix of this thesis all the SPSS outputs are presented for additional information. All the results of this reliability assessment already include the best possible outcome,

obtained with the elimination of items in certain cases, with the goal of increasing the Alpha coefficient. A value of 0.650 was used as a rule to keep or dismiss factor's reliability, in conjunction with the corrected mean inter-item.

Construct	Factor	Cronbach's Alpha	Items
Theory of Planned Behaviour	**Attitude towards Behaviour**	0.669	4
	Subjective Norm	0.793	4
	Perceived behavioural control	0.608	removed

Table 7 - Theory of Planned Behaviour Cronbach's Alpha
Source: Personal elaboration

The first construct is the *Theory of Planned Behaviour*. It is made of three factors: "*attitude towards behaviour*", "*Subjective norm*" and "*Perceived behavioural control*". The Cronbach's Alpha of the first two factors is acceptable, scoring both over 0.650, while the third one was removed from the measurement model because of its low score. In the first factor one item was removed to improve the Cronbach alpha, leaving four out of five items in the scale.

Construct	Factor	Cronbach's Alpha	Items
Technology Acceptance	**Expected advantage of fully self-driving cars**	0.668	3
	New technologies fan	0.469	removed
	Interest in use-cases	0.869	4

Table 8 - Technology Acceptance Cronbach's Alpha
Source: Personal elaboration

Technology Acceptance comes next with three factors. In this case one factor ("New technologies fan") was deleted too because of the low score of 0.469. obtains a very good 0.869, followed by 0.668 of "*Expected advantage of fully self-driving cars*" which required the deletion of an item to reach this score. The aforementioned item is: "*It would be possible to drive under the influence of alcohol or medication*".

Construct	Factor	Cronbach's Alpha	Items
Car Perception	**Instrumental**	0.676	3
	Symbolic	0.804	3
	Affective	0.807	3

Table 9 - Car Perception Cronbach's Alpha
Source: Personal elaboration

This construct taken from (Steg, 2005) was left unchanged from its implementation in her research and it is not surprising that it performs very well as a previously validated scale. The scale is used to measure *Car Perception* with three possible car use motives and relative factors: "Instrumental", "Symbolic" and "Affective". There are no removed items and all three factors achieve a good level of reliability.

Construct	Factor	Cronbach's Alpha	Items
Commute Benefit	**Implicit trip motivations**	0.763	5
	Motivation for car use	0.515	removed
	Ride sharing	0.822	4
	Car-sharing	0.838	3
	Utility of travel	0.528	removed

Table 10 - Commute Benefit Cronbach's Alpha
Source: Personal elaboration

Commute Benefit is the biggest construct, being made by five factors. Out of the total, three of them pass the testing for reliability, while "Motivation for car use" (0.515) and "Utility of travel" (0.528) need to be removed because of their low internal consistency. The Remaining three factors show a strong result, with no items eliminated.

Construct	Factor	Cronbach's Alpha	Items
Travel Time Benefit	**Multitasking during travel**	0.840	4
	Motivation for car use	0.666	3
	Ride sharing	0.729	3

Table 11 - Travel Time Benefit Cronbach's Alpha

Source: Personal elaboration

All three factors are kept for probably the most important construct of the measurement model: *Travel Time Benefit.* Being the core of the research question of this thesis this was a crucial element since it will be the construct that is explained by one of the two multiple regressions in the analysis chapter.

Construct	Factor	Cronbach's Alpha	N of items
Safety concern	**Objective safety performance**	0.804	5
	Perceived technology safety	0.637	removed

Table 12 - Safety Concern Cronbach's Alpha
Source: Personal elaboration

The last construct is *Safety Concern*. In this case only the first factor is reliable with a score of over 0.8 for the Cronbach Alpha and no items removed. The second one was deleted since it was not possible to improve it by eliminating items over a score of 0.637.

4.4.2 Validity

Validity refers to the *extent to which the differences in observed scale scores reflect true differences among objects on the characteristic being measured*, rather than systematic or random error. It requires no measurement error and it can be checked in different elements: *content* validity, *criterion* validity, *predictive* validity and *construct* validity (Malhotra & Birks, 2007). It is important because It is a step further for a scale since if a measure is perfectly valid, it is also perfectly reliable. On the contrary the other way around is not true, so if a scale is only reliable it is not for sure valid. Therefore for this measurement model all the scale used were taken from the literature as explained in the previous pages. For this reason, the author thinks that there is no need to do a confirmatory factor analysis to prove their validity.

V. FINDINGS

5.1 Sample description

In this last chapter of the research the focus will be on the analysis of the data gathered with the survey. *Qualtrics.com* was used to build the survey with the constructs, factors and items showed in the previous chapter. *IBM SPSS Statistics 25* was used to clean and analyze data making possible testing hypothesis, replying to the main research question and overall supporting the reasoning of the research. In this chapter only a small portion of SPSS outputs will be displayed. For the total number of tables, graphs, scatters and other outputs, they are all in the appendix of this thesis as a reference.

After about two weeks of waiting and about 70 euros spent, 507 people were interviewed through the Amazon Mturk platform. The survey was published in batches divided in the age groups as shown in the table below with the 28 European Union countries filtered in the country filter on the platform. An additional question was asked about the citizenship of the respondent, early on as the 4th question of the survey. The question was a simple yes/no and if the respondent chose "no" the survey would end, not letting him/her continue. By law only people 18 years old and above are allowed to drive cars in basically all the European states and the same can be said for Mturk since 18 is the minimum age required to be a worker on the platform (Amazon.com, 2019). The target set by the author with a 95% confidence level was 385 respondents. The final number of responses after two weeks of data collection and a data cleaning was 397, a +3% over the minimum needed and more than 100 responses discarded for incomplete answers.

For the sake of data cohesion, ***age groups*** were left five year long, using Eurostat data for the EU population (Eurostat, 2019). By looking at the single age groups the 25-29 is the most over-sampled category by +80%, while 55-59 has the largest under-sample. Eight out of eleven age groups reported a difference of 15% or less from the ideal value adjusted to 385 which is a decent result. The average age of the sample was 40,79 years with a standard deviation of 14,538. Gender distribution was more biased towards the male side with 66,2% of the respondents being male and the consequent 33,8% being female. Additional tables about age distribution can be found in the appendix.

Age group	EU population in age groups (2018)	Ideal sample	Final sample	Difference in %
15-19	26.920.857	29	24	-16
20-24	28.534.367	30	35	15

25-29	31.778.765	34	61	80
30-34	32.925.273	35	37	5
35-39	34.631.923	37	39	6
40-44	35.349.272	38	39	3
45-49	37.000.342	39	40	1
50-54	37.366.888	40	34	-15
55-59	34.983.987	37	30	-20
60-64	32.033.978	34	30	-12
65-69	29.261.131	31	28	-10
Total	360.786.783	385	397	3

Table 13 - Sample vs European Population

Source: Personal elaboration of data, Eurostat.com

Gender		
	Frequency	Percent
Male	263	66,2
Female	134	33,8
Total	397	100,0

Table 14 - Gender distribution

Source: Personal elaboration of data

Speaking about ***country distribution***; twenty-five out of the twenty-eight EU countries were represented in the sample which is a good result for such a small sample. In the table it is possible to see the percentage of nationality gathered in the survey, compared to the EU28 percentage. The biggest over-represented countries were United Kingdom and Italy, exceeding their "real-world" value by about double their weight. Germany on the other hand, which accounts for the biggest country in the EU with a population of about 82 million people, represents only 5% of the sample, while it should be *three* times that figure at about 16,2%. These differences are inevitable and since the research considers the European Union, they should not be seen as faults of the sample.

EU Countries			
	Frequency	%	% EU 28
Austria	4	1,0	1,7
Belgium	1	0,3	2,2
Bulgaria	1	0,3	1,4
Croatia	2	0,5	0,8
Cyprus	2	0,5	0,2

Czechia	6	1,5	2,1
Denmark	6	1,5	1,1
Finland	5	1,3	1,1
France	35	8,8	13,1
Germany	20	5,0	16,2
Greece	10	2,5	2,1
Hungary	6	1,5	1,9
Ireland	16	4,0	0,9
Italy	80	20,2	11,8
Malta	1	0,3	0,1
Netherlands	9	2,3	3,4
Poland	3	0,8	7,4
Portugal	9	2,3	2,0
Romania	4	1,0	3,8
Slovakia	2	0,5	1,1
Slovenia	1	0,3	0,4
Spain	62	15,6	9,1
Sweden	1	0,3	2,0
United Kingdom	111	28,0	12,9
Total	397	100,0	98,8

Table 15 - Sample by country

Source: Personal elaboration of data, Eurostat.com

In terms of ***education*** the sample showed as the main category of response "high school diploma" with 40,1%, which considering the 2,5% of the sample not even have a high school diploma, brings the total of people without a degree to 42,6%. Talking about people with at least a university degree data shows 30,0% of the sample with a bachelor's degree, 23,4% with a bachelor + master's degree and the remaining 4% with a doctorate.

Regarding ***employment status***, the most represented category was "*employed full-time*" which accounted for 48,6% of the sample, followed by part-time workers with 22,7%. This means that 71,3% of the 18-69 range of population interviewed had a job. This figure is quite accurate since Eurostat data for 2018 depict a similar picture for the European Union with 73,1% of people employed aged between 20 and 64. 30,8% of women works part-time, while for men this number is quite lower at only 8% (Eurostat, 2019). As of the remaining categories, 10,6% of the respondents were students, 7,6% were retired and 1,3% were disabled people.

Family status is next with 45,8% of the sample being married with roughly half of that with at least one child. The next big group are the never married which account for about 42% of the sample with the last 11% being divorced.

Another crucial factor, especially for a research about mobility, is ***city population***. The biggest category here is "*rural areas of less than 50000 people*" which accounted for 27,7% of the sample. By comparison Eurostat data from 2015 show how 28% of the EU28 population lives in rural areas (Eurostat, 2017) so the data is quite spot on for this particular parameter. The second largest category are cities between 50 and 100 thousand inhabitants, with a share of 19,6%. The least frequent category is "more than 5 million people" which weighted in at about 7% of the sample.

Household income is another crucial variable in the process of choosing a car or even mobility options in our daily lives. The most represented income class is 20-to-30 thousand euros per year, closely followed by 10-to-20 thousand. It is quite difficult to compare it with real world figures since the average salary of Sweden will be a lot higher than the one in Portugal, with even more difference compared to Romania. Just for reference for a single person net-earning, Luxembourg had 56300 euros per-capita while Bulgaria recorded only 6100 euros (Eurostat, 2019). In this question the focus was on household earnings and the average is quite low, meaning that only people with low incomes value their time as low as the below average pay of Amazon Mturk survey competition. This was to be expected to some degree and it is connected to the table with the age distribution that we saw previously. The sample over-represents lower classes in terms of both age and income. This problem is inevitable in research since higher earning classes won't bother spending time doing an 8-minute survey for the mere sum of 15 cents. Results will have to be taken in consideration with this distortion in mind.

Owning a car is the last relevant factor to be considered as descriptive of the sample: 82,6% of the respondents have a personal car. This will have consequences on people's perception as we will see in the next sub-chapters, since having firsthand experience in driving one own's car is very important to shape people's perception of it.

5.2 Relationship identification for economic and demographic variables

In this section a series of significant relationships will be presented between variables and economic/demographic factors. The analysis presented will mainly discuss results of *Pearson correlation (r)* and *one-way ANOVA*. This will introduce the core element of the research found in the next two sub-chapters and it will help understand some of the factors that influence it. The structure will follow clusters of findings related to single variables that were just presented in 5.1 and

the complete outputs will be attached in the appendix for reference. All the analysis was done with a 95% confidence interval (p-value=0,05).

Correlation *describes the strength and direction of the linear relationship between two variables* (Saunders, Lewis, & Thornhill, 2016). It is about how two variables are connected to each other and how they are related. It summarizes the strength of association between two variables. It varies between -1 and 1 and it is used to determine whether a linear or straight-line relationship exists between the two variables compared (Malhotra & Birks, 2007). Both variables need to be *continue* here.

One-way ANOVA instead is used *to compare the scores of two different groups or conditions* (Saunders, Lewis, & Thornhill, 2016). It is an analysis of variance examining the differences in the mean values of the dependent variable for one or more independent factor. It involves one independent variable (called factor) which has several different levels which correspond to different groups or conditions. A significant F test indicates that we can reject the null hypothesis, which states that the population means are equal. ANOVA will give us an indication of whether there are significant differences between groups (Pallant, 2011). All the results presented in this chapter had been checked for *homogeneity* on top of being significant, and none of them violated the assumption of homogeneity of variance, displaying a significance value >0.5 for the Levene's test (Pallant, 2011).

First of all, the analysis will start from the last-mentioned element of the previous paragraph: ***owning a car***. As we will see this factor has the widest range of effect on differences in means for various variables. The significant ANOVAs explain differences between groups for the factor "*owning a car*" for the variables: *travel time benefit* (construct), *theory of planned behavior* (construct), *time saving* (factor), *symbolic* (factor), *safety concern* (factor) and *technology acceptance* (factor).

By looking at the "*Travel Time benefit*" construct the ANOVA result passes the homogeneity test and is significant (p-value=0,005), showing a *higher mean for travel time benefit for people owning a car*. Same can be said for the differences in means for "*Theory of Planned behavior*" factor: people owning a car score higher and this difference is significant (p-value=0,007), showing a *higher intention in using or owning an autonomous driving vehicle for those people already owning a car*.

It is more of the same for the "Time saving" (p-value=0,006) and "symbolic" (p-value=0,042) factors which both show a higher score for people owning a car. This means that people that already own a vehicle value with higher score the benefit of saving time that autonomous driving tech could give them, and the status symbol that a car gives them, respectively. It is possible to say that owning a car

raises people's awareness of safety too since the results is the same for the "safety concern" scale (p-value=0,001).

Last ANOVA connected with owning a car is about its *effect on score for "technology acceptance" factor for autonomous driving tech and again the result is the same as all the previous ones* (p-value=0,040). Owning a personal vehicle has a significant effect on people's perception of many factors and this is a crucial insight for managerial implications. This could mean that instead of investing marketing efforts to attract new people to the use of autonomous vehicle the focus should focus on converting those that already own a personal vehicle by, for example, making them test drive the new technology since first-hand experience seem so important for perception.

A similar scenario of likelihood to use was investigated through a ***Person's Correlation*** for two variables which seem interesting, at least on paper, for the subject matter. These two are the "*interest in use*" factor and the "*ride sharing*" factor which represent respectively people's interest in the innovation and how much someone enjoys the benefits of ride sharing services. In this case the result is quite strong and positive with a value of ***Pearson's r=0,605***, significant at the 0,01 level. This result is quite strong and suggest how present users of ride-sharing services might be having the closest current experience to autonomous driving in the way they use the service like a taxi on demand in the case of Uber (which was the example of ride sharing provided in the questions of this factor). This result has many interesting consequences, they will be discussed at the end of this chapter.

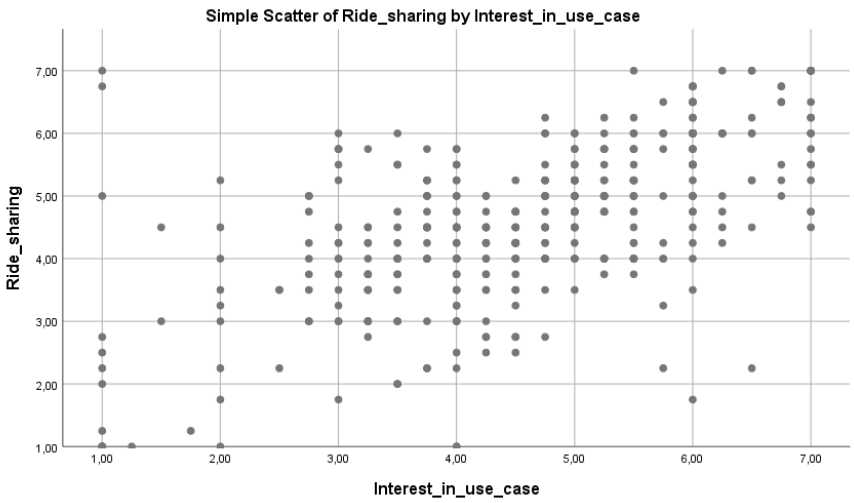


Figure 18 - Scatter of "Ride sharing" and "Interest in use"
Source: Personal elaboration of data with SPSS

The next main factor about driving and travel time is ***city population***. In fact, where people live relates to urban structure of that area. As was seen in the previous sub-chapter, about 45% of European citizens live in *cities smaller than 100-thousand inhabitants* and this has serious consequences to some variables. For instance, the expected advantage of autonomous driving, explained by the "*expected advantage scale*" showed that relative to the city population there is a significant difference with a p-value of 0,1 and F=2,835. This was true mainly for the difference between small cities with population between 50 and 100 thousand people and metropolis with more than 5 million people. These two groups recorded the lowest and highest score respectively with a mean difference of -0,86 as is possible to see in the figure below. This could be explained by the huge difference in "hassle" of driving in traffic and highly condensed areas, this being a lot higher for people living in cities, like London, compared to a small Dutch town, where most people use bikes and traffic is not a problem at all. The possible advantage of an autonomous vehicle seems a lot higher for people having to deal with huge traffic daily.

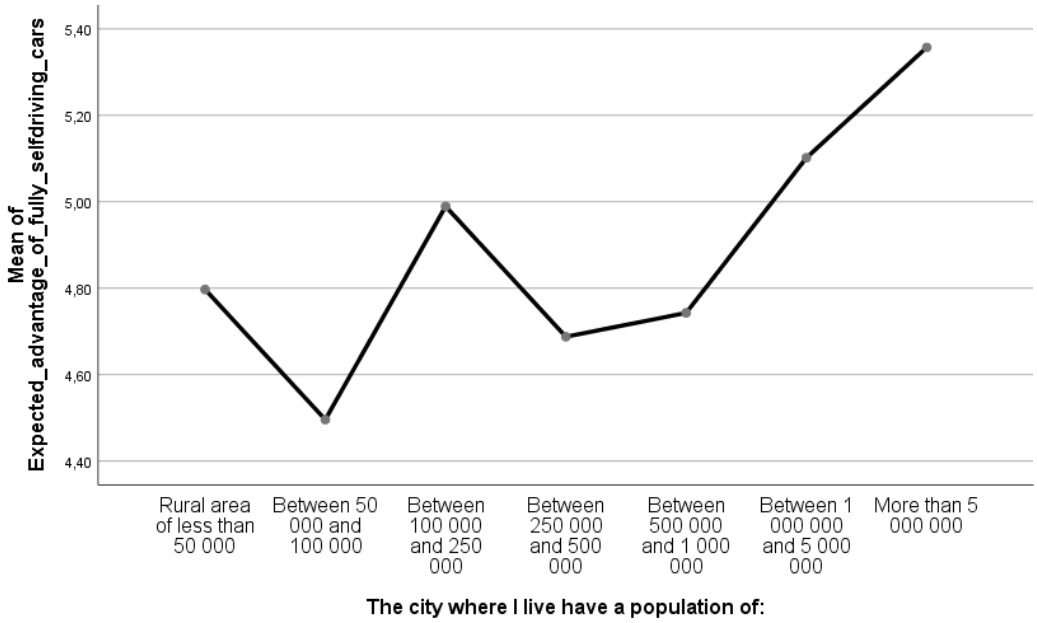


Figure 19 - ANOVA for city population and Expected advantage of Self Driving cars
Source: Personal elaboration of data with SPSS

Another factor which is influenced by city population is the "*technology acceptance*" factor. Scores for this factor differ with a significance of p-value=0,002 in the case of biggest discrepancy: *5 million and upwards people cities score higher versus rural areas of less than 50 thousand people*. The nature of this difference is not easy to understand but the author thinks that it might be for the different levels

of education. By looking at Eurostat data it was found that "people living in rural areas are generally more inclined to leaving education early" (Eurostat, 2017) which leads to lower general level of education. Another ANOVA was run comparing means of the "*technology acceptance*" factor by ***education level*** which led to a significant outcome (p-value=0,043). This is supporting in part this hypothesis since *lower education levels showed a lower score for the factor* with a difference of almost 1 (0,97509) in the score between bachelor + master degree and less than high school.

The next factor that showed significance is people's ***income***. Following the previous two cases related to "*technology acceptance*", it turns out that there is a significant (p-value=0,001) difference between different income classes too for the factor technology acceptance, with a max (significant) difference of -1,47 in score between less than 10k euros and 90-99k euros household incomes. It is a quite similar situation for the difference between 20-29k and 90-99k, 50-59 and 90-99k, and 60-69k and 90-99k so a good quantity of groups shows quite important dissimilarity. By comparing scores in the "*travel time benefit"* construct it turns out that *people with higher household incomes tend to score higher in their potential benefit of time thanks to autonomous driving*. This is to be expected since people with higher wages per-hour will have a higher loss of money for each hour they lose not working because they have to drive. This is very interesting for the research since it shows the variation of the value of time for different categories of people in the society.

Age follows as an impossible to ignore determinant of our life choices. In the context of this thesis age was asked as a precise number in the measurement model and then divided in 5-year segments to make it more comparable to Eurostat data as was shown in the previous sub-chapter. The ANOVA analysis showed significance (p-value=0,006) difference between the following pairs of age groups for the "*time saving*" factor: 35-39 was compared with 65-59 and 45-49 with 65-69. As seen below in the graph, middle aged people in the ***45 to 49 age group tended to value a possible time saving more than any other group***, closely followed by 35-39. These high scores are there because people between 35 to 50 tend to have kids. Raising children requires a lot of time and effort, hence why these people value a lot the time saving factor. On the other side of the spectrum people aged more than 65 show that they don't value at all the possibility of saving time; that's because they are mostly retired and don't really have to work anymore, leaving them with a lot of free time in their hands.

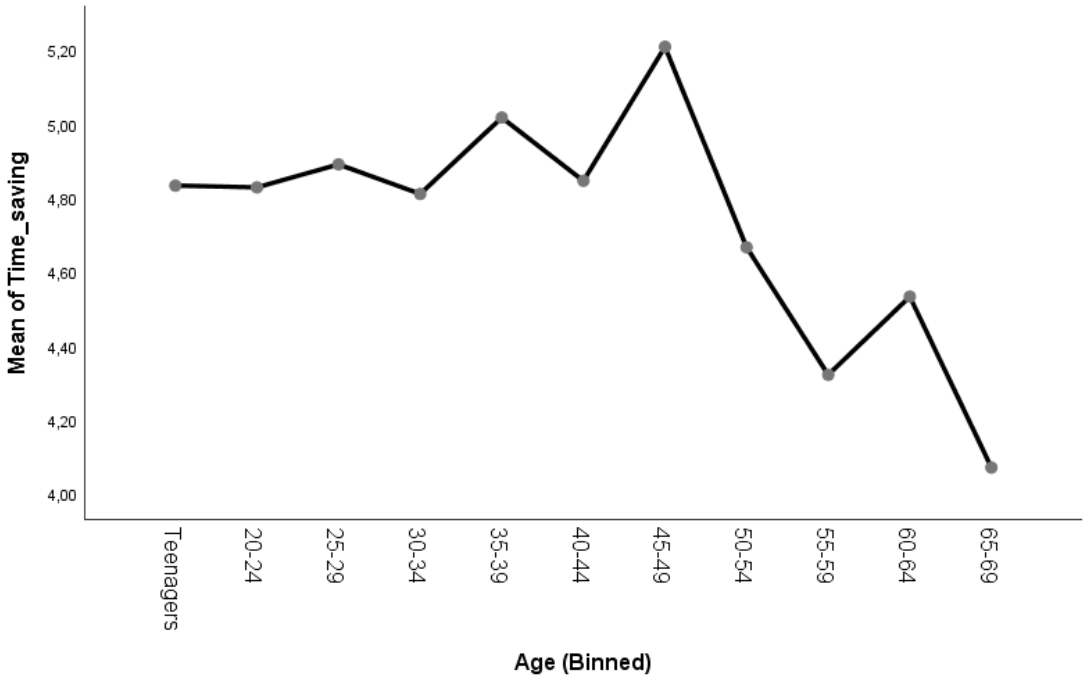


Figure 20 - ANOVA for age and time saving factor
Source: Personal elaboration of data with SPSS

"*Ride sharing*" is another factor that is massively influential. It explains how much someone intends using services like Uber and BlaBlaCar and it is quite important as we saw before with its high correlation with "*intention of adoption*". The ANOVA for it shows that there is significance (p-value=0,028) and that both groups between 20-24 and 45-49 are different in their mean compared to 65-69 by about -1,1. This is again a useful insight for which segments of the market should be the perfect target for these new kinds of vehicles, as people over 60 as of 2019 are definitely not into ride sharing services. They happen to be the closest representation of what it means having a car that can drive itself to destination though, minus the driver of course, which Uber itself is trying to replace with AI to cut its biggest cost. So this factor has great consequences.

5.3 Explaining travel time benefit

It is now time to deep dive into the core of the research. In this chapter the main research question will be addressed, and all the related hypotheses tested. The analysis will be carried on the concept of "**Travel time benefit**" introduced by the author, which is the foundation of the main research question about "*the perception of effect of autonomous driving on travel time benefit for the consumer*". A series of factors were chosen and adapted from literature to explain the concept of *utility of the added time made available by not driving.* Hypotheses were formulated at the end of the literature review process; they were based on these factors' relationship with the newly introduced

construct of "*Travel time benefit*" and in this sub-chapter they will be tested. The model used to find these relationships is a multiple regression, which will be explained here, while all the unfiltered resulting outputs can be found for reference in the appendix of this work.

A multiple regression is used, which involves explaining the "Travel time benefit" construct with five reliable and valid factors which were included in the model. The used factors as independent variables are: *expected advantage of fully self-driving cars*, *interest in use case*, *ride sharing*, *car sharing* and *objective safety performance*. The result of this regression will indicate how well this set of variables is able to predict travel time benefit and it will also tell how much unique variance each of the independent variables explain (Pallant, 2011).

Before looking at results it is important to ***check assumptions*** for this kind of analysis. First of all, *multicollinearity* has to be avoided. It can be easily spotted by looking at the SPSS output, in particular to Tolerance (has to be more than 0.1) and VIF (has to be less than 10) values which in this model are kept under control for all variables (Pallant, 2011). All tolerance values are above 0,308 and all VIF values are under 3,245, which means an overall absence of multicollinearity. For the total results, they are available in the table "coefficients" below.

Furthermore, ***residuals*** need to be checked with both Normal Probability Plot (P-Plot) and the standardised scatterplot of residuals. In the first case, points should follow the diagonal (which means normality), while in the case of the scatterplot, there should be no apparent relationship or pattern (Pallant, 2011). These two graphs can be seen below and both show a green flag for assumptions related to residuals like normality, linearity and homoscedasticity (Saunders, Lewis, & Thornhill, 2016).

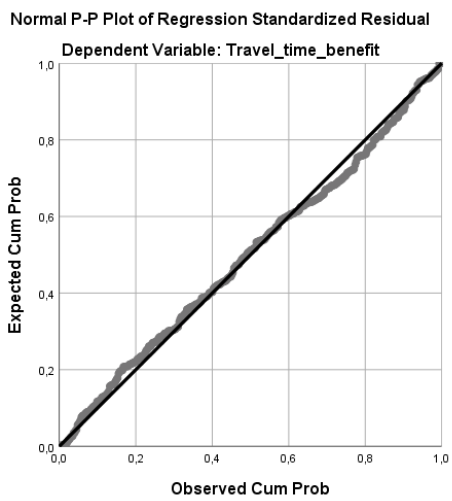


Figure 21 - P-Plot of Regression Standardized Residuals of the "Travel time benefit" multiple regression
Source: Personal elaboration of data with SPSS

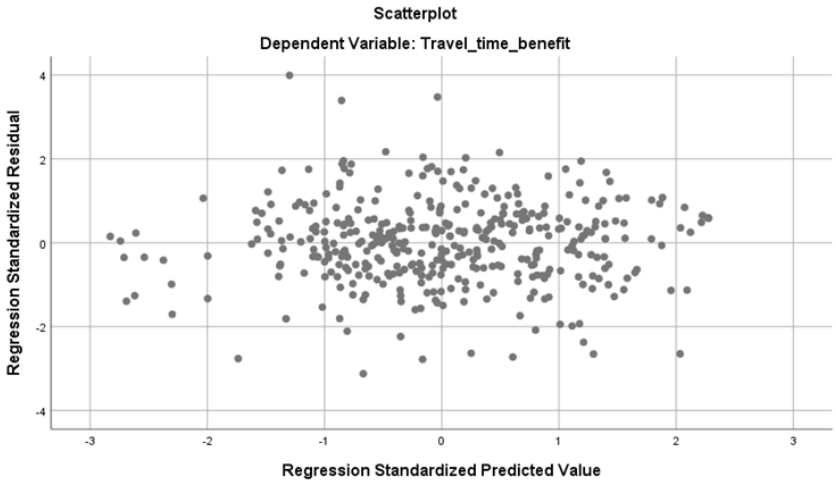


Figure 22 - Scatterplot of residuals of the "Travel time benefit" multiple regression
Source: Personal elaboration of data with SPSS

The ***Correlations*** table output (present in the appendix) shows how all the correlations between the dependent variable (travel time benefit) and the independent ones, giving an overall idea of how strong the linear relationship is each one. In this case, values are quite high and all positive, scoring 0,570 for "expected advantage of fully self-driving cars", 0,618 for "interest in use case", 0,676 for "ride sharing", 0,588 for "car sharing" and 0,445 for "objective safety performance".

Looking at the overall *model summary*, the coefficient of multiple determination is the value to check and the model achieves a quite good ***adjusted R^2=0,607***. This result is quite significant as usually values between 0,5 and 0,7 are the minimum for a model to be a good fit. This coefficient *explains the capability of the estimated model to explain the variability in the data*. It condensates in one number between 0 a 1 the strength of the association and the adjusted R^2 takes into consideration the number of independent variables and sample size to give a more precise representation. This means that the regression explains about 61% of the variance of the model, which is a *respectable* goodness of fit with a *reasonably good* closeness of the scatter to the regression line (Malhotra & Birks, 2007). The ANOVA confirms the statistical significance of the result with a Sig.=0,000 which is indeed significant (Pallant, 2011).

By looking at the single variables' *standardised beta coefficients* it is possible to see the ***single contribution to the dependent variable*** and consequently test the hypotheses based in literature (Pallant, 2011). All variables' contribution on travel time benefit is significant and positive as seen in the figure below.

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.	95,0% Confidence Interval for B Lower Bound	95,0% Confidence Interval for B Upper Bound	Correlations Zero-order	Correlations Partial	Correlations Part	Collinearity Statistics Tolerance	Collinearity Statistics VIF
1	(Constant)	,653	,203		3,225	,001	,255	1,052					
	Expected_advantage_of_fully_selfdriving_cars	,162	,035	,186	4,560	,000	,092	,232	,570	,226	,145	,603	1,659
	Interest_in_use_case	,170	,031	,234	5,399	,000	,108	,232	,618	,265	,171	,536	1,866
	Ride_sharing	,201	,045	,255	4,465	,000	,113	,290	,676	,222	,142	,308	3,245
	car_sharing	,132	,038	,177	3,519	,000	,058	,206	,588	,177	,112	,398	2,515
	objective_safety_performance	,200	,037	,191	5,428	,000	,128	,273	,445	,267	,172	,810	1,235

a. Dependent Variable: Travel_time_benefit

Table 16 - Coefficients for the "Travel time benefit" multiple regression
Source: Personal elaboration of data with SPSS

The biggest influence on travel time benefit comes from the "***ride sharing"*** factor, with a standardised coefficient **β=0,255**, which is by no means a high contribution, but is still present. This stresses previous results that found how ride sharing was closely correlated with interest in use, resulting in the strongest factor to determine travel time benefit. This means that people using and appreciating ride sharing services like Uber once again result to have the biggest travel time benefit for the perception of autonomous driving technology. The second factor, closely following, is "***interest in use"*** with a standardized **β=0,234**, highlighting the strong influence of interest in the possible perceived benefit, which seems common sense and It is to be expected. Third most influential factor is "***objective safety performance"*** with **β=0,186** which has an even less pronounced effect, showing how the car's safety equipment make travelling less stressful and safer. The two least powerful coefficients are "***expected advantage of self-driving cars***" and "***car sharing***" with a beta coefficient **β=0,191** and **β=0,177** respectively. Expected advantage explains the convenience of having a vehicle with autonomous capability and probably scores quite low because of its not so specified focus. On the other hand, car sharing's score is low probably because of its less similar nature to an autonomous vehicle compared to ride sharing, since the end user has to actually drive the car. The model explains the perception of the effects of a series of factors found in literature on travel time benefit, giving insight and answer to the main research question.

Looking at the formulated hypotheses about this first multiple regression model, we can see how some factors were not included because of poor reliability or because they were not significant. ***Hypothesis testing*** will be done only on those five factors, coming from three constructs, that were retained in the model.

About the "*Expected advantage of fully self-driving cars*" factor, H2a is accepted as we just saw with a positive beta in the multiple regression. H2b is rejected though as the ANOVA between the entire construct and age proved to be non-significant (p-value=0,318).

Moving to "*interest in use case*" factor, all three hypotheses are accepted. The first hypothesis about this factor is accepted as saw before with the assessment of a strong positive correlation between ridesharing and interest in use. The second one because of the beta in the multiple regression is positive, while the third one showed a mean score of 4,91 which was indeed the highest of the factor.

Ride sharing and *car sharing* both showed positive betas in the multiple regression and for this reason both hypotheses are accepted.

Safety concern is the last construct and the hypothesis about its only factor proved to be rejected. In fact, correlation between "*age*" and objective "*safety performance*" proved to have a significance of 0,385 which is not significant. H6a must be rejected.

Construct	Factor	Hypothesis	Result
Technology acceptance	**Expected advantage of fully self-driving cars**	H2a: "*A high expected advantage score will have a positive effect on travel time benefit*"	Accepted
		H2b: "*Older people will be less open-minded about the acceptance of autonomous driving technology*"	Rejected
	Interest in use case	H2d: "*People already using services like ride-sharing will be more open to trying this new technology*"	Accepted
		H2e: "*The interest in use case factor will have a positive effect on travel time benefit*"	Accepted
		H2f "*It is to be expected that the item regarding shuttle usage for self-driving cars will be the one with the higher positive score towards this factor*"	Accepted
Commute benefit	**Ride sharing**	H4c: "*The ride sharing factor will have a positive effect on travel time benefit*"	Accepted
	Car sharing	H4d: "*The car-sharing factor will have a positive effect on travel time benefit*"	Accepted
Safety concern	**Objective safety performance**	H6a: "*Older people require a higher level of security for self-driving cars than younger generations*"	Rejected

Table 17 - Hypothesis testing for "Travel time benefit" multiple regression

Source: Personal elaboration of data with SPSS

5.4 Investigating people's intention to use an autonomous vehicle with the Theory of planned behavior

After the main research question was answered, the research will change its perspective. In the previous section the travel time benefit concept was explained using a series of factors that had certain influences on it. The model showed a decent ability to explain the relationship with an R-squared of more than 0.6. In this section the stream of thought will continue by looking at people's intentions, using a theory which is perfect to explain behavioral intentions: the *Theory of Planned Behavior* by Ajzen (Ajzen I. , 1991). In particular the focus will switch to the effort of explaining the intention of usage of autonomous driving technology, with the exact target behavior described as: *"Using in the future an autonomous driving vehicle for my journeys"*. This will consist of a second multiple regression with the just proven concept of travel time benefit used to explain the dependent variable. This is quite innovative since the author is stating that the concept introduced will be *enough* to explain people's intention to use an autonomous vehicle. The key element here is that for sure there are many factors that lead a person to create the intention, but the benefit of added time available could be enough for some to adopt this new behavior. Out of the three factors present in the "Travel time benefit" construct just explained in the first multiple regression, only two out of three factors were retained since adding the third one would have reduced the model's adjusted R^2.

Checking assumptions is the first step of the process. The values that are interesting here are Tolerance and VIF, which tell us if the model violated the multicollinearity assumption. Both values are solid with a Tolerance of 0,565 (needs to be more than 0,1) and VIF of 1,789 (need to be less than 10).

By looking at the P-Plot of the ***residuals*** the model seems very good, but it's while checking the scatterplot that things already are not that promising. It is less centered to zero, like the first model was, and this is not a good sign as some points are aligned at the right side. The overall distribution is still acceptable though and the assumptions are barely passed.

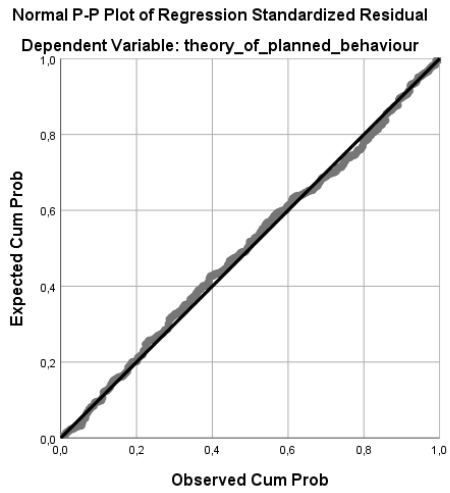


Figure 23 - P-Plot of Regression Standardized Residuals of the "Theory of planned behaviour" multiple regression
Source: Personal elaboration of data with SPSS

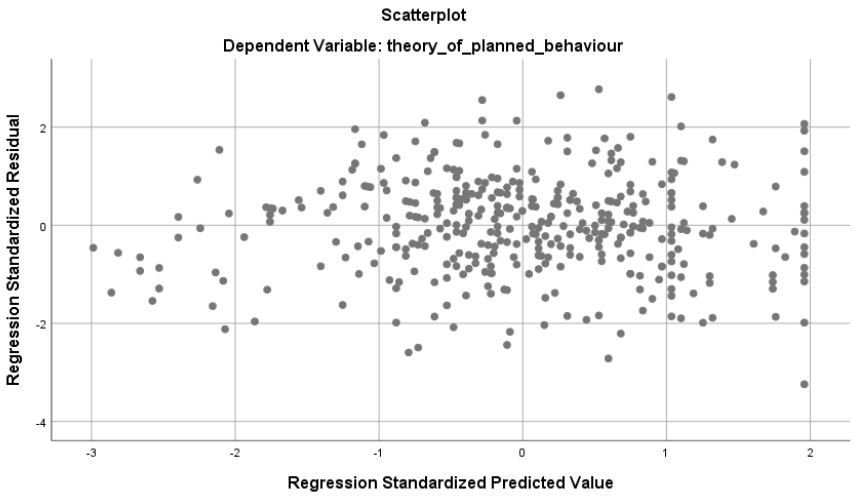


Figure 24 - Scatterplot of residuals of "Theory of planned behaviour" multiple regression
Source: Personal elaboration of data with SPSS

Correlation is the next thing to be checked. In this case values are still quite good and all positive, scoring 0,417 for "*multitasking during travel*" and 0,495 for "*interest in use case*" compared to the dependent variable represented by the construct "theory of planned behaviour".

By looking at the capability of the model to explain data in the model summary tables, the result shows a quite unimpressive ***adjusted R^2=0,256.*** This number is lower than expected and It means that only 25,6% of the variability is explained, which is not a sufficient result from a statistical point of view. A value of at least 0,6 or 0,7 is advised to be the minimum acceptable when observing the

coefficient of multiple determination. This means that this second multiple regression doesn't have a good enough result, and this is probably due to the fact that "travel time benefit" is not enough to explain the intention of using an autonomous driving vehicle for the average person. There are probably more factors involved and this result is quite reasonable in the end, since to adapt a new intention of behaviour is quite a difficult and cognitive expensive for our brain.

Next up, it's time to see the *single contribution of the model's variables.* This can be done using the standardized beta coefficients, which explain the strength of the effect on the dependent variable relative to the other independent variables. In this case we have only two factors, which also partly explain a low *adjusted* R^2 for the model since with an increasing number of variables, the coefficient tends to increase (Saunders, Lewis, & Thornhill, 2016). The biggest contribution is made by the "***convenient efficiency***" factor with a standardized **β=0,390**, which is positive and much bigger than the coefficient of "***multitasking during travel***" which tops at **β=0,160**. This means that people see a greater incentive to adopt an autonomous vehicle from its benefits of *convenience*, like being more relaxed while driving and waste less time concentrating on driving, compared to the benefit of doing other activities, like being more productive or do business/personal related stuff.

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95,0% Confidence Interval for B		Correlations			Collinearity Statistics	
		B	Std. Error	Beta			Lower Bound	Upper Bound	Zero-order	Partial	Part	Tolerance	VIF
1	(Constant)	1,732	,211		8,204	,000	1,317	2,147					
	multitasking_during_travel	,141	,051	,160	2,769	,006	,041	,240	,417	,138	,120	,565	1,769
	Convenient_efficiency	,348	,052	,390	6,753	,000	,247	,449	,495	,322	,293	,565	1,769

a. Dependent Variable: theory_of_planned_behaviour

Table 18 - Coeffcients of the second Multiple Regression

Source: Personal elaboration of data with SPSS

These results are actually in line with the **hypotheses** formulated in the literature review with both factors showing a positive influence on the dependent variable "theory of planned behavior". Both H1a and H1b are accepted with both "*multitasking during travel*" and "*convenient efficiency*" having a positive effect on the intention of adoption of an autonomous vehicle.

Construct	Factor	Hypothesis	Result
Travel time benefit	**Multitasking during travel**	H1a: "*A high multitasking during travel score will have a positive effect on theory of planned behavior*"	Accepted

	Convenient Efficiency	H1b: "*A high convenient efficiency score will have a positive effect on theory of planned behavior*"	Accepted

Table 19 - Hypothesis testing for the second multiple regression
Source: Personal elaboration of data with SPSS

5.5 Managerial implications of the research on the automotive industry

The results of the analysis made in this chapter are for sure interesting from an academic point of view, buy in the end business implications are the most connected with the more practical reality. To bridge this gap a relative new concept of business model introduced in 2010 by Osterwalder in his book "*Business model generation: a handbook for visionaries, game changers, and challengers*" (Osterwalder & Pigneur, 2010). In the Osterwalder's definition a ***business model describes the rationale of how an organization creates, delivers, and captures value***.

The business model canvas supports a shared language that allows to easily describe and manipulate business models to create new strategic alternatives. It describes through nine building blocks the blueprint of how a company or an entire industry make money. These blocks are at the foundation of four areas of business: customers, offer, infrastructure and financial viability. The nine blocks are: *customer relationships, value proposition*, *key partners*, *key activities*, *customers*, *revenue*, *channels*, *key resources* and *costs* (Osterwalder & Pigneur, 2010).

In the figure below, its structure is outlined and in this chapter the analysis will evaluate the impact of the findings of this thesis on the entire *automotive industry business model*, looking at the single building blocks. It won't be a comprehensive overview of the industry, since it will focus on the actions and differences compared to the current situation for both OEMs, mobility-as-a-service and recent mobility players. The focus will be in particular on the "*customer*" and "*value proposition"* blocks since they are the closes to the research done in this thesis.

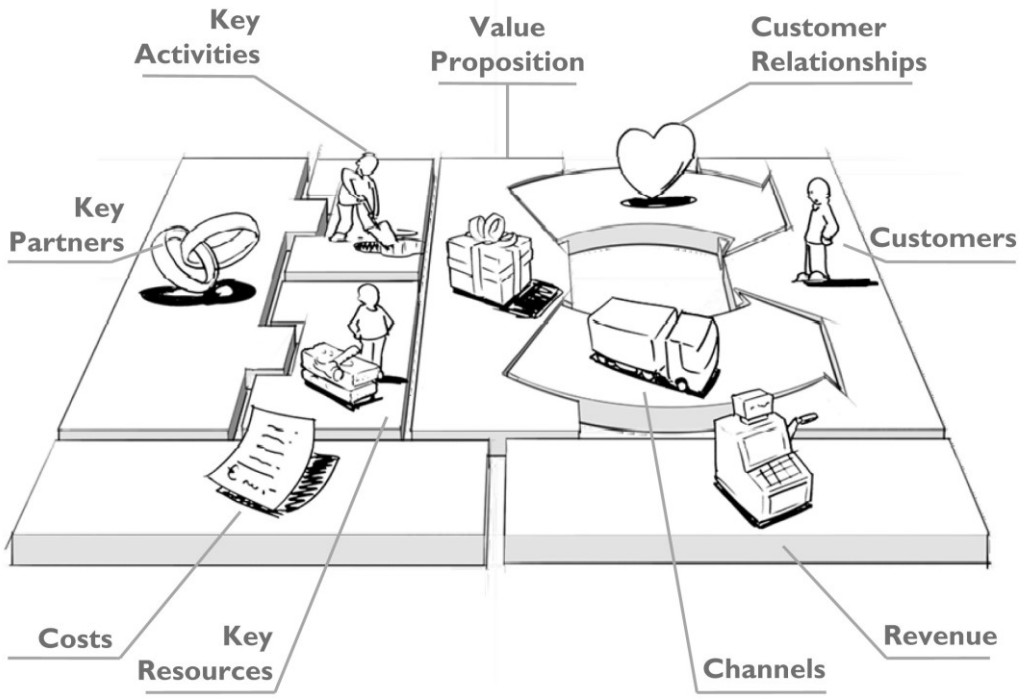


Figure 25 - Osterwalder's Business model canvas
Source: Osterwalder & Pigneur (2010)

Customers is the first block. From this research many insights were discovered on the optimal segment of end users to target in this period of pre-launch of the technology. *Owning a personal vehicle* has a significant effect on people's perception of many factors and this is a crucial insight for managerial implications related to this technology. People already owning a vehicle showed higher travel time benefit perception in a possible use of a self-driving vehicle for themselves, compared to people not owning one. It also boosted their intention to use a self-driving car and their acceptance of the technology, which are both very important indicators to delineate the ideal customer.

Age is another crucial factor for marketing and selling and the research found that for people aged 35-49 the time saving factor connected to this technology is very strong. This should be leveraged, focusing marketing efforts on this lever of saving time due to the fact of not having to drive. In the case of mobility services instead there are two main age groups that are more likely to use a self-driving taxi: 20-24 and 45-49. Both categories should be at the top of the list for companies like Waymo or Uber as their most interested customers.

Other important demographic factors found are linked to *education* and *city population*. The former has a positive effect on technology acceptance since well-educated people (at least a bachelor's degree) are more open to technology acceptance than less educated people. The latter relates to the

first one, since people living in big urban areas are more likely to have a higher degree of education. In particular, they both show a higher expected advantage and technology acceptance for autonomous driving compared to rural areas, especially people living in huge cities with more than 5 million people. For these reasons, marketing efforts for both mobility services and car sales will have to be tailored to big cities because early adoption will start there. High population density also means higher coverage and higher average income as we will see in the next paragraphs.

A correlation had been also found between the *benefit of ride-sharing* services and the *interest in use* for a vehicle driven by this technology. This is quite important since this means that users of ride sharing services like Uber are a better target for marketing autonomous driving since they are already experiencing a sort of similar way of travelling when they are using the platform. This is coherent with latest Uber effort in investing billions in R&D for autonomous vehicles (The New York Times, 2019) as a way to cut its cost and tailor its value proposition for people that are already accustomed to being driven around and with the convenience of it.

Another factor that needs to be used to target the best possible ideal customer is *household income*. It is safe to say from the research findings that for now this technology appeals the wealthier side of society, with higher technology acceptance scores. Furthermore, travel time benefit is also higher for richer people, suggesting that for them the cost/opportunity of time is higher than a lower-class income citizen.

We now move to the second focus of the chapter: the ***value proposition*** block. The value proposition is based on the products and services provided to the final customers, focusing on the benefits and value they create for them (Osterwalder & Pigneur, 2010). Latest years are bringing disruptive change in an industry that focused on incremental innovation for decades. Autonomous driving is one of major new technologies and the research question of this research aimed at investigating it. By looking at the *perception of the effect of autonomous driving on travel time benefit for the consumer,* the author tried to define and legitimate this new concept of benefit for the consumer. In the opinion of the author this is crucial to find what OEMs and mobility companies can bring to the table in terms of value for the end customer.

Probably the most interesting result is related to the *connection existing between ride-sharing services and this technology*. This is clear in this research, as It found how ride sharing was closely correlated with interest in use, resulting in the strongest factor to determine travel time benefit too. This segment will be expanding a lot in the next few years since all sorts of mobility service that are already present in big cities will switch to offering driverless taxi services.

From the analysis, people see a greater incentive to adopt an autonomous vehicle from its ***benefits of convenience***, like being more relaxed while driving and waste less time concentrating on driving, compared to the benefit of doing other activities, like being more productive or do business/personal related stuff. This is very interesting as the author wanted to investigate if travel time benefit is enough of a factor in itself to justify the adoption. Even if both these factors have a positive effect on intention, they are not enough to justify it as was seen from the low adjusted R square of the second multiple regression model. There are for sure other factors driving adoption that need to be taken into account, like safety of the occupants for example, which in this study was used to explain travel time benefit. For sure convenience is embodied by ride-sharing services and "robo-taxis" which will populate the streets of big cities, offering a 24/7 service on demand, being the core of mobility-as-a-service paradigm. These findings are coherent to what The Boston Consulting group found: *convenience is key*, with the biggest single attraction of SDVs being not having to find a parking space (The Boston Consulting Group, 2016).

The convenience factor, on top of the interest in use will be the two main factors to use in marketing messages. ***People want to worry less while driving***, this is the main point, after that if they prefer using that time productively or not it is a personal choice. People want that choice. This will have to be the main marketing message delivered to convince people that there are benefits of the technology. On top of that safety will have to be stressed too. Right now, for level 1-2 of autonomous driving safety is the centre of the marketing message. It will have to be expanded on in the future with more 3rd party certifications and tests to assess the actual capability of the systems.

Price is already quite high as of now, where autonomous driving tech is present on flagship models of the different car manufacturers. In the next few years more tech will be added to reach level 3 and above. Perspective on price is not that great since components are currently expensive, especially lidar tech, but new low-cost solutions might brought to the market to improve on cost-efficiency (Wired.com, 2019). Players like Tesla, frontrunning the adoption of the technology might find themselves at a huge advantage, especially in the miles driven department, since they have years of proven technology on the road. That is why OEMs need to step on the accelerator for testing in a massive way. Competition will be fierce from all sides with both tech giants and start-ups heavily targeting the automotive industry in this moment of change. The risk is incurring in a similar revolution that brought the smartphone to the market at the end of the 2000s, where previous market leaders like Nokia had a very though time to adapt, and so many new players came on top.

Third building block is ***key partners***. In this moment of transition in technology for the industry, both technological solutions and software are at the centre of the revolution. As Porsche did with Rimac,

by acquiring stocks and creating a technological partnership for its electric cars (Porsche, 2019) the same will happen for many OEMs. *Partnerships* will have to happen to share the costs and only huge groups, that can spread those costs among various brands, will be able to do it efficiently. Not many can do it like the Volkswagen group can for example, even if in that case the brand is still facing the brand damage of 2016 "*Diesel gate*" (Fortune.com, 2018) still to this day in its stock price and reputation. Nvidia and CPU-GPU manufacturers like Intel will be other key partners, since the technology to process in real time data lies in the chip inside cars. Also Radar and especially Lidar manufacturers will develop massively and multi-billion deals will have to be done. On top of that, the 5G infrastructure will have to be ready, since so much more bandwidth will be needed for so many more vehicles exchanging information in real time. Partnerships will have to be created to bring the best-connected car services. Key partners will also be all the mobility services that will launch in the new few years, bringing mobility on demand to smaller cities, as the new mobility paradigm advances.

Key activities is the next one. Offering on-demand mobility services will be the most crucial challenge here, offering flexibility, availability and low costs for the end user. Strong R&D investments are paying off and being able to create a software and AI infrastructure to drive vehicles will have a huge asset value for a company. Here competition from the same companies that are considered key partners is already fierce, since OEMs are quite lacking in the software side of things they will have to acquire either companies or the know how to do it in-house. Dealers will become even more showrooms just to test drive the technology. In the opinion of the author it will be crucial to get people trying with their first-hand experience. In the research this had a massive beneficial effect on travel time benefit, intention to use the technology and to the acceptance of the technology. The author would advise to spend a lot of effort into making people test drive the technology.

Customers relationships will change too. With internet more people will buy cars online after trying them in showrooms. Dealers will become a centre for support and cars exchange as more and more people will subscribe to cars with services like Care by Volvo, as discussed in the context chapter. People want flexibility and no hassle and internet will become more and more important to bridge the gap between end user and OEMs, creating a more customized and personal relationship.

The sixth element is ***revenue streams***. Since this thesis's goal was totally different, this factor won't be discussed much. For sure less cars are will be sold in the traditional dealer way. More subscription and leasing services will be available, becoming the new status quo.

Coming up next there's ***channels***. There is not much change here regarding strictly application of autonomous driving vehicles, the consequences are more of a general take on the industry. As

mentioned before channels for selling cars will change becoming more digital. Services like Carwow.com in the UK are the example of a modern take on the traditional dealer

About ***key resources***, this entire category can be summarized with one word: *data*. Data about sensors, miles drive, people's habit, usage and everything in between will be crucial and will be at the foundation of AI algorithms created through machine learning to improve how cars can take decisions. The battle between companies will lie in software and its integration with user experience. Hardware will also be a key resource, but competition there will be on a different level as no company is able to be vertically integrated to the point of being able to use 100% hardware and software made by itself.

Costs of the disruptive moment the industry is facing are already billions, Volkswagen alone will invest more than €30 billion by 2023 (Volkswagen, 2019) in electrification, autonomous driving and connected car, shaping the future of mobility for the masses. As already mentioned, 5G infrastructure will be another huge investment needed for all this technology to function with the necessary response times.

Key Partners	***Key Activities***	***Value Proposition***	***Customer Relationships***	***Customer Segments***
→Google, Uber and other tech companies very good at software development and Machine learning →Nvidia, Intel and processor manufacturers for car autonomous driving capability →Radar, Lidar and other sensors manufacturers →R&D intensive start-ups →5G infrastructure players →safety 3rd party certification bodies	→offering on demand mobility services →offering flexibility →Strong R&D investment in software →make people try the technology has beneficial consequences for their perception ***Key Resources*** →software and machine learning algorithms →data about miles driven	→focus on ride sharing services →focus on convenience, instead of travel time benefit →rise of mobility-as-a-service →price and accessibility are a challenge in the short to medium term →safety will be a crucial point, with 3rd party certifications becoming more important	→flexible and on demand apps to deliver services →digital relations with OEMs →dealers will become showrooms and will change their primary aim ***Channels*** →developing of internet selling of cars will be a reality in the future	→living in a big city →educated (at least a bachelor's degree) → 90-100K household income and up →35-49 years old to save time →20-24 and 45-49for ride sharing service →people already owning a car
Cost Structure			***Revenue Streams***	
→Huge R&D investments in technology and road testing will be necessary, decades of time for ROI			→steady growth of subscription-based services and leasing	

Table 20 - Consequences of Autonomous driving on the automotive industry's business model

Source: personal elaboration of Osterwalder & Pigneur (2010)

In the table it was possible to see the summary of the Business model changes in the Automotive Industry because of autonomous driving technology. It is meant to only represent what are the differences compared to the current state, not to describe the entire industry for obvious time and space reasons in this research. With this business model representation this chapter ends and now it's time to wrap things up in the conclusion.

VI. CONCLUSION

6.1 Final discussion on the research

Autonomous driving is for sure one of the most interesting and challenging changes of the last decades in the automotive industry. In this research the sector was analyzed through its current challenges, leading to massive change compared to the previous decades. Electrification, autonomous driving, connected car and the rise of mobility-as-a-service with shared platforms are the four main pillars of disruption in the short to medium term. Automakers are spending billions to get ahead of competitors during this moment of uncertainty to what will be the new standard of quality, while newcomers are bringing huge innovation and creating space in the market for themselves.

Literature about travel time perception was widely analyzed with a secondary focus on safety perception. The research found a scarce quantity of literature focusing on the topic since it is a quite upcoming topic of the automotive sector. The measurement model was created, by taking into account scales found in literature and adapted to achieve good reliability and validity results. Hypotheses were formulated for each factor of the model and a survey was submitted to about 400 people, all European Union citizens between the age of 18 and 69. Amazon Mturk was used to dispense the questionnaire online using Qualtrics as base platform, while SPSS statistics was chosen for the data analysis.

After assessing the model's reliability and describing the sample, the analysis was carried through descriptive statistics to compare the sample to the current European population using Eurostat data about population, employment, people's education, household income and other variables like city population (Eurostat, 2019). Preliminary statistics on relationships between groups and variables found a strong relationship with owning a car and with already using ride sharing and car sharing service. On top of that the ideal customer was found to be quite rich, living in a big town and with a high degree of education and quite open to new technologies.

The main analysis was carried in two steps with as many multiple regression models. This research gave an explanation to this **technology's current perception**, trying to explain the *travel time benefit construct* and the *intention of usage* for autonomous driving technology.

In the former, which was a creation of the author, the analysis proved its legitimacy as a factor able to explain one of the main benefits of autonomous vehicles. This model was the foundation to explain the main research question about "*the perception of effect of autonomous driving on travel time benefit for the consumer*". The most influential effect in terms of benefit proved to be directly connected with people's present opinion of ride-sharing services. This is a crucial managerial

implication of the research, on top of the interest for the new technology, safety and expected advantage factors.

In the latter proved that travel time benefit is not enough to explain intention of adoption, using Ajzen "Theory of planned behavior" model (Ajzen I. , 1991). This resulted in a quite low adjusted R square of the model, in contrast to the author hypothesis of being able to explain the three antecedents of intention of behavior. A very interesting result here proved to be the higher effect of ***convenience*** compared to the ability to multitask while travelling, showing that *people see this technology as a way to reduce their stress related to travelling more than anything else*.

Other strategic insights were found through the analysis of data. the author presented them and then used them to create an *updated Business model canvas of the automotive sector*. This practice follows Osterwalder's template (Osterwalder & Pigneur, 2010) and focused on the differences that these results about autonomous driving could bring to the industry through the nine building blocks of the mode. The main interest were implications about consumers and value proposition, since they are the closely related with the analysis done in this research.

In this moment in time, the ideal customer segment remains a *niche* of rich people, middle aged and living in a big town, educated and interested in the latest mobility services like car-sharing. The main benefit of this disruptive change remains convenience, since people are still imaging it like it would be like being driven in a taxi. A crucial element for perception remains ***first-hand experience*** of a phenomenon. To boost reputation of the technology, a very effective way will be to make people try it by themselves, as leaving control of the wheel while driving is something out of people's comfort zone. Only after this initial cognitive block, final customers will accept the technology and the marketing will be able to focus on other selling points like safety and travel time benefit. *Multitasking during travel is currently not very important in the mind of the customer*, with him/her preferring more practical sides of the tech on paper like the car parking itself or not having to worry in traffic. It will be interesting to see in the future if this perception will shift to more productivity related benefits, once the technology is more widely accepted and its benefits consolidated.

The objective of this research was to bring something tangible and relevant on the table, taking part in the research done in the automotive industry. The outcome were some very interesting insights and managerial implications for a border research topic as autonomous driving and people's current perception about it. For sure there are many other factors that weren't considered, but the research delivered on most of its premises, giving a quite complete answer to the research question, evaluating its implication on the industry as a whole.

6.2 Space for further research

For obvious time and cognitive limitations this research could not cover a 360 degrees perspective of the autonomous driving topic. Some choices had to be made and focus had to be pointed at a certain point of view on the matter. This was true also for the secondary focus of research: *safety perception*. It was possible to include it in the first multiple regression as an explaining construct, while for a serious approach an entire thesis should have been devoted to it. After seeing the huge consequences on people's answers of owning a car or not owning one, the author suggests to test people's perception of the technology before and after trying it first-hand.

The *role of intentions* and *habits* in consumer behavior are two huge topics that are not addressable in research if not in cross sectional studies. They are still very relevant and interesting to look at and a relevant portion of literature is developing around them. During this thesis the attempt to include intentions was made using (Ajzen I. , 1991), but still it was only a secondary objective of the research that obtained a low adjusted R square. More can be done about it since the role of habits is crucial in our daily lives and in the choices that we make, but only a cross sectional study when the technology is more widespread will be able to shed light on the matter.

Regulations are another element that was not possible to predict. Present regulation is still lackluster in this field and is clearly behind car development, especially in the EU. An analysis of European regulations and laws and their future plans to let level 3 and above autonomous driving become legal will be for sure object of research.

Another element that needs more attention is *people's reaction to car sickness*, as autonomous driving technology will become more available and tests on human beings will be possible in huge numbers. This is very relevant as a consequence of the technology, since for a lot of people this is a problem even today. As people will do other kind of activities while the car drives itself the consequences will likely to be even worse and they will have to be taken into consideration by OEMs.

VII. REFERENCES

Aarts, H., & Dijksterhuis, A. (2000). Habits as knowledge structures: Automaticity in goal-directed behavior. *Journal of personality and social psychology, 78*(1), 53.

Accenture. (2016). *Electric vechicle market attractiveness.*

ACEA. (2018). *Vechicles in use Europe 2018.* European Automobile Manufacturers Association.

Ajzen, I. (1991). The theory of planned behavior. *Organizational behavior and human decision processes, 50*(2), 179-211.

Ajzen, I. (2006). *Behavioral interventions based on the theory of planned behavior*. Retrieved from https://people.umass.edu/: https://people.umass.edu/aizen/

Amazon.com. (2019, September). *About Amazon Mechanical Turk*. Retrieved from www.mturk.com: https://www.mturk.com/help

Amstrdam Roundtable Foundation. (2014). *Evolution: Electric vehicles in Europe: gearing up for a new phase?*

Andrews, J. G., Buzzi, S., Choi, W., Hanly, S. V., Lozano, A., Soong, A. C., & Zhang, J. C. (2014). What will 5G be? *IEEE Journal on selected areas in communications, 6*(32), 1065-1082.

Ansa. (2019, January 7). *Smog, Torino ferma anche diesel Euro 5.* Retrieved from www.ansa.it: http://www.ansa.it/piemonte/notizie/2019/01/07/smog-torino-ferma-anche-diesel-euro-5_c68508ae-27b9-4217-a42e-a6a1ac7b59a6.html

Athira, I. C., Muneera, C. P., Krishnamurthy, K., & Anjaneyulu, M. V. (2016). Estimation of Value of travel time for work trips. *Transportation Research Procedia, 17*, 116-123.

Auld, J., Williams, C., Mohammadian, A., & Nelson, P. (2009). An automated GPS-based prompted recall survey with learning algorithms. *Transportation Letters, 1*(1), 59-79.

Awad, E., Dsouza, S., Kim, R., Schulz, J., Henrich, J., Shariff, A., & ... Rahwan, I. (2018). The moral machine experiment. *Nature, 563*(7729), 59.

Baroncello, M., Husain, A., & Moller, T. (2018). Setting the framework for car connectivity and user experience. *McKinsey Quarterly*.

Bartl, M., Jawecki, G., & & Wiegandt, P. (2010). Co-creation in new product development: conceptual framework and application in the automotive industry. *Conference Proceedings*

R&D Management Conference–Information, Imagination and Intelligence, (pp. 1-9). Manchester.

Bartnik, R., Wilhelm, M., & Fujimoto, T. (2018). Introduction to innovation in the East Asian automotive industry: Exploring the interplay between product architectures, firm strategies and national innovation systems. *Technovation, 70-71*, 1-6.

Bloomberg. (2019, June 29). *Europe's Tough Emissions Rules Come With $39 Billion Threat*. Retrieved from www.bloomberg.com: https://www.bloomberg.com/news/articles/2019-06-26/europe-s-tough-new-emissions-rules-come-with-39-billion-threat

Bloomberg New Energy Finance. (2018). *Electric Vehicle Outlook 2018.* Retrieved from https://bnef.turtl.co/story/evo2018?teaser=true

BMW. (2019, March 2). *BMW i3 model page*. Retrieved from BMW.com: https://www.bmw.it/it/gamma/bmw-i/i3/2017/in-sintesi.html

Buhrmester, M., Kwang, T., & Gosling, S. D. (2011). Amazon's Mechanical Turk: A new source of inexpensive, yet high-quality, data? *Perspectives on psychological science, 6*(1), 3-5.

Cambridge Dictionary. (2019, August 4). *Meaning of security in English.* Retrieved from www.dictionary.cambridge.org: https://dictionary.cambridge.org/dictionary/english/security

Cambridge Dictonary. (2019, August 8). *Meaning of ethical in English.* Retrieved from www.dictionary.cambridge.org: https://dictionary.cambridge.org/dictionary/english/ethical

Ciarapica, F. E. (2013). Quality, environmental and economic factors influencing electric vehicles penetration in the Italian market. *AIDI Italian Association of Industrial Operation*.

Clark, J. E. (1982). Modeling Travelers' Perceptions of Travel Time. *Transportation Research Record, 890*, 7-11.

Cook, R., & Garver, M. (2002). Subscription supply chains: the ultimate collaborative paradigm. *American Journal of Business, 17*(2), 37-46.

Curl, A. (2018). The importance of understanding perceptions of accessibility when addressing transport equity. *11*(1), 1147-1162.

de Winter, J. C., & Dodou, D. (2014). Why the Fitts list has persisted throughout the history of function allocation. *Cognition, Technology & Work, 16*(1), 1-11.

Deloitte. (2019). *L'auto del futuro, secondo i consumatori.*

den Hartog, J., & Zannone, N. (2018). Security and privacy for innovative automotive applications: A survey. *Computer Communications, 132*, 17-41.

Diana, M. (2008). Making the "primary utility of travel" concept operational: a measurement model for the assessment of the intrinsic utility of reported trips. *ransportation research part A: policy and practice, 42*(3), 455-474.

Dimitropoulos, A. (2014). The Influence of Environmental Concerns on Driver's Preferences for electric cars.

Docherty, I., Marsden, G., & Anable, J. (2018). The governance of smart mobility. *Transportation Research Part A: Policy and Practice*(115), 114-125.

Edmunds. (2017). *Lease market report.*

Edmunds.com. (2018, January 8). *What are car subscription services?* Retrieved from edmunds.com: https://www.edmunds.com/car-leasing/what-are-car-subscription-services.html

electrive.com. (2018, December 11). *France: Electric car sales up 111% in November*. Retrieved from electrive.com: https://www.electrive.com/2018/12/11/france-electric-car-sales-up-111-in-november/

Ernst & Young. (2017). *The six trends driving change in the automotive industry.* Retrieved from https://www.ey.com/en_gl/automotive-transportation/the-six-trends-driving-change-in-the-automotive-industry

Ernst & Young. (2018). *How automotive supply chains must evolve for electric vehicles.* Retrieved from ey.com: https://www.ey.com/en_gl/automotive-transportation/how-automotive-supply-chains-must-evolve-for-electric-vehicles

Ernst & Young. (2018, Arpil). *How much human does a car need.* Retrieved from www.ey.com: https://www.ey.com/en_gl/digital/how-much-human-does-a-car-need

EURO NCAP. (2019, July 7). *Driver Assistance Systems.* Retrieved from www.euroncap.com: https://www.euroncap.com/en/ratings-rewards/driver-assistance-systems

European Commission. (2012). *Cities in Europe: the new OECD-EC Definition.*

European Commission. (2017). *Quantifying the Factors Influencing People's Car Type Choices in Europe: Results of a Stated Preference Survey.*

European Commission. (2018). *A Clean Planet for all: a european strategic long term vision for a prospdrous, modern, competitive and climate neutral economy.*

European Commission. (2018). On the road to automated mobility: An EU strategy for mobility of the future. *COMMUNICATION FROM THE COMMISSION TO THE EUROPEAN PARLIAMENT, THE COUNCIL, THE EUROPEAN ECONOMIC AND SOCIAL COMMITTEE, THE COMMITTEE OF THE REGIONS* (pp. 2-5). Brussels: European Commission.

European Commission. (2019, April 17th). *Post-2020 CO2 emission performance standards for cars and vans.* Retrieved from www.ec.europa.eu: https://ec.europa.eu/clima/policies/transport/vehicles/proposal_en

European Commission. (2019, February 28). *Reducing CO2 emissions from passenger cars*. Retrieved from http://ec.europa.eu/: https://ec.europa.eu/clima/policies/transport/vehicles/cars_en

Eurostat. (2017, February). *Statistics on rural areas in the EU* . Retrieved from ec.europa.eu: https://ec.europa.eu/eurostat/statistics-explained/index.php/Statistics_on_rural_areas_in_the_EU

Eurostat. (2019, September). *Employment statistics* . Retrieved from ec.europa.eu: https://ec.europa.eu/eurostat/statistics-explained/index.php/Employment_statistics

Eurostat. (2019, August). *Population on january 1.* Retrieved from https://ec.europa.eu/eurostat/: https://ec.europa.eu/eurostat/tgm/table.do?tab=table&init=1&language=en&pcode=tps00001&plugin=1

Eurostat. (2019, April). *Wages and labour costs* . Retrieved from ec.europa.eu: https://ec.europa.eu/eurostat/statistics-explained/index.php/Wages_and_labour_costs#Gross_wages.2Fearnings

FAA. (2019, July). *Aircraft Certification Software and Airborne Electronic Hardware.* Retrieved from www.faa.gov: https://www.faa.gov/aircraft/air_cert/design_approvals/air_software/

Ferràs-Hernández, X., Tarrats-Pons, E., & Arimany-Serrat, N. (2017). Disruption in the automotive industry: A Cambrian moment. *Business Horizons, 60*(6), 855-863.

Financial Times. (2018). *Tesla batteries prove best value in class — UBS.* Retrieved from ft.com: https://www.ft.com/content/d403516c-eca7-11e8-8180-9cf212677a57

Firnkorn, J., & Müller, M. (2011). Selling Mobility instead of Cars: New Business Strategies of Automakers and the Impact on Private Vehicle Holding. *Business Strategy and the Environment, 21*(4).

Forbes. (2018, March 25). *Autonomous Cars Won't Work - Until We Have 5G.* Retrieved from www.Forbes.com: https://www.forbes.com/sites/bijankhosravi/2018/03/25/autonomous-cars-wont-work-until-we-have-5g/#7843543b437e

Fortune.com. (2016). *Hoaxwagen: how the massive diesel fraud incinerated VW's reputation - and will hobble the company for years to come.* Retrieved from Fortune.com: http://fortune.com/inside-volkswagen-emissions-scandal/

Fortune.com. (2018). *How VW Paid $25 Billion for 'Dieselgate' — and Got Off Easy.* Retrieved from Fortune.com: http://fortune.com/2018/02/06/volkswagen-vw-emissions-scandal-penalties/

Fuller, J., Hutter, K., & Faullant, R. (2011). Why co-creation experience matters? Creativity experience and its impact on the quantity and quality of cretive contributions. *R&D management, 41*(3), 259-273.

Gabszewicz, J. J., & Sonnac, N. (1999). Subscription as a price discrimination device. *Recherches Économiques de Louvain/Louvain Economic Review*(65(4)), 421-433.

Gebauer, F., Vilimek, R., Keinath, A., & Carbon, C. C. (2016). Changing attitudes towards e-mobility by actively elaborating fast-charging technology. *Technological Forecasting and Social Change, 106*, 31-36.

Grant-Muller, S., & Usher, M. (2014). Intelligent Transport Systems: The propensity for environmental and economic benefits. *Technological Forecasting and Social Change*(82), pp. 149-166.

Gruyer, D., Magnier, V., H. K., Claussmann, L., Orfila, O., & Rakotonirainy, A. (2017). Perception, information processing and modeling: Critical stages for autonomous driving applications. *Annual Reviews in Control*(44), 323-341.

Guardian, T. (2018, December 18). *Carmakers criticise 'unrealistic' EU plan to slash vehicle emissions.* Retrieved from The Guardian: https://www.theguardian.com/business/2018/dec/18/carmakers-criticise-unrealistic-eu-plan-slash-vehicle-emissions

Gunn, H. F. (1981). Travel budgets—a review of evidence and modelling implications. *Transportation Research Part A: General, 15*(1), 7-23.

Handy, S., Weston, L., & Mokhtarian, P. L. (2005). Driving by choice or necessity? *Transportation Research Part A: Policy and Practice, 39*(2-3), 183-203.

Hart, S. L., & Milstein, M. B. (2003). Creating sustainable value. *Academy of management executive, 17*(2).

Hensher, D. A. (2011). Valuation of travel time savings. *A handbook of transport economics*, 135-159.

Hinduja, J., Thanekar, K., Valecha, K., & Gujar, P. (2018). SELF DRIVING CARS. *International Journal of Recent Innovation in Engineering and Research*.

Hong, J., Shin, J., & Lee, D. (2016). Strategic management of next-generation connected life: Focusing on smart key and car–home connectivity. *Technological Forecasting and Social Change, 103*, 11-20.

Il Sole 24 ore. (2019, July 4). *Auto elettrica, quanto costa la ricarica? Italia in fondo alla classifica.* Retrieved from www.ilsole24ore.com: https://www.infodata.ilsole24ore.com/2019/07/04/auto-elettrica-quanto-costa-la-ricarica/?refresh_ce=1

ISO - International Organization for Standardization. (2018). *ISO 26262: Road vehicles — Functional safety — Part 1: Vocabulary.*

J.P.Morgan. (2018, October 10). *Driving into 2025: The Future of Electric Vehicles.* Retrieved from www.jpmorgan.com: https://www.jpmorgan.com/global/research/electric-vehicles

Kelly, P., Doherty, A., Berry, E., Hodges, S., Batterham, A. M., & Foster, C. (2011). Can we use digital life-log images to investigate active and sedentary travel behaviour? Results from a pilot study. *International Journal of Behavioral Nutrition and Physical Activity, 8*(1), 44.

Kelly, P., Krenn, P., Titze, S., Stopher, P., & Foster, C. (2013). Quantifying the difference between self-reported and global positioning systems-measured journey durations: a systematic review. *Transport Reviews, 33*(4), 443-459.

Kolarova, V., Steck, F., Cyganski, R., & Trommer, S. (2018). Estimation of the value of time for automated driving using revealed and stated preference methods. *Transportation research procedia, 31*, 35-46.

Krueger, R., Rashidi, T. H., & Rose, J. M. (2016). Preferences for shared autonomous vehicles. *Transportation research part C: emerging technologies, 69*, 343-355.

Kyriakidis, M., de Winter, J. C., Stanton, N., Bellet, T., van Arem, B., Brookhuis, K., & ... & Reed, N. (2019). A human factors perspective on automated driving. *Theoretical Issues in Ergonomics Science, 20*(1), 223-249.

Lachnit, C. (2018, May 4). *To buy or not to buy? Car subscriptions offer alternative for new car shoppers.* Retrieved from usatoday.com: https://eu.usatoday.com/story/money/cars/2018/05/04/buy-not-buy-car-subscriptions-alternative/572538002/

Lanzini, P. (2017). *Responsible Citizens and Sustainable Consumer Behavior: New Interpretive Frameworks.* Routledge.

Lime. (2019, July). *Your Ride Anytime.* Retrieved from www.li.me: https://www.li.me/

Liu, P., Zhang, Y., & He, Z. (2019). The effect of population age on the acceptable safety of self-driving vehicles. *Reliability Engineering & System Safety*, 341-347.

Macher, G., Armengaud, E., Brenner, E., & Kreiner, C. (2016). Threat and risk assessment methodologies in the automotive domain. *Procedia computer science*(83), 1288-1294.

Malhotra, N., & Birks, D. (2007). *Marketing Research: an applied approach: 3rd European Edition.* Pearson education.

Mauborgne, P., Deniaud, S., Levrat, É., Bonjour, É., Micaëlli, J. P., & Loise, D. (2017). The Determination of Functional Safety Concept coupled with the definition of Logical Architecture: a framework of analysis from the automotive industry. *IFAC-PapersOnLine, 50*(1), 7278-7283.

McKinsey & Company . (2018). *Race 2050 - A vision for the european automotive industry.*

McKinsey & Company. (2016). *Automotive revolution – perspective towards 2030.*

McKinsey & Company. (2017). *An integrated perspective of mobility, part 2: Transforming urban delivery.*

McKinsey & Company. (2017). *The future(s) of mobility: How cities can benefit.*

McKinsey&Company. (2017). *Autonomous-driving disruption: Technology, use cases, and opportunities.*

McKinsey&Company. (2017). *Self-driving car technology: When will the robots hit the road?*

McKinsley & Company. (2019). *An integrated perspective on the future of mobility.*

MIT . (2019, August 7). *What should the self-driving car do?* Retrieved from Moral Machine: http://moralmachine.mit.edu/

Mokhtarian, P. L., & Chen, C. (2004). TTB or not TTB, that is the question: a review and analysis of the empirical literature on travel time (and money) budgets. *Transportation Research Part A: Policy and Practice, 38*(9-10), 643-675.

Mokhtarian, P. L., & Salomon, I. (2001). How derived is the demand for travel? Some conceptual and measurement considerations. *Transportation research part A: Policy and practice, 8*(35), 695-719.

Mokhtarian, P. L., Salomon, I., & Redmond, L. S. (2001). Understanding the demand for travel: It's not purely'derived'. *Innovation: The European Journal of Social Science Research, 14*(1), 355-380.

Montemerlo, M., Becker, J., Bhat, S., Dahlkamp, H., Dolgov, D., Ettinger, S., & Johnston, D. (2008). Junior: The stanford entry in the urban challenge. *Journal of field Robotics, 25*(9), 569-597.

Moradi, A., & Vagnoni, E. (2018). A multi-level perspective analysis of urban mobility system dynamics: What are the future transition pathways? *Technological Forecasting and Social Change, 126*, 231-243.

Murphy, C. (2015, January 12). Murphy, C. (2015). China's automobile sales to slow further in 2015. *The Wall Street Journal*.

Neoh, J. G., Chipulu, M., Marshall, A., & Tewkesbury, A. (2018). How commuters' motivations to drive relate to propensity to carpool: Evidence from the United Kingdom and the United States. *Transportation Research Part A: Policy and Practice, 110*, 128-148.

Nielsen, T. A., & Haustein, S. (2018). On sceptics and enthusiasts: What are the expectations towards self-driving cars? *Transport policy, 66*, 49-55.

Nkenyereye, L., & Jang, J. W. (2016). Integration of big data for connected cars applications based on tethered connectivity. *Procedia computer science, 98*, 554-559.

Noy, I. Y., Shinar, D., & Horrey, W. J. (2018). Automated driving: Safety blind spots. *Safety science*(102), 68-78.

Nvidia. (2018). *Self-Driving Safety Report* .

Nvidia. (2019). *Self-Driving cars - Nvidia Drive AGX*. Retrieved from www.nvidia.com: https://www.nvidia.com/en-us/self-driving-cars/drive-platform/hardware/

Osterwalder, A., & Pigneur, Y. (2010). *Business model generation: a handbook for visionaries, game changers, and challengers.* John Wiley & Sons.

Oxford English Dictionary. (2019, March 4). *lease definition*. Retrieved from oed.com: http://www.oed.com/view/Entry/106729#eid39576431

Oxford English Dictionary. (2019, March 4). *rent definition*. Retrieved from oed.com: http://www.oed.com/view/Entry/162527?rskey=7YybTj&result=2&isAdvanced=false#eid

Oxford English Dictionary. (2019, march 6). *Subscription definition.* Retrieved from oed.com: http://www.oed.com/view/Entry/192959?redirectedFrom=subscription#eid

Palattella, M. R., Dohler, M., Grieco, A., Rizzo, G., Torsner, J., Engel, T., & Ladid, L. (2016). Internet of things in the 5G era: Enablers, architecture, and business models. *IEEE Journal on Selected Areas in Communications, 34*(3), 510-527.

Pallant, J. (2011). *SPSS Survival guide: A step by step guide to data analysis using SPSS* (4th edition ed.). Allen&Unwin.

Payne, A. F., Storbacka, K., & Frow, P. (2008). Managing the co-creation of value. *Journal of the academy of marketing science, 36*(1), 83-96.

Payne, A., Storbacka, K., Frow, P., & Knox, S. (2009). o-creating brands: Diagnosing and designing the relationship experience. *Journal of Business Research, 62*(3), 379-389.

Porsche. (2019, September 6). *Porsche increases stake in Rimac to 15.5 percent.* Retrieved from www.newsroom.porsche.com: https://newsroom.porsche.com/en/2019/company/porsche-stake-rimac-automobili-technology-sports-car-company-zagreb-18611.html

PwC. (2018). *Mobility Insights - Analyst note volume 2: Workforce of the future.*

PwC. (2018). *Transforming vehicle production.*

PwC. (2019). *An ecosystem approach to reducing congestion.*

Qualtrics. (2019, August). *Determining.* Retrieved from Qualtrics.com: https://www.qualtrics.com/blog/calculating-sample-size/

Roland Berger. (2018). *A new breed of cars: Purpose-built electric vehicles for mobility on demand.*

Roland Berger. (2018). *Automotive Disruption Radar 4.*

Roland Berger. (2018). *E-Mobility index 2018.*

Rotmans, J., Kemp, R., & Van Asselt, M. (2001). More evolution than revolution: transition management in public policy. *foresight, 3*(1), 15-31.

SAE International. (2018, June). SURFACE VEHICLE RECOMMENDED PRACTICE - J3016 - JUN 2018 - (R) Taxonomy and Definitions for Terms Related to Driving Automation Systems for On-Road Motor Vehicles.

SAE International. (2019). *About SAE International*. Retrieved from www.sae.org: https://www.sae.org/about/

Saunders, M., Lewis, P., & Thornhill, A. (2016). *Research Methods for Business Students* (7th ed.). Pearson.

Schade, W., Krail, M., & Kühn, A. (2014). New mobility concepts: myth or emerging reality. *Transport Research Arena*.

Schafer, A., & Victor, D. G. (2000). The future of the world population. *ransportation Research Part A: Policy and Practice, 34*(3), 171-205.

ShareNow. (2019). *Your Personal Freedom — NOW.* Retrieved from your-now.com: https://www.your-now.com/our-solutions/share-now

Skeete, J. (2018). Level 5 autonomy: The new face of disruption in road transport. *Technological Forecasting and Social Change*(134), pp. 22-34.

Slaper, T. F., & Hall, T. J. (2017). The triple bottom line: what is it and how does it work? *Indiana Business Review* .

SMMT. (2018). *2018 UK automotive Sustainability Report.* Society of motor manufacturers and traders (SMMT).

Sprei, F. (2018). Disrupting mobility. *Energy Research & Social Science, 37*, 238-242.

Steg, L. (2005). Car use: lust and must. Instrumental, symbolic and affective motives for car use. *Transportation Research Part A: Policy and Practice, 39*(2-3), 147-162.

Swann Jr, W. B., Gómez, Á., Dovidio, J. F., Hart, S., & Jetten, J. (2010). Dying and killing for one's group: Identity fusion moderates responses to intergroup versions of the trolley problem. *Psychological Science, 21*(8), 1176-1183.

Tesla. (2019, July). *Autopilot*. Retrieved from www.tesla.com: https://www.tesla.com/it_IT/autopilot

Tesla Inc. (2019, March 2). *Ricarica in viaggio.* Retrieved from Tesla.com: https://www.tesla.com/it_IT/supercharger

Tesla Inc. (2019, March 1). *Superchargers*. Retrieved from Tesla.com: https://www.tesla.com/it_IT/supercharger

Thaler, R. H., & Sunstein, C. R. (2009). *Nudge: Improving decisions about health, wealth, and happiness.* Penguin.

The Boston Consulting Group. (2016). *Self-Driving vehicles, Robo-taxis, and the urban mobility revolution.*

The Boston Consulting Group. (2017). *The reimagined car.*

The Boston Consulting Group. (2018). *It's time for a new way to sell cars.*

The Boston consulting group. (2018). *The electric car tripping point.*

The Boston Consulting Group. (2018). *The Great Mobility Tech Race:Winning the Battle for Future Profits.* Retrieved from https://www.bcg.com/en-gb/d/press/11january2018-automotive-profit-pools-180934

The Boston Consuting Group. (2018). *Where to profit as tech transforms mobility.*

The New York Times. (2019, April 18). *Uber's Self-Driving Cars Are Valued at $7.25 Billion by Investors*. Retrieved from www.nytimes.com: https://www.nytimes.com/2019/04/18/technology/uber-atg-autonomous-cars-investment.html

The Verge. (2018, March 7). *Uber reportedly thinks its self-driving car killed someone because it 'decided' not to swerve.* Retrieved from www.theverge.com: https://www.theverge.com/2018/5/7/17327682/uber-self-driving-car-decision-kill-swerve

The Wall Street Journal. (2019, June 21). *EU Auto Makers Have to Sell More Electric Cars as New Emission Targets Loom.* Retrieved from www.wsj.com: https://www.wsj.com/articles/eu-auto-makers-have-to-sell-more-electric-cars-as-new-emission-targets-loom-11561139522

Thomson, J. J. (1984). The trolley problem. *Yale LJ, 94*.

Thrun, S., Montemerlo, M., Dahlkamp, H., Stavens, D., Aron, A., Diebel, J., & Lau, K. (2006). Stanley: The robot that won the DARPA Grand Challenge. *Journal of field Robotics, 23*(9), 661-692.

Toole, J. L., Colak, S., Alhasoun, F., Evsukoff, A., & Gonzalez, M. C. (2014). The path most travelled: mining road usage patterns from massive call data. *Transportation Research*.

Torrente, A., & Schlesinger, P. (2011). *Manuale di diritto privato.* Giuffrè editore.

Uber. (2019, July). *Uber Advanced Technology Group.* Retrieved from www.uber.com: https://www.uber.com/it/it/atg/

United Nations. (2019, March 1). *About the Sustainable Development Goals*. Retrieved from United Nations: https://www.un.org/sustainabledevelopment/sustainable-development-goals/

Verplanken, B. (2012). Old habits and new routes to sustainable behaviour. *Engaging the public with climate change*, Routledge.

Volkswagen. (2019, March 12). *Volkswagen plans 22 million electric vehicles in ten years.* Retrieved from www.volkswagen-newsroom.com: https://www.volkswagen-newsroom.com/en/press-releases/volkswagen-plans-22-million-electric-vehicles-in-ten-years-4750

Volvo. (2019, July). *What is autonomous driving?* Retrieved from www.volvocars.com: https://www.volvocars.com/en-kw/own/own-and-enjoy/autonomous-driving

Volvo cars. (2019, March 5). *Care by Volvo*. Retrieved from volvocars.com: https://www.volvocars.com/intl/cars/care-by-volvo

Waymo. (2019, July). *Technology*. Retrieved from www.waymo.com: https://waymo.com/tech/

Wedeniwski, S. (2016). *The Mobility Revolution in the Automotive Industry.* Springer Berlin.

Wired.com. (2018, October 18). *Why People Keep Rear-Ending Self-Driving Cars.* Retrieved from www.Wired.com: https://www.wired.com/story/self-driving-car-crashes-rear-endings-why-charts-statistics/

Wired.com. (2019, July 11). *This Lidar Is So Cheap It Could Make Self-Driving a Reality.* Retrieved from www.wired.com: https://www.wired.com/story/lidar-cheap-make-self-driving-reality/

Wired.com. (2019, March 6). *Waymo's Move to Sell Lidar Units Is a Bet on a Bigger Market.* Retrieved from www.wired.com: https://www.wired.com/story/waymo-selling-lidar-fought-uber-protect/

Yang, Q., Lim, A., & Agrawal, P. (2008). Connectivity aware routing in vehicular networks. *2008 IEEE Wireless Communications and Networking Conference* (pp. 2218-2223). IEEE.

Yeh, E., Choi, J., Prelcic, N. G., Bhat, C. R., & Heath, R. W. (2018). *Cybersecurity Challenges and Pathways in the Context of Connected Vehicle Systems.* University of Texas at Austin, Data-Supported Transportation Operations & Planning Center (D-STOP).

Yong, T., & Park, C. (2017). A qualitative comparative analysis on factors affecting the deployment of electric vehicles. *Environmental and Climate Technologies* (pp. 497-503). Riga, Latvia: Energy Procedia.

Zago, M. (2018, October 22). *The subscription model in Automotive Industry : a tool for co-creators identification.* Retrieved from Repositorio Institucional Universidade Catolica Portuguesa: https://repositorio.ucp.pt/handle/10400.14/25912

Zawieska, J., & Pieriegud, J. (2018). Smart city as a tool for sustainable mobility and transport decarbonisation. *Transport Policy*(63), 39-50.

Zmud, J., Sener, I., & Wagner, J. (2016). Self-driving vehicles: Determinants of adoption and conditions of usage. *Transportation Research Record, 2565*(1), 57-64.

VIII. APPENDIX

In this appendix all the SPSS output used in this research project will be included as a reference to the numbers mentioned in the research and to be transparent on the findings.

8.1 Measurement Model

In this section outputs for the *Cronbach's Alpha* of all the 19 factors of the measurement model will be included.

8.1.1 "Theory of planned behavior" construct

8.1.1.1 "Attitude towards Behaviour" factor

Case Processing Summary

		N	%
Cases	Valid	397	100,0
	Excluded[a]	0	,0
	Total	397	100,0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
,669	,671	4

Inter-Item Correlation Matrix

	My commute is a real hassle	The travelling that I need to do interferes with doing other things I like	Travelling is generally tiring for me becasue I have to drive	Using an autonomous driving vehicle for my journeys might improve how I use my time
My commute is a real hassle	1,000	,426	,334	,304
The travelling that I need to do interferes with doing other things I like	,426	1,000	,328	,313
Travelling is generally tiring for me becasue I have to drive	,334	,328	1,000	,322
Using an autonomous driving vehicle for my journeys might improve how I use my time	,304	,313	,322	1,000

Summary Item Statistics

	Mean	Minimum	Maximum	Range	Maximum / Minimum	Variance	N of Items
Inter-Item Correlations	,338	,304	,426	,122	1,400	,002	4

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
My commute is a real hassle	13,13	12,816	,478	,242	,585
The travelling that I need to do interferes with doing other things I like	12,72	12,805	,479	,242	,584
Travelling is generally tiring for me becasue I have to drive	13,30	12,156	,436	,191	,615
Using an autonomous driving vehicle for my journeys might improve how I use my time	12,45	13,516	,413	,171	,626

Scale Statistics

Mean	Variance	Std. Deviation	N of Items
17,20	20,534	4,531	4

8.1.1.2 "Subjective Norms" factor

Case Processing Summary

		N	%
Cases	Valid	396	99,7
	Excluded[a]	1	,3
	Total	397	100,0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
,793	,794	4

Item Statistics

	Mean	Std. Deviation	N
I would consider owning a self driving car because people would approve of my behaviour	3,89	1,722	396
I will think about using this technology if my friends/relatives reccommended it	4,48	1,492	396
I would consider owning a self driving car to show off/status symbol	3,48	1,797	396
Using this technology would show how my personality is	3,87	1,672	396

Inter-Item Correlation Matrix

	I would consider owning a self driving car because people would approve of my behaviour	I will think about using this technology if my friends/relatives reccommended it	I would consider owning a self driving car to show off/status symbol	Using this technology would show how my personality is
I would consider owning a self driving car because people would approve of my behaviour	1,000	,498	,483	,512
I will think about using this technology if my friends/relatives reccommended it	,498	1,000	,401	,454
I would consider owning a self driving car to show off/status symbol	,483	,401	1,000	,595
Using this technology would show how my personality is	,512	,454	,595	1,000

Summary Item Statistics

	Mean	Minimum	Maximum	Range	Maximum / Minimum	Variance	N of Items
Inter-Item Correlations	,491	,401	,595	,193	1,481	,004	4

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
I would consider owning a self driving car because people would approve of my behaviour	11,84	16,234	,612	,380	,738
I will think about using this technology if my friends/relatives reccommended it	11,24	18,494	,544	,310	,771
I would consider owning a self driving car to show off/status symbol	12,24	15,760	,611	,403	,740
Using this technology would show how my personality is	11,86	16,118	,654	,442	,716

Scale Statistics

Mean	Variance	Std. Deviation	N of Items
15,73	27,696	5,263	4

8.1.1.3 “Perceived Behavioural control” factor

Case Processing Summary

		N	%
Cases	Valid	397	100,0
	Excluded[a]	0	,0
	Total	397	100,0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
,608	,613	3

Item Statistics

	Mean	Std. Deviation	N
I feel like I am more in control when I am driving compared to someone else driving for me	4,99	1,483	397
I feel like I am a better driver than the average driver on the road	4,82	1,488	397
I feel like self driving tech will never be as good as an average human driver	4,06	1,643	397

Inter-Item Correlation Matrix

	I feel like I am more in control when I am driving compared to someone else driving for me	I feel like I am a better driver than the average driver on the road	I feel like self driving tech will never be as good as an average human driver
I feel like I am more in control when I am driving compared to someone else driving for me	1,000	,461	,355
I feel like I am a better driver than the average driver on the road	,461	1,000	,221
I feel like self driving tech will never be as good as an average human driver	,355	,221	1,000

Summary Item Statistics

	Mean	Minimum	Maximum	Range	Maximum / Minimum	Variance	N of Items
Inter-Item Correlations	,346	,221	,461	,240	2,083	,012	3

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
I feel like I am more in control when I am driving compared to someone else driving for me	8,88	5,995	,518	,280	,361
I feel like I am a better driver than the average driver on the road	9,05	6,626	,407	,217	,522
I feel like self driving tech will never be as good as an average human driver	9,81	6,450	,337	,130	,631

Scale Statistics

Mean	Variance	Std. Deviation	N of Items
13,87	11,959	3,458	3

8.1.2 “Technology acceptance” construct

8.1.2.1 “Expected advantage of fully self driving cars” factor

Case Processing Summary

		N	%
Cases	Valid	397	100,0
	Excluded[a]	0	,0
	Total	397	100,0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
,668	,669	3

Item Statistics

	Mean	Std. Deviation	N
I would be able to do other activities while driving a fully autonomous vehicle	4,82	1,447	397
I would be relieved from paying attention to traffic	4,61	1,531	397
I would not have to park the car myself	5,01	1,485	397

Inter-Item Correlation Matrix

	I would be able to do other activities while driving a fully autonomous vehicle	I would be relieved from paying attention to traffic	I would not have to park the car myself
I would be able to do other activities while driving a fully autonomous vehicle	1,000	,545	,397
I would be relieved from paying attention to traffic	,545	1,000	,267
I would not have to park the car myself	,397	,267	1,000

Summary Item Statistics

	Mean	Minimum	Maximum	Range	Maximum / Minimum	Variance	N of Items
Inter-Item Correlations	,403	,267	,545	,278	2,044	,015	3

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
I would be able to do other activities while driving a fully autonomous vehicle	9,63	5,760	,593	,365	,421
I would be relieved from paying attention to traffic	9,84	6,006	,483	,300	,568
I would not have to park the car myself	9,44	6,853	,375	,161	,705

Scale Statistics

Mean	Variance	Std. Deviation	N of Items
14,45	11,975	3,461	3

8.1.2.2 “New Technologies fan” factor

Case Processing Summary

		N	%
Cases	Valid	397	100,0
	Excluded[a]	0	,0
	Total	397	100,0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
,469	,467	3

Item Statistics

	Mean	Std. Deviation	N
I like trying new technologies when they are still under development	4,4836	1,55305	397
I try out new technologies when the majority has already tested them	3,2972	1,39346	397
I do not feel the need to try out new technologies	4,4156	1,68657	397

Inter-Item Correlation Matrix

	I like trying new technologies when they are still under development	I try out new technologies when the majority has already tested them	I do not feel the need to try out new technologies
I like trying new technologies when they are still under development	1,000	,159	,269
I try out new technologies when the majority has already tested them	,159	1,000	,250
I do not feel the need to try out new technologies	,269	,250	1,000

Summary Item Statistics

	Mean	Minimum	Maximum	Range	Maximum / Minimum	Variance	N of Items
Inter-Item Correlations	,226	,159	,269	,111	1,697	,003	3

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
I like trying new technologies when they are still under development	7,7128	5,963	,276	,081	,395
I try out new technologies when the majority has already tested them	8,8992	6,667	,259	,072	,423
I do not feel the need to try out new technologies	7,7809	5,040	,342	,117	,272

Scale Statistics

Mean	Variance	Std. Deviation	N of Items
12,1965	10,471	3,23595	3

8.1.2.3 "Interest in use-cases" factor

Case Processing Summary

		N	%
Cases	Valid	397	100,0
	Excluded[a]	0	,0
	Total	397	100,0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
,869	,870	4

Item Statistics

	Mean	Std. Deviation	N
I wouldn't mind travelling in a self-driving taxi without driver	4,42	1,639	397
I wouldn't mind travelling to a place of work, education or similar in a self driving car	4,75	1,573	397
I wouldn't mind travelling for short shuttle rides (like from the airport to the city) in a self driving vehicle	4,91	1,571	397
I wouldn't mind riding in a self-driving bus without driver	4,34	1,726	397

Inter-Item Correlation Matrix

	I wouldn't mind travelling in a self-driving taxi without driver	I wouldn't mind travelling to a place of work, education or similar in a self driving car	I wouldn't mind travelling for short shuttle rides (like from the airport to the city) in a self driving vehicle	I wouldn't mind riding in a self-driving bus without driver
I wouldn't mind travelling in a self-driving taxi without driver	1,000	,649	,547	,686
I wouldn't mind travelling to a place of work, education or similar in a self driving car	,649	1,000	,710	,586
I wouldn't mind travelling for short shuttle rides (like from the airport to the city) in a self driving vehicle	,547	,710	1,000	,577
I wouldn't mind riding in a self-driving bus without driver	,686	,586	,577	1,000

Summary Item Statistics

	Mean	Minimum	Maximum	Range	Maximum / Minimum	Variance	N of Items
Inter-Item Correlations	,626	,547	,710	,162	1,297	,004	4

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
I wouldn't mind travelling in a self-driving taxi without driver	14,01	17,737	,728	,564	,830
I wouldn't mind travelling to a place of work, education or similar in a self driving car	13,67	17,964	,753	,604	,821
I wouldn't mind travelling for short shuttle rides (like from the airport to the city) in a self driving vehicle	13,51	18,554	,699	,544	,842
I wouldn't mind riding in a self-driving bus without driver	14,08	17,307	,710	,533	,839

Scale Statistics

Mean	Variance	Std. Deviation	N of Items
18,42	30,477	5,521	4

8.1.3 “Car Perception” construct

8.1.3.1 “Instrumental” factor

Case Processing Summary

		N	%
Cases	Valid	397	100,0
	Excluded[a]	0	,0
	Total	397	100,0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
,676	,676	3

Item Statistics

	Mean	Std. Deviation	N
For me, the car has instrumental functions only	4,38	1,469	397
It does not matter to me which type of car I drive	4,26	1,696	397
If I did not need a car, I would dispose of it immediately	4,20	1,715	397

Inter-Item Correlation Matrix

	For me, the car has instrumental functions only	It does not matter to me which type of car I drive	If I did not need a car, I would dispose of it immediately
For me, the car has instrumental functions only	1,000	,400	,374
It does not matter to me which type of car I drive	,400	1,000	,457
If I did not need a car, I would dispose of it immediately	,374	,457	1,000

Summary Item Statistics

	Mean	Minimum	Maximum	Range	Maximum / Minimum	Variance	N of Items
Inter-Item Correlations	,411	,374	,457	,083	1,222	,001	3

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
For me, the car has instrumental functions only	8,47	8,477	,454	,206	,628
It does not matter to me which type of car I drive	8,58	6,987	,519	,270	,540
If I did not need a car, I would dispose of it immediately	8,64	7,030	,500	,253	,568

Scale Statistics

Mean	Variance	Std. Deviation	N of Items
12,84	14,518	3,810	3

8.1.3.2 "Symbolic" factor

Case Processing Summary

		N	%
Cases	Valid	397	100,0
	Excluded[a]	0	,0
	Total	397	100,0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
,804	,807	3

Item Statistics

	Mean	Std. Deviation	N
A car provides status/prestige	4,14	1,687	397
My car shows who I am	3,94	1,698	397
I may be jealous of someone with a nice car	3,76	1,846	397

Inter-Item Correlation Matrix

	A car provides status/prestige	My car shows who I am	I may be jealous of someone with a nice car
A car provides status/prestige	1,000	,691	,534
My car shows who I am	,691	1,000	,519
I may be jealous of someone with a nice car	,534	,519	1,000

Summary Item Statistics

	Mean	Minimum	Maximum	Range	Maximum / Minimum	Variance	N of Items
Inter-Item Correlations	,582	,519	,691	,172	1,332	,007	3

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
A car provides status/prestige	7,70	9,544	,699	,520	,682
My car shows who I am	7,90	9,579	,687	,510	,695
I may be jealous of someone with a nice car	8,09	9,690	,573	,329	,818

8.1.3.3 "Affective" factor

Case Processing Summary

		N	%
Cases	Valid	397	100,0
	Excluded[a]	0	,0
	Total	397	100,0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
,807	,810	3

Item Statistics

	Mean	Std. Deviation	N
I love driving	4,76	1,622	397
I know of a dream car that I would love to possess	4,70	1,784	397
I like to drive just for the fun	4,45	1,671	397

Inter-Item Correlation Matrix

	I love driving	I know of a dream car that I would love to possess	I like to drive just for the fun
I love driving	1,000	,530	,684
I know of a dream car that I would love to possess	,530	1,000	,546
I like to drive just for the fun	,684	,546	1,000

Summary Item Statistics

	Mean	Minimum	Maximum	Range	Maximum / Minimum	Variance	N of Items
Inter-Item Correlations	,587	,530	,684	,154	1,291	,006	3

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
I love driving	9,14	9,229	,688	,503	,705
I know of a dream car that I would love to possess	9,20	9,133	,586	,344	,812
I like to drive just for the fun	9,45	8,880	,699	,515	,691

Scale Statistics

Mean	Variance	Std. Deviation	N of Items
13,90	18,636	4,317	3

8.1.4 “Commute benefit” construct

8.1.4.1 “Implicit trip motivations” factor

Case Processing Summary

		N	%
Cases	Valid	397	100,0
	Excluded[a]	0	,0
	Total	397	100,0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
,763	,764	5

Item Statistics

	Mean	Std. Deviation	N
Travelling means exploring new places	5,51	1,178	397
I tend to take an unsual itinerary to reach a known destination	4,32	1,534	397
I love travelling just for relax	4,70	1,524	397
Sometimes I take a trip without a well defined purpose	4,45	1,673	397
I tend to travel for fun	4,96	1,418	397

Inter-Item Correlation Matrix

	Travelling means exploring new places	I tend to take an unsual itinerary to reach a known destination	I love travelling just for relax	Sometimes I take a trip without a well defined purpose	I tend to travel for fun
Travelling means exploring new places	1,000	,271	,373	,291	,421
I tend to take an unsual itinerary to reach a known destination	,271	1,000	,324	,369	,261
I love travelling just for relax	,373	,324	1,000	,541	,581
Sometimes I take a trip without a well defined purpose	,291	,369	,541	1,000	,496
I tend to travel for fun	,421	,261	,581	,496	1,000

Summary Item Statistics

	Mean	Minimum	Maximum	Range	Maximum / Minimum	Variance	N of Items
Inter-Item Correlations	,393	,261	,581	,320	2,228	,012	5

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
Travelling means exploring new places	18,43	21,660	,444	,220	,749
I tend to take an unsual itinerary to reach a known destination	19,62	20,034	,402	,177	,766
I love travelling just for relax	19,24	17,467	,638	,442	,681
Sometimes I take a trip without a well defined purpose	19,49	16,963	,592	,377	,699
I tend to travel for fun	18,98	18,497	,607	,423	,694

Scale Statistics

Mean	Variance	Std. Deviation	N of Items
23,94	27,916	5,284	5

8.1.4.2 "Motivation for car use" factor

Case Processing Summary

		N	%
Cases	Valid	397	100,0
	Excluded[a]	0	,0
	Total	397	100,0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
,515	,531	4

Item Statistics

	Mean	Std. Deviation	N
Public transportation requires too many changes between means of transportation	4,99	1,364	397
No public transport goes to my workplace	3,80	1,878	397
I use the car after work for personal reasons (for example shopping)	5,29	1,483	397
No incentive can persuade me to give up driving	4,09	1,669	397

Inter-Item Correlation Matrix

	Public transportation requires too many changes between means of transportation	No public transport goes to my workplace	I use the car after work for personal reasons (for example shopping)	No incentive can persuade me to give up driving
Public transportation requires too many changes between means of transportation	1,000	,206	,372	,170
No public transport goes to my workplace	,206	1,000	,172	,181
I use the car after work for personal reasons (for example shopping)	,372	,172	1,000	,224
No incentive can persuade me to give up driving	,170	,181	,224	1,000

Summary Item Statistics

	Mean	Minimum	Maximum	Range	Maximum / Minimum	Variance	N of Items
Inter-Item Correlations	,221	,170	,372	,202	2,187	,005	4

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
Public transportation requires too many changes between means of transportation	13,18	11,715	,357	,164	,410
No public transport goes to my workplace	14,37	10,234	,262	,070	,496
I use the car after work for personal reasons (for example shopping)	12,89	11,141	,361	,170	,399
No incentive can persuade me to give up driving	14,08	11,110	,271	,076	,475

Scale Statistics

Mean	Variance	Std. Deviation	N of Items
18,17	16,912	4,112	4

8.1.4.3 “Ride sharing” factor

Case Processing Summary

		N	%
Cases	Valid	397	100,0
	Excluded[a]	0	,0
	Total	397	100,0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
,822	,822	4

Item Statistics

	Mean	Std. Deviation	N
I would share a self-driving taxi (like Uber) to work with colleagues	4,66	1,665	397
I would consider commuting in a self driving taxi as my first choice of transportation to work	4,28	1,602	397
I look forward to using a self-driving ride-sharing service to work in the future	4,50	1,581	397
I would use a ride sharing service if my employer provides me with benfits like a company membership to one of these services	4,95	1,434	397

Inter-Item Correlation Matrix

	I would share a self-driving taxi (like Uber) to work with colleagues	I would consider commuting in a self driving taxi as my first choice of transportation to work	I look forward to using a self-driving ride-sharing service to work in the future	I would use a ride sharing service if my employer provides me with benfits like a company membership to one of these services
I would share a self-driving taxi (like Uber) to work with colleagues	1,000	,546	,588	,467
I would consider commuting in a self driving taxi as my first choice of transportation to work	,546	1,000	,634	,452
I look forward to using a self-driving ride-sharing service to work in the future	,588	,634	1,000	,525
I would use a ride sharing service if my employer provides me with benfits like a company membership to one of these services	,467	,452	,525	1,000

Summary Item Statistics

	Mean	Minimum	Maximum	Range	Maximum / Minimum	Variance	N of Items
Inter-Item Correlations	,535	,452	,634	,181	1,401	,004	4

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
I would share a self-driving taxi (like Uber) to work with colleagues	13,73	14,787	,643	,418	,778
I would consider commuting in a self driving taxi as my first choice of transportation to work	14,11	15,033	,660	,456	,769
I look forward to using a self-driving ride-sharing service to work in the future	13,89	14,609	,719	,522	,741
I would use a ride sharing service if my employer provides me with benfits like a company membership to one of these services	13,44	17,050	,565	,325	,811

Scale Statistics

Mean	Variance	Std. Deviation	N of Items
18,39	25,794	5,079	4

8.1.4.5 “Car sharing” factor

Case Processing Summary

		N	%
Cases	Valid	391	98,5
	Excluded[a]	6	1,5
	Total	397	100,0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
,838	,837	3

Item Statistics

	Mean	Std. Deviation	N
I would use a car sharing service (like DriveNow, Car2Go) to work with colleagues	4,56	1,549	391
I would consider commuting using a car sharing service as my first choice of transportation to work	4,45	1,611	391
I would use a car sharing service if my employer provides me with benfits like a company membership to one of these services	4,89	1,463	391

Inter-Item Correlation Matrix

	I would use a car sharing service (like DriveNow, Car2Go) to work with colleagues	I would consider commuting using a car sharing service as my first choice of transportation to work	I would use a car sharing service if my employer provides me with benfits like a company membership to one of these services
I would use a car sharing service (like DriveNow, Car2Go) to work with colleagues	1,000	,733	,584
I would consider commuting using a car sharing service as my first choice of transportation to work	,733	1,000	,579
I would use a car sharing service if my employer provides me with benfits like a company membership to one of these services	,584	,579	1,000

Summary Item Statistics

	Mean	Minimum	Maximum	Range	Maximum / Minimum	Variance	N of Items
Inter-Item Correlations	,632	,579	,733	,154	1,266	,006	3

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
I would use a car sharing service (like DriveNow, Car2Go) to work with colleagues	9,34	7,465	,745	,575	,731
I would consider commuting using a car sharing service as my first choice of transportation to work	9,45	7,187	,739	,572	,737
I would use a car sharing service if my employer provides me with benfits like a company membership to one of these services	9,01	8,656	,625	,390	,845

Scale Statistics

Mean	Variance	Std. Deviation	N of Items
13,90	16,172	4,021	3

8.1.4.6 "Utility of travel" factor

Case Processing Summary

		N	%
Cases	Valid	397	100,0
	Excluded[a]	0	,0
	Total	397	100,0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
,528	,525	3

Item Statistics

	Mean	Std. Deviation	N
Travel time during my commute is generally wasted time	3,2267	1,38133	397
My commute is a useful home-work transition	4,2317	1,47254	397
I currently use my commute time productively	4,0453	1,55146	397

Inter-Item Correlation Matrix

	Travel time during my commute is generally wasted time	My commute is a useful home-work transition	I currently use my commute time productively
Travel time during my commute is generally wasted time	1,000	,219	,194
My commute is a useful home-work transition	,219	1,000	,394
I currently use my commute time productively	,194	,394	1,000

Summary Item Statistics

	Mean	Minimum	Maximum	Range	Maximum / Minimum	Variance	N of Items
Inter-Item Correlations	,269	,194	,394	,200	2,030	,010	3

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
Travel time during my commute is generally wasted time	8,2771	6,378	,247	,062	,565
My commute is a useful home-work transition	7,2720	5,148	,403	,177	,324
I currently use my commute time productively	7,4584	4,966	,381	,168	,358

Scale Statistics

Mean	Variance	Std. Deviation	N of Items
11,5038	10,008	3,16357	3

8.1.5 “Travel time benefit” construct

8.1.5.1 “Multitasking during travel” factor

Case Processing Summary

		N	%
Cases	Valid	397	100,0
	Excluded[a]	0	,0
	Total	397	100,0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
,840	,841	4

Item Statistics

	Mean	Std. Deviation	N
I would do other activities while travelling if i didn't have to drive	5,01	1,436	397
I expect I would be more productive since my travel time would become usable time for other activities	4,84	1,413	397
It would be easier to conduct business while the car is driving itself compared to when I am driving	4,88	1,420	397
It would be easier to spend personal time with people while the car is driving itself compared to when I am driving	4,86	1,467	397

Inter-Item Correlation Matrix

	I would do other activities while travelling if i didn't have to drive	I expect I would be more productive since my travel time would become usable time for other activities	It would be easier to conduct business while the car is driving itself compared to when I am driving	It would be easier to spend personal time with people while the car is driving itself compared to when I am driving
I would do other activities while travelling if i didn't have to drive	1,000	,685	,565	,456
I expect I would be more productive since my travel time would become usable time for other activities	,685	1,000	,552	,505
It would be easier to conduct business while the car is driving itself compared to when I am driving	,565	,552	1,000	,648
It would be easier to spend personal time with people while the car is driving itself compared to when I am driving	,456	,505	,648	1,000

Summary Item Statistics

	Mean	Minimum	Maximum	Range	Maximum / Minimum	Variance	N of Items
Inter-Item Correlations	,568	,456	,685	,229	1,502	,007	4

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
I would do other activities while travelling if i didn't have to drive	14,58	13,173	,672	,520	,798
I expect I would be more productive since my travel time would become usable time for other activities	14,76	13,160	,691	,526	,790
It would be easier to conduct business while the car is driving itself compared to when I am driving	14,72	13,011	,705	,522	,784
It would be easier to spend personal time with people while the car is driving itself compared to when I am driving	14,73	13,378	,626	,451	,819

Scale Statistics

Mean	Variance	Std. Deviation	N of Items
19,60	22,246	4,717	4

8.1.5.2 "Convenient efficiency" factor

Case Processing Summary

		N	%
Cases	Valid	397	100,0
	Excluded[a]	0	,0
	Total	397	100,0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
,666	,665	3

Item Statistics

	Mean	Std. Deviation	N
I would arrive relaxed at my destination if I didn't have to drive	4,82	1,539	397
I would waste less working hours If I didn't have to drive	4,63	1,553	397
I would let the car drive itself in boring travels on highways	5,17	1,407	397

Inter-Item Correlation Matrix

	I would arrive relaxed at my destination if I didn't have to drive	I would waste less working hours If I didn't have to drive	I would let the car drive itself in boring travels on highways
I would arrive relaxed at my destination if I didn't have to drive	1,000	,490	,427
I would waste less working hours If I didn't have to drive	,490	1,000	,277
I would let the car drive itself in boring travels on highways	,427	,277	1,000

Summary Item Statistics

	Mean	Minimum	Maximum	Range	Maximum / Minimum	Variance	N of Items
Inter-Item Correlations	,398	,277	,490	,213	1,771	,010	3

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
I would arrive relaxed at my destination if I didn't have to drive	9,80	5,601	,575	,332	,432
I would waste less working hours If I didn't have to drive	9,99	6,199	,459	,245	,597
I would let the car drive itself in boring travels on highways	9,45	7,122	,407	,188	,657

Scale Statistics

Mean	Variance	Std. Deviation	N of Items
14,62	12,161	3,487	3

8.1.5.3 “Time saving” factor

Case Processing Summary

		N	%
Cases	Valid	397	100,0
	Excluded[a]	0	,0
	Total	397	100,0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
,729	,736	3

Item Statistics

	Mean	Std. Deviation	N
I wouldn't have to stop to rest on long journeys if the car could drive me to destination	4,73	1,598	397
I would get done personal matters while commuting so I could have more free time when home	4,94	1,336	397
I would feel like I am using public transportation but without wasting time to between means of transportation	4,63	1,393	397

Inter-Item Correlation Matrix

	I wouldn't have to stop to rest on long journeys if the car could drive me to destination	I would get done personal matters while commuting so I could have more free time when home	I would feel like I am using public transportation but without wasting time to between means of transportation
I wouldn't have to stop to rest on long journeys if the car could drive me to destination	1,000	,455	,424
I would get done personal matters while commuting so I could have more free time when home	,455	1,000	,568
I would feel like I am using public transportation but without wasting time to between means of transportation	,424	,568	1,000

Summary Item Statistics

	Mean	Minimum	Maximum	Range	Maximum / Minimum	Variance	N of Items
Inter-Item Correlations	,482	,424	,568	,144	1,339	,005	3

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
I wouldn't have to stop to rest on long journeys if the car could drive me to destination	9,57	5,836	,496	,248	,724
I would get done personal matters while commuting so I could have more free time when home	9,36	6,378	,601	,378	,592
I would feel like I am using public transportation but without wasting time to between means of transportation	9,67	6,278	,573	,357	,619

Scale Statistics

Mean	Variance	Std. Deviation	N of Items
14,30	12,216	3,495	3

8.1.6 “Safety concern” construct

8.1.6.1 “Objective safety performance” factor

Case Processing Summary

		N	%
Cases	Valid	397	100,0
	Excluded[a]	0	,0
	Total	397	100,0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
,759	,768	5

Item Statistics

	Mean	Std. Deviation	N
Safety is an important factor for cars	6,05	1,243	397
I highly value 3rd party safety certifications like EuroNCAP when I buy a car	5,22	1,340	397
I like the latest implementations of auto emergency breaking and safety features in cars	5,45	1,303	397
I highly value safety of the occupants concerning accidents	5,73	1,337	397
I think that computers and sensors will be safer than a human being at the wheel when the technology will be developed	4,86	1,478	397

Inter-Item Correlation Matrix

	Safety is an important factor for cars	I highly value 3rd party safety certifications like EuroNCAP when I buy a car	I like the latest implementations of auto emergency breaking and safety features in cars	I highly value safety of the occupants concerning accidents	I think that computers and sensors will be safer than a human being at the wheel when the technology will be developed
Safety is an important factor for cars	1,000	,400	,562	,608	,236
I highly value 3rd party safety certifications like EuroNCAP when I buy a car	,400	1,000	,549	,414	,162
I like the latest implementations of auto emergency breaking and safety features in cars	,562	,549	1,000	,512	,308
I highly value safety of the occupants concerning accidents	,608	,414	,512	1,000	,228
I think that computers and sensors will be safer than a human being at the wheel when the technology will be developed	,236	,162	,308	,228	1,000

Summary Item Statistics

	Mean	Minimum	Maximum	Range	Maximum / Minimum	Variance	N of Items
Inter-Item Correlations	,398	,162	,608	,446	3,745	,024	5

Scale Statistics

Mean	Variance	Std. Deviation	N of Items
27,31	22,963	4,792	5

8.1.6.2 “Perceived technology safety” factor

Case Processing Summary

		N	%
Cases	Valid	397	100,0
	Excluded[a]	0	,0
	Total	397	100,0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
,637	,642	4

Item Statistics

	Mean	Std. Deviation	N
I am worried that I will lose my driving skills by using an autonomous vehicle	4,57	1,623	397
I am worried about the legal responsibility in the case of an accident involving self driving vehicles	5,09	1,456	397
I am worried that a self-driving vehicle will make me feel less in control	4,91	1,512	397
I am worried about potential software hacking/vulnerabilities	5,10	1,556	397

Inter-Item Correlation Matrix

	I am worried that I will lose my driving skills by using an autonomous vehicle	I am worried about the legal responsibility in the case of an accident involving self driving vehicles	I am worried that a self-driving vehicle will make me feel less in control	I am worried about potential software hacking/vulnerabilities
I am worried that I will lose my driving skills by using an autonomous vehicle	1,000	,304	,373	,092
I am worried about the legal responsibility in the case of an accident involving self driving vehicles	,304	1,000	,380	,422
I am worried that a self-driving vehicle will make me feel less in control	,373	,380	1,000	,286
I am worried about potential software hacking/vulnerabilities	,092	,422	,286	1,000

Summary Item Statistics

	Mean	Minimum	Maximum	Range	Maximum / Minimum	Variance	N of Items
Inter-Item Correlations	,310	,092	,422	,330	4,572	,013	4

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
I am worried that I will lose my driving skills by using an autonomous vehicle	15,10	11,758	,335	,177	,629
I am worried about the legal responsibility in the case of an accident involving self driving vehicles	14,57	10,982	,521	,284	,497
I am worried that a self-driving vehicle will make me feel less in control	14,76	10,991	,484	,240	,521
I am worried about potential software hacking/vulnerabilities	14,57	11,983	,346	,203	,619

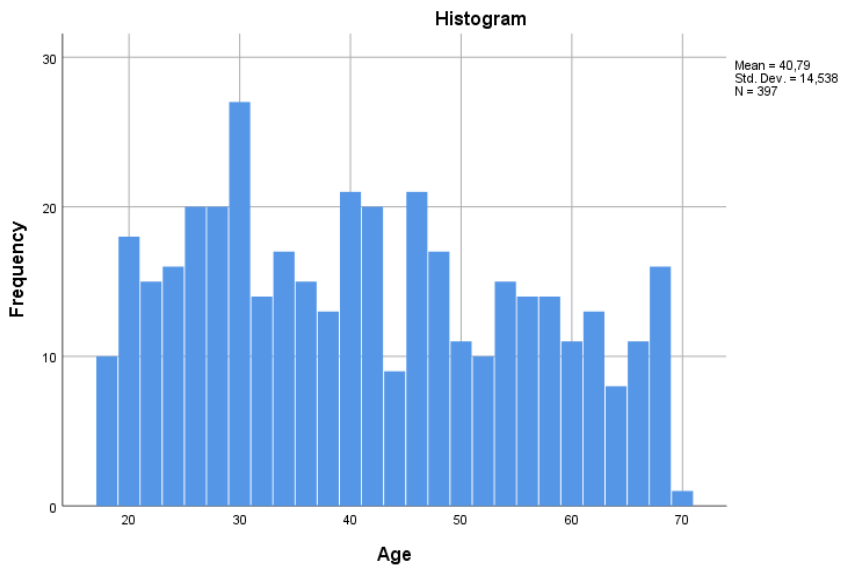
Scale Statistics

Mean	Variance	Std. Deviation	N of Items
19,67	18,127	4,258	4

8.2 Findings chapter

8.2.1 Description of the sample

8.2.1.1 Age



8.2.1.2 Education Level

Education level		
	Frequency	Percent
Less than high school	10	2,5
High school graduate	159	40,1
Bachelor university degree	119	30,0
Bachelor + Master degree	93	23,4
Doctorate	16	4,0
Total	397	100,0

8.2.1.3 Employment status

Employment status		
	Frequency	Percent
Employed full time	193	48,6
Employed part time	90	22,7
Unemployed looking for work	26	6,5
Unemployed not looking for work	11	2,8
Retired	30	7,6
Student	42	10,6
Disabled	5	1,3
Total	397	100,0

8.2.1.4 Family status

Family status		
	Frequency	Percent
Married	93	23,4
Married with at least one children	89	22,4
Divorced	32	8,1
Divorced with at least one children	14	3,5
Never married	159	40,1
Never married with at least one children	10	2,5
Total	397	100,0

8.2.1.5 City population

The city where I live have a population of:		
	Frequency	Percent
Between 50 000 and 100 000	78	19,6
Between 100 000 and 250 000	62	15,6
Between 250 000 and 500 000	48	12,1
Between 500 000 and 1 000 000	35	8,8
Between 1 000 000 and 5 000 000	36	9,1
More than 5 000 000	28	7,1
Rural area of less than 50 000	110	27,7
Total	397	100,0

8.2.1.6 Household Income

Your household income		
	Frequency	Percent
Less than €10,000	41	10,3
€10,000 - €19,999	72	18,1
€20,000 - €29,999	73	18,4
€30,000 - €39,999	53	13,4
€40,000 - €49,999	36	9,1
€50,000 - €59,999	38	9,6
€60,000 - €69,999	25	6,3
€70,000 - €79,999	10	2,5
€80,000 - €89,999	13	3,3
€90,000 - €99,999	10	2,5
€100,000 - €149,999	16	4,0
More than €150,000	10	2,5
Total	397	100,0

8.2.1.7 Owning a car

Do you own a car?		
	Frequency	Percent
Yes	328	82,6
No	69	17,4
Total	397	100,0

8.2.2 Relationship identification for economic and demographic variables

8.2.2.1 Owning a car

Test of Homogeneity of Variances

		Levene Statistic	df1	df2	Sig.
Travel_time_benefit	Based on Mean	1,073	1	395	,301
	Based on Median	1,317	1	395	,252
	Based on Median and with adjusted df	1,317	1	390,598	,252
	Based on trimmed mean	1,127	1	395	,289

ANOVA

Travel_time_benefit

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	7,818	1	7,818	7,925	,005
Within Groups	389,672	395	,987		
Total	397,490	396			

Test of Homogeneity of Variances

		Levene Statistic	df1	df2	Sig.
theory_of_planned_behaviour	Based on Mean	,331	1	394	,566
	Based on Median	,315	1	394	,575
	Based on Median and with adjusted df	,315	1	387,480	,575
	Based on trimmed mean	,344	1	394	,558

ANOVA

theory_of_planned_behaviour

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	7,723	1	7,723	7,295	,007
Within Groups	417,117	394	1,059		
Total	424,839	395			

Test of Homogeneity of Variances

		Levene Statistic	df1	df2	Sig.
Time_saving	Based on Mean	1,144	1	395	,285
	Based on Median	1,000	1	395	,318
	Based on Median and with adjusted df	1,000	1	393,259	,318
	Based on trimmed mean	1,104	1	395	,294

ANOVA

Time_saving

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	10,346	1	10,346	7,752	,006
Within Groups	527,180	395	1,335		
Total	537,525	396			

Test of Homogeneity of Variances

		Levene Statistic	df1	df2	Sig.
Symbolic	Based on Mean	,097	1	395	,756
	Based on Median	,176	1	395	,675
	Based on Median and with adjusted df	,176	1	393,687	,675
	Based on trimmed mean	,111	1	395	,739

ANOVA

Symbolic

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	9,072	1	9,072	4,183	,042
Within Groups	856,741	395	2,169		
Total	865,813	396			

Test of Homogeneity of Variances

		Levene Statistic	df1	df2	Sig.
safety_concern	Based on Mean	,001	1	395	,978
	Based on Median	,005	1	395	,941
	Based on Median and with adjusted df	,005	1	393,769	,941
	Based on trimmed mean	,002	1	395	,969

ANOVA

safety_concern

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	6,441	1	6,441	10,822	,001
Within Groups	235,105	395	,595		
Total	241,546	396			

Test of Homogeneity of Variances

		Levene Statistic	df1	df2	Sig.
technology_acceptance	Based on Mean	,036	1	395	,849
	Based on Median	,029	1	395	,865
	Based on Median and with adjusted df	,029	1	394,962	,865
	Based on trimmed mean	,032	1	395	,859

ANOVA

technology_acceptance

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	5,258	1	5,258	4,248	,040
Within Groups	488,909	395	1,238		
Total	494,167	396			

8.2.2.2 Correlation

Descriptive Statistics

	Mean	Std. Deviation	N
Ride_sharing	4,5976	1,26970	397
Interest_in_use_case	4,6052	1,38014	397

Correlations

		Ride_sharing	Interest_in_use_case
Ride_sharing	Pearson Correlation	1	,605**
	Sig. (2-tailed)		,000
	N	397	397
Interest_in_use_case	Pearson Correlation	,605**	1
	Sig. (2-tailed)	,000	
	N	397	397

**. Correlation is significant at the 0.01 level (2-tailed).

8.2.2.3 City population

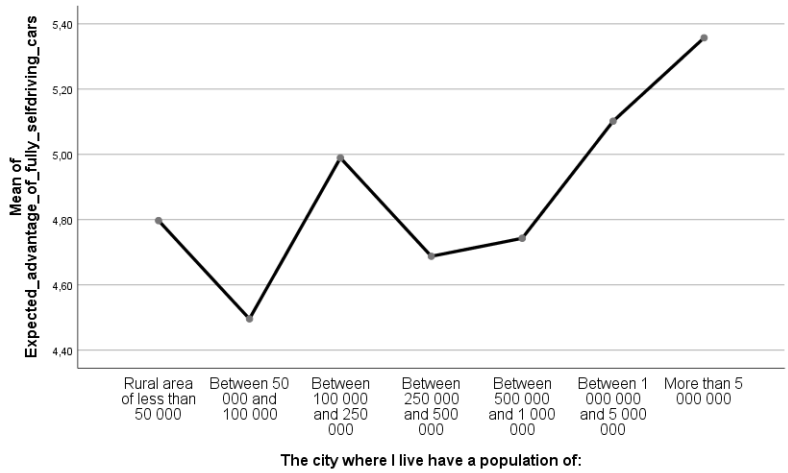
Test of Homogeneity of Variances

		Levene Statistic	df1	df2	Sig.
Expected_advantage_of_fully_selfdriving_cars	Based on Mean	,839	6	390	,540
	Based on Median	,641	6	390	,697
	Based on Median and with adjusted df	,641	6	374,151	,697
	Based on trimmed mean	,782	6	390	,585

ANOVA

Expected_advantage_of_fully_selfdriving_cars

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	22,022	6	3,670	2,835	,010
Within Groups	504,899	390	1,295		
Total	526,921	396			



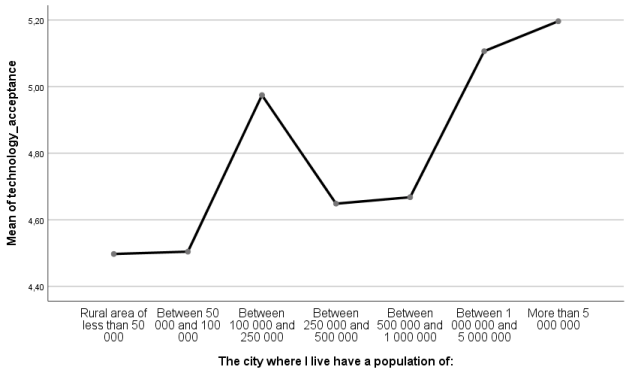
Test of Homogeneity of Variances

		Levene Statistic	df1	df2	Sig.
technology_acceptance	Based on Mean	2,457	6	390	,024
	Based on Median	2,302	6	390	,034
	Based on Median and with adjusted df	2,302	6	369,436	,034
	Based on trimmed mean	2,404	6	390	,027

ANOVA

technology_acceptance

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	25,140	6	4,190	3,484	,002
Within Groups	469,027	390	1,203		
Total	494,167	396			



8.2.2.4 Education level

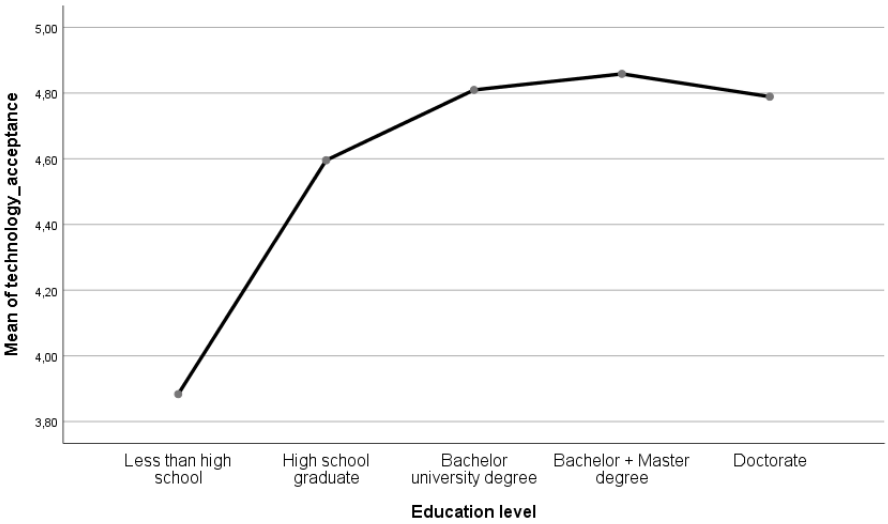
Test of Homogeneity of Variances

		Levene Statistic	df1	df2	Sig.
technology_acceptance	Based on Mean	1,867	4	392	,115
	Based on Median	1,836	4	392	,121
	Based on Median and with adjusted df	1,836	4	384,706	,121
	Based on trimmed mean	1,855	4	392	,118

ANOVA

technology_acceptance

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	12,249	4	3,062	2,491	,043
Within Groups	481,918	392	1,229		
Total	494,167	396			



8.2.2.5 Household income

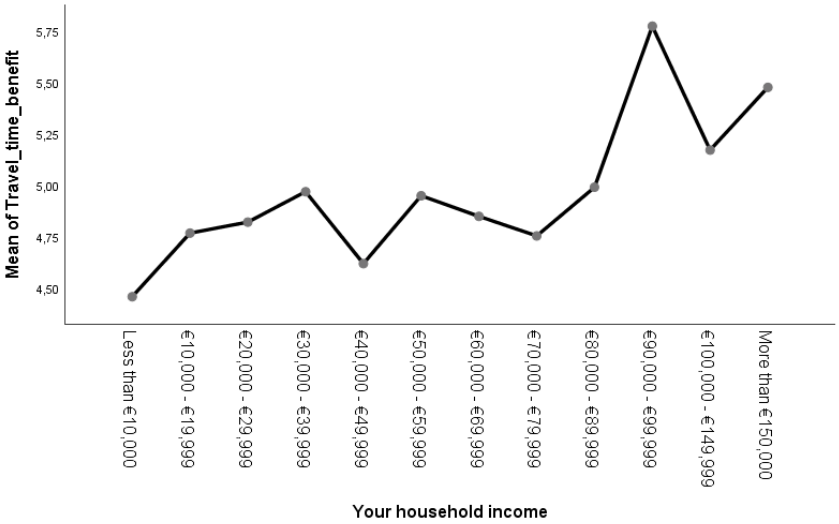
Test of Homogeneity of Variances

		Levene Statistic	df1	df2	Sig.
Travel_time_benefit	Based on Mean	,761	11	385	,679
	Based on Median	,704	11	385	,735
	Based on Median and with adjusted df	,704	11	351,960	,734
	Based on trimmed mean	,780	11	385	,660

ANOVA

Travel_time_benefit

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	24,318	11	2,211	2,281	,010
Within Groups	373,172	385	,969		
Total	397,490	396			



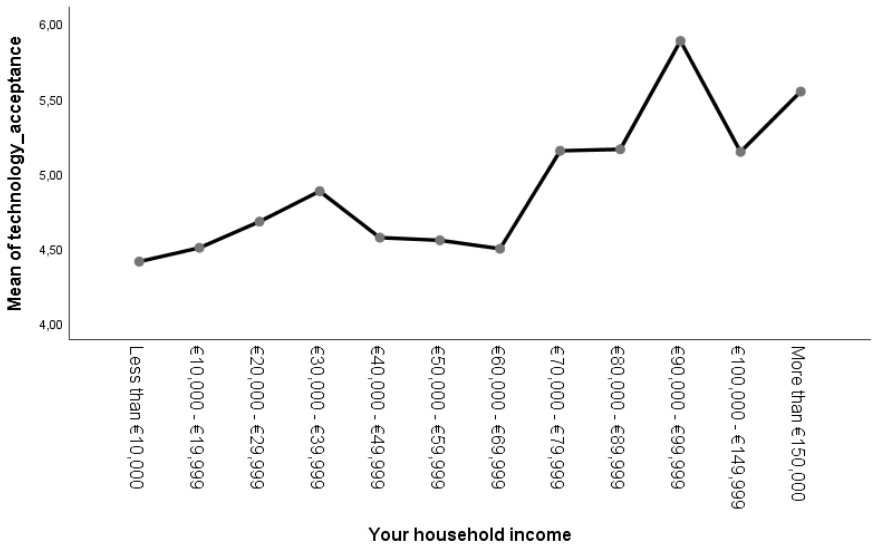
Test of Homogeneity of Variances

		Levene Statistic	df1	df2	Sig.
technology_acceptance	Based on Mean	,615	11	385	,816
	Based on Median	,582	11	385	,843
	Based on Median and with adjusted df	,582	11	375,293	,843
	Based on trimmed mean	,608	11	385	,823

ANOVA

technology_acceptance

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	39,488	11	3,590	3,040	,001
Within Groups	454,679	385	1,181		
Total	494,167	396			



8.2.2.6 Age

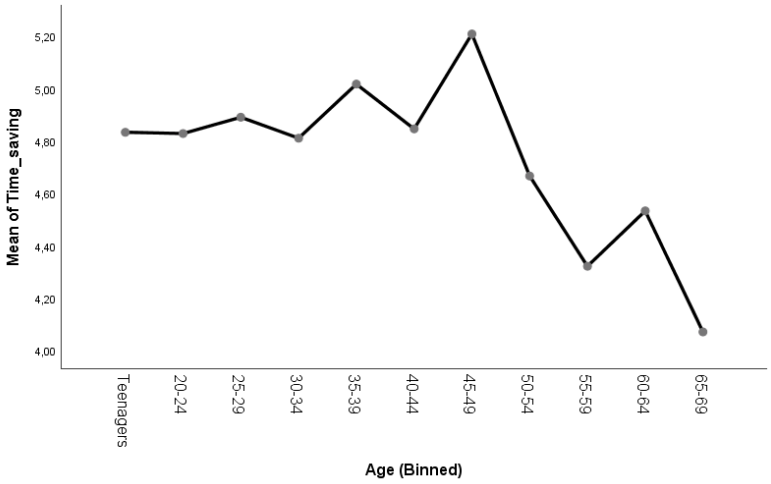
Test of Homogeneity of Variances

		Levene Statistic	df1	df2	Sig.
Time_saving	Based on Mean	1,418	10	386	,170
	Based on Median	1,183	10	386	,301
	Based on Median and with adjusted df	1,183	10	323,011	,301
	Based on trimmed mean	1,339	10	386	,207

ANOVA

Time_saving

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	33,180	10	3,318	2,539	,006
Within Groups	504,346	386	1,307		
Total	537,525	396			



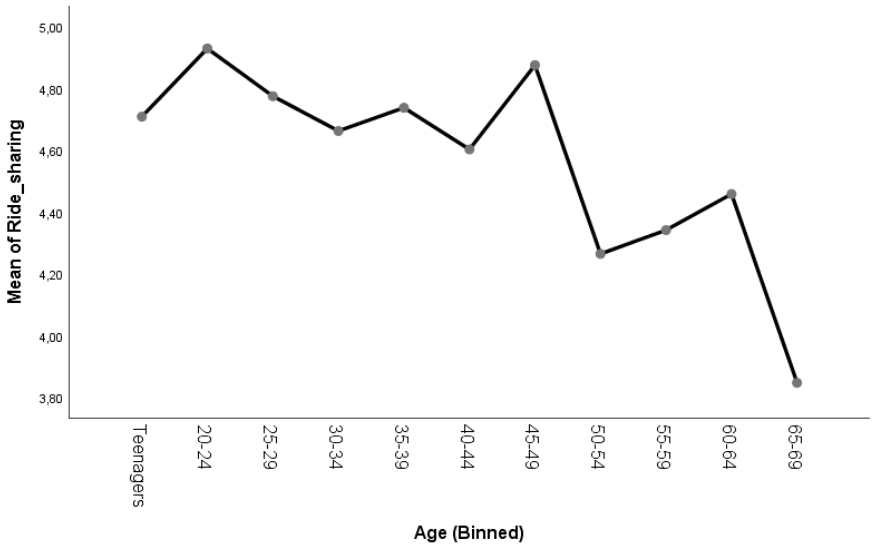
Test of Homogeneity of Variances

		Levene Statistic	df1	df2	Sig.
Ride_sharing	Based on Mean	1,352	10	386	,201
	Based on Median	1,321	10	386	,217
	Based on Median and with adjusted df	1,321	10	345,271	,217
	Based on trimmed mean	1,337	10	386	,209

ANOVA

Ride_sharing

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	32,071	10	3,207	2,042	,028
Within Groups	606,334	386	1,571		
Total	638,405	396			



8.2.3 Explaining travel time benefit

Descriptive Statistics

	Mean	Std. Deviation	N
Travel_time_benefit	4,8466	1,00188	397
Expected_advantage_of_fully_selfdriving_cars	4,8170	1,15352	397
Interest_in_use_case	4,6052	1,38014	397
Ride_sharing	4,5976	1,26970	397
car_sharing	4,6334	1,34048	391
objective_safety_performance	5,4625	,95839	397

Correlations

		Travel_time_benefit	Expected_advantage_of_fully_selfdriving_cars	Interest_in_use_case	Ride_sharing	car_sharing	objective_safety_performance
Pearson Correlation	Travel_time_benefit	1,000	,570	,618	,676	,588	,445
	Expected_advantage_of_fully_selfdriving_cars	,570	1,000	,552	,453	,334	,416
	Interest_in_use_case	,618	,552	1,000	,605	,450	,247
	Ride_sharing	,676	,453	,605	1,000	,776	,299
	car_sharing	,588	,334	,450	,776	1,000	,240
	objective_safety_performance	,445	,416	,247	,299	,240	1,000
Sig. (1-tailed)	Travel_time_benefit	.	,000	,000	,000	,000	,000
	Expected_advantage_of_fully_selfdriving_cars	,000	.	,000	,000	,000	,000
	Interest_in_use_case	,000	,000	.	,000	,000	,000
	Ride_sharing	,000	,000	,000	.	,000	,000
	car_sharing	,000	,000	,000	,000	.	,000
	objective_safety_performance	,000	,000	,000	,000	,000	.
N	Travel_time_benefit	397	397	397	397	391	397
	Expected_advantage_of_fully_selfdriving_cars	397	397	397	397	391	397
	Interest_in_use_case	397	397	397	397	391	397
	Ride_sharing	397	397	397	397	391	397
	car_sharing	391	391	391	391	391	391
	objective_safety_performance	397	397	397	397	391	397

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	objective_safety_performance, car_sharing, Interest_in_use_case, Expected_advantage_of_fully_selfdriving_cars, Ride_sharing[b]	.	Enter

a. Dependent Variable: Travel_time_benefit

b. All requested variables entered.

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	,783[a]	,613	,607	,62768	2,006

a. Predictors: (Constant), objective_safety_performance, car_sharing, Interest_in_use_case, Expected_advantage_of_fully_selfdriving_cars, Ride_sharing

b. Dependent Variable: Travel_time_benefit

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	239,785	5	47,957	121,724	,000[b]
	Residual	151,683	385	,394		
	Total	391,467	390			

a. Dependent Variable: Travel_time_benefit

b. Predictors: (Constant), objective_safety_performance, car_sharing, Interest_in_use_case, Expected_advantage_of_fully_selfdriving_cars, Ride_sharing

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.	95,0% Confidence Interval for B Lower Bound	95,0% Confidence Interval for B Upper Bound	Correlations Zero-order	Correlations Partial	Correlations Part	Collinearity Statistics Tolerance	Collinearity Statistics VIF
1	(Constant)	,653	,203		3,225	,001	,255	1,052					
	Expected_advantage_of_fully_selfdriving_cars	,162	,035	,186	4,560	,000	,092	,232	,570	,226	,145	,603	1,659
	Interest_in_use_case	,170	,031	,234	5,399	,000	,108	,232	,618	,265	,171	,536	1,866
	Ride_sharing	,201	,045	,255	4,465	,000	,113	,290	,676	,222	,142	,308	3,245
	car_sharing	,132	,038	,177	3,519	,000	,058	,206	,588	,177	,112	,398	2,515
	objective_safety_performance	,200	,037	,191	5,428	,000	,128	,273	,445	,267	,172	,810	1,235

a. Dependent Variable: Travel_time_benefit

Collinearity Diagnostics[a]

Model	Dimension	Eigenvalue	Condition Index	Variance Proportions (Constant)	Expected_advantage_of_fully_selfdriving_cars	Interest_in_use_case	Ride_sharing	car_sharing	objective_safety_performance
1	1	5,830	1,000	,00	,00	,00	,00	,00	,00
	2	,067	9,352	,06	,04	,02	,07	,13	,08
	3	,049	10,876	,03	,06	,51	,01	,12	,03
	4	,024	15,429	,15	,84	,34	,00	,01	,02
	5	,016	19,363	,35	,05	,01	,41	,31	,47
	6	,014	20,701	,41	,01	,11	,52	,43	,40

a. Dependent Variable: Travel_time_benefit

Casewise Diagnostics[a]

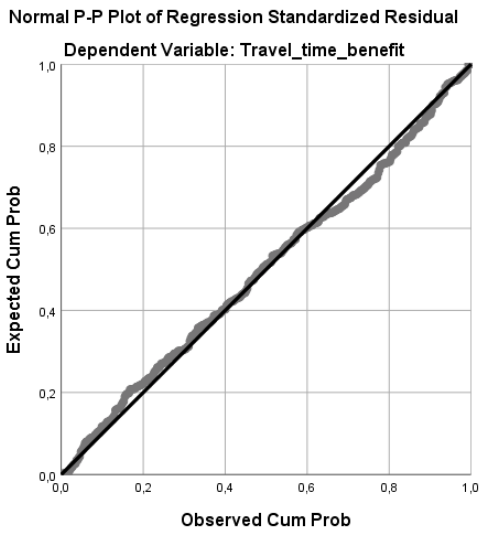
Case Number	Std. Residual	Travel_time_benefit	Predicted Value	Residual
124	3,393	6,31	4,1761	2,12948
155	3,476	7,00	4,8182	2,18183
214	-3,123	2,36	4,3216	-1,96044
220	3,992	6,33	3,8277	2,50567

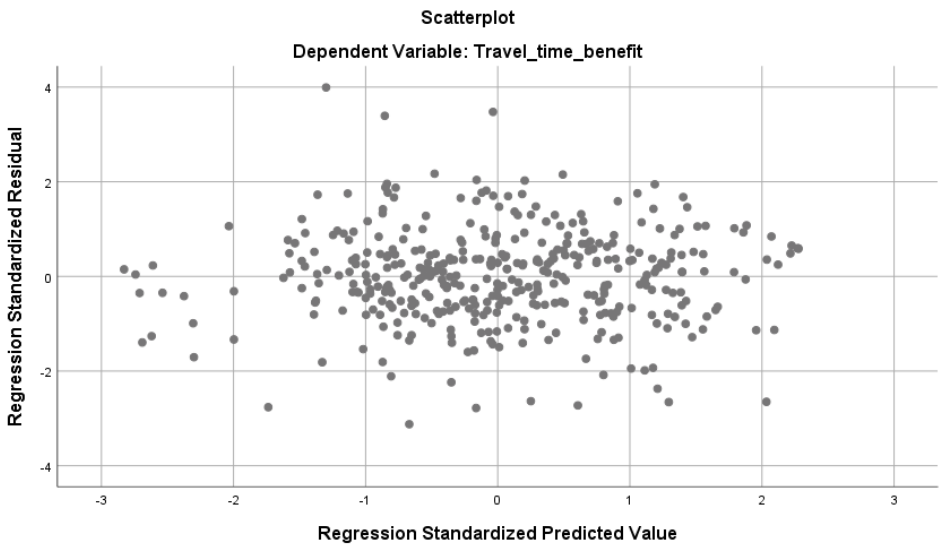
a. Dependent Variable: Travel_time_benefit

Residuals Statistics[a]

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	2,6288	6,6310	4,8532	,78459	391
Residual	-1,96044	2,50567	-,00300	,62364	391
Std. Predicted Value	-2,828	2,276	,008	1,001	391
Std. Residual	-3,123	3,992	-,005	,994	391

a. Dependent Variable: Travel_time_benefit





8.2.3.1 Hypothesis testing

ANOVA

Expected_advantage_of_fully_selfdriving_cars

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	12,161	10	1,216	,912	,522
Within Groups	514,760	386	1,334		
Total	526,921	396			

Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation
I wouldn't mind travelling in a self-driving taxi without driver	397	1	7	4,42	1,639
I wouldn't mind travelling to a place of work, education or similar in a self driving car	397	1	7	4,75	1,573
I wouldn't mind travelling for short shuttle rides (like from the airport to the city) in a self driving vehicle	397	1	7	4,91	1,571
I wouldn't mind riding in a self-driving bus without driver	397	1	7	4,34	1,726
Valid N (listwise)	397				

Correlations

		objective_safety_performance	Age
objective_safety_performance	Pearson Correlation	1	-,044
	Sig. (2-tailed)		,385
	Sum of Squares and Cross-products	363,731	-241,278
	Covariance	,919	-,609
	N	397	397
Age	Pearson Correlation	-,044	1
	Sig. (2-tailed)	,385	
	Sum of Squares and Cross-products	-241,278	83691,063
	Covariance	-,609	211,341
	N	397	397

8.2.4 Investigating on people's intentions with the Theory of planned behavior

Descriptive Statistics

	Mean	Std. Deviation	N
theory_of_planned_behaviour	4,1155	1,03708	396
multitasking_during_travel	4,8992	1,17915	397
Convenient_efficiency	4,8732	1,16240	397

Correlations

		theory_of_planned_behaviour	multitasking_during_travel	Convenient_efficiency
Pearson Correlation	theory_of_planned_behaviour	1,000	,417	,495
	multitasking_during_travel	,417	1,000	,659
	Convenient_efficiency	,495	,659	1,000
Sig. (1-tailed)	theory_of_planned_behaviour	.	,000	,000
	multitasking_during_travel	,000	.	,000
	Convenient_efficiency	,000	,000	.
N	theory_of_planned_behaviour	396	396	396
	multitasking_during_travel	396	397	397
	Convenient_efficiency	396	397	397

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	Convenient_efficiency, multitasking_during_travel[b]	.	Enter

a. Dependent Variable: theory_of_planned_behaviour

b. All requested variables entered.

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	,510[a]	,260	,256	,89459	1,801

a. Predictors: (Constant), Convenient_efficiency, multitasking_during_travel

b. Dependent Variable: theory_of_planned_behaviour

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	110,324	2	55,162	68,928	,000[b]
	Residual	314,515	393	,800		
	Total	424,839	395			

a. Dependent Variable: theory_of_planned_behaviour

b. Predictors: (Constant), Convenient_efficiency, multitasking_during_travel

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95,0% Confidence Interval for B		Correlations			Collinearity Statistics	
		B	Std. Error	Beta			Lower Bound	Upper Bound	Zero-order	Partial	Part	Tolerance	VIF
1	(Constant)	1,732	,211		8,204	,000	1,317	2,147					
	multitasking_during_travel	,141	,051	,160	2,769	,006	,041	,240	,417	,138	,120	,565	1,769
	Convenient_efficiency	,348	,052	,390	6,753	,000	,247	,449	,495	,322	,293	,565	1,769

a. Dependent Variable: theory_of_planned_behaviour

Collinearity Diagnostics[a]

Model	Dimension	Eigenvalue	Condition Index	Variance Proportions		
				(Constant)	multitasking_during_travel	Convenient_efficiency
1	1	2,951	1,000	,01	,00	,00
	2	,030	9,843	,99	,18	,15
	3	,018	12,647	,00	,81	,84

a. Dependent Variable: theory_of_planned_behaviour

Casewise Diagnostics[a]

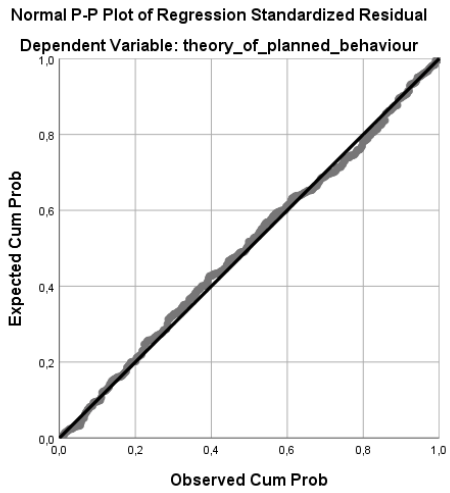
Case Number	Std. Residual	theory_of_planned_behaviour	Predicted Value	Residual
160	-3,242	2,25	5,1506	-2,90058

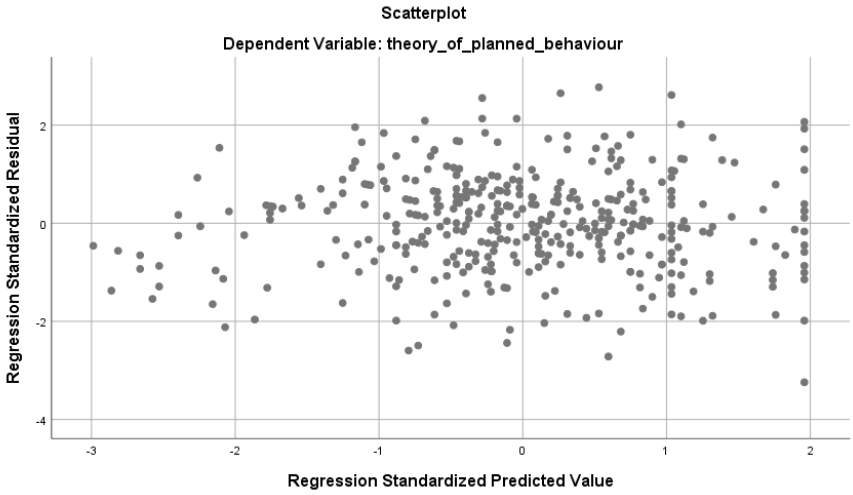
a. Dependent Variable: theory_of_planned_behaviour

Residuals Statistics[a]

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	2,5365	5,1506	4,1155	,52849	397
Residual	-2,90058	2,47983	-,00129	,89230	396
Std. Predicted Value	-2,988	1,958	,000	1,000	397
Std. Residual	-3,242	2,772	-,001	,997	396

a. Dependent Variable: theory_of_planned_behaviour





8.2.5 Hypothesis testing

8.2.5.1 H2b

ANOVA

technology_acceptance

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	68,704	51	1,347	1,092	,318
Within Groups	425,463	345	1,233		
Total	494,167	396			

8.2.5.1 H2f

Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation
I wouldn't mind travelling in a self-driving taxi without driver	397	1	7	4,42	1,639
I wouldn't mind travelling to a place of work, education or similar in a self driving car	397	1	7	4,75	1,573
I wouldn't mind travelling for short shuttle rides (like from the airport to the city) in a self driving vehicle	397	1	7	4,91	1,571
I wouldn't mind riding in a self-driving bus without driver	397	1	7	4,34	1,726
Valid N (listwise)	397				

8.2.5.2 H6a

Correlations

		objective_safety_performance	Age
objective_safety_performance	Pearson Correlation	1	-,044
	Sig. (2-tailed)		,385
	N	397	397
Age	Pearson Correlation	-,044	1
	Sig. (2-tailed)	,385	
	N	397	397