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Drivers' Perspective on the Acceptance of SAE Level 4 Self-Driving Cars: Introducing the AVA model

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Abstract

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Autonomous Vehicles (AV) are destinated to revolutionise people transportation bringing huge benefits in personal safety and environmental sustainability. In particular, Society Automotive Engineers (SAE) level 4 and level 5 cars are expected to reduce 90% of car accidents and the level of ecological print. However, to achieve those improvements an elevated acceptance level is necessary, which makes Strategic Communication a fundamental instrument to complete this revolution. This thesis analyses the acceptance of SAE level 4 self-driving cars by assuming the point of view of the drivers, including their previous personal experiences. The new Automated Vehicle Adoption model (AVA) is proposed, which states acceptance to be driven by relative utilitarian performance expectancy, current hedonic performance, perceived ease of use and automation trust. The model is tested on a sample of 321 Italian drivers who filled out an online survey and data were analysed through confirmative factor analysis and multiple regression analysis. Findings show a statistical significance influence of all the independent variable involved, with a stronger contribution by relative utilitarian performance expectancy and automated trust. In addition, contribution of current hedonic performance in negative. Finally, suggestions are given to better tailor strategic communication campaigns and about how to expand the research on this topic.

Keywords: Automated Vehicles, Self-Driving Cars, Acceptance, SAE Level 4, AVA.

Word count: 18.615

Foreword

I would like to express my gratitude to my supervisor Ilkin Mehrabov, who supported me through this challenge always trusting my ideas and my decisions. In his confidence lies the greatest praise.

This thesis is intimately dedicated to all the students who suffer from mental disorders. Even more, it is dedicated to those who have departed under a burden that none should endure alone.

Face up… make your stand
And realize you're living in the golden years!

Wasted Years, by Iron Maiden, 1986

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Abbreviation Index

ABS	Anti-lock braking system
ADAS	Advanced driver assistance systems
AI	Artificial intelligence
AIDUA	AI device use acceptance
Anova	One-way analysis of variance
AT	Automation trust
AV	Automated vehicle
AVA	Automated vehicle acceptance
BI	Behavioural intention
CHP	Current hedonic performance
CT	Contextual trust
DOI	Diffusion of innovations
DT	Dispositional trust
GSR	General Safety Regulation
L 1/2/3/4/5	Level 1/2/3/4/5
MRA	Multiple regression analysis
MRR	Matter related risk
PE	Performance expectancy
PEOU	Perceived ease of use
RUPE	Relative utilitarian performance expectancy
SAE	Society of Automotive Engineers
SDC	Self-Driving Cars
SPSS	Statistical Package for the Social Sciences
TAM	Technology acceptance model
UTAUT	Unified theory of acceptance and use of technology

1. Introduction

In recent years, the use of Artificial Intelligence (AI) to automate pre-existing products has increased dramatically. Although the attempt to design machines which emulate human behaviour has been there since the past century (Jones, 2023), the efficiency of automation is exponentially growing nowadays. One of the most used products which is being widely modified by AI is the car. Despite AI being already used in some side equipment of vehicles (ABS, adaptive cruise control etc.), the true revolution will be brought when a car can fully drive itself without needing constant human supervision.

Based on this long-term process, the expression "automated vehicles" (AVs) defines a large span of transportation means between those equipped with at least adaptive cruise control and others in which the driver is not necessary anymore. The term automation refers to a technology that plays an active role in selecting data, transforming information, making decisions, or controlling processes (Lee & See, 2004). Additionally, the expression self-driving cars (SDCs) only refers to vehicles which can actually dispense with the driver for the majority of the travel. Furthermore, although the individual term "vehicle" indicates other transportation ways than just private automobiles, previous research about this topic utilises the concept to refer exclusively to this type of vehicle (Park et al., 2021). Hence, for what concerns this thesis, the expressions 'automated vehicles' and 'automated cars' are considered equivalent.

The benefits coming from the car automation process are huge. Complete automated cars are expected to bring several advantages to the automotive world, starting with a drastic decrease in accidents (European Parliament, 2019). The various estimations fluctuate around 90% of overall accidents and 40% about the fatal ones which are caused by human errors, distraction, tiredness, drunkenness and so avoidable through a self-driving vehicle (Fagnant & Kockelman, 2015). Other major benefits rely on lighter ecological print, due to lower necessity for spare parts, a general saving on fuel consumption and a decrease in traffic flow (Foroughi et al., 2023; König & Neumayr, 2017).

Considering the cited pros, making people buy automated cars in exchange for traditional ones becomes a topic of societal interest. For this reason, AV adoption, described as the process through which individuals or groups decide to incorporate new technology into their daily lives (Rogers, 1962/2003), is a theme of growing interest in different research fields (Valor et al., 2022; Nordhoff et al., 2020). These studies fall into a general research topic which investigates the acceptance, described as the inclination or readiness to utilise, purchase, or experiment with a product or service (Kelly et al., 2022), of Artificial Intelligence in various fields and with heterogeneous applications (Mariani et al., 2021; Mitra et al., 2022; Gaczek et al., 2023). However, differently from completely new AI-based products, the presence of a pre-existing automotive market sets the stage for Schumpeter's concept of innovation as the disruptor of previous habits and best practices, leading to a more consistent resistance towards the change of a such known product as the car (Ziemnowicz, 2013; König & Neumayr, 2017). Although many things have changed since the very first cars of the late XIX century, the hands of the driver have always been on the steering wheel. Making the driver take those hands off is a challenge which deeps its roots not only in the technological field, but also in numerous other disciplines including in the field of Strategic Communication.

From this perspective, in the last few years, some research has been conducted regarding the acceptance and willingness to adopt automated and self-driving vehicles. The large majority of the previous studies analyse the phenomenon through pre-existing models like the Technology Acceptance Model (TAM) (Davis et al., 1989), the second version of the Unified Theory of Acceptance and Use of Technology (Venkatesh et al., 2012) and the AI Device Use Acceptance model (AIDUA) (Gursoy et al., 2019). Although these models lead to relevant results regarding the AV adoption issue (Nordhoff et al., 2020; Ribeiro et al., 2021; Jászberényi et al., 2022), there is room to believe that their general nature struggles to comprehend some specific details of the automotive market.

1.1 Aim of the Study

This study aims to understand which precursors anticipate people's attitudes towards the acceptance of SAE level 4 self-driving cars[1]. The choice of the specific automation level is owed to level 4 vehicles being the first to prioritise autonomous driving mode over human control. From this perspective, levels 3 and lower can be seen as incremental safety improvements, but without a true paradigm shift in the mobility conception. At the other extreme, level 5 automation is believed to be too underdeveloped, hence lacking adequate conditions to conduct a perception study with sufficient validity (BMW, 2020). Furthermore, excluding level 0, level 4 cars are expected to become the most diffused among the automated vehicles by 2035 (McKinsey, 2023).

The study proposes a new Automated Vehicles Adoption model (AVA), which individuates *relative utilitarian performance expectancy* (claiming that respondent believes AV to improve performance and safety of traditional cars), *current hedonic performance* (claiming that consumer is, to some extent, a car enthusiast), *perceived ease of use* (claiming that AV are perceived as easy to use) and *automation trust* (claiming that respondent believes AV to be safe) as determinant variables in defining the intention of adopting an L4 self-driving car. The model builds upon Akerlof's (1970) theory of information asymmetry to the extent that a too-wide gap of information between producers and consumers results in market inefficiencies and upon a consumer-centric perspective. Furthermore, conceptual contribution comes from Hall's (1996) work in the context of Cultural Studies, which revolutionised the way of studying mass communication and culture consumption. In particular, attention is given to conceptualising the model around the expertise level of the consumer, who cannot grasp, in the majority of cases, the technological details that underlie the functioning of a self-driving car. Furthermore, considering consumers' familiarity with driving, the model takes into account the chance of people evaluating AVs based on their previous experience on the road (Rogers, 1962/2003; Hoff & Bashir, 2015; Kotler et al., 2019). In this sense, influences on this thesis from other disciplines and fields like Economics, Marketing and Mass Communication are evident.

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[1] The Society of Automotive Engineers level system is detailed explained in *Paragraph 1.3.1*

The study adopts a quantitative approach based on an online structured questionnaire gathering answers from 321 Italian licensed drivers in the period between March and April 2024. Data are grouped in indexes following the new AVA model and then analysed through several preliminary tests (bivariate correlations and compare means) to end up in a multivariate linear regression. Additionally, one part of the questionnaire is designed based on a face-to-face semi-structured interview with an expert on the car enthusiasm phenomenon. Considering what explained in the previous lines as well as the available resources, this study aims to answer to the following research question.

RQ: What are the precursors of the acceptance of SAE Level 4 self-driving cars in the Italian market?

1.2 Relevance

This study contributes to the field of Strategic Communication by acquiring information to set the communicative strategy around new self-driving cars. Previously defined as the purposeful use of communication (Falkheimer & Heide, 2018), Strategic Communication is based on a long-term planning process oriented to maximise the efficiency towards an objective normally connected with a public, in this case, drivers. Furthermore, the etymology of Communication resides in the Latin expression “to put in common”. The concept can be applied to an object, an idea, or a vision (Oxford English Dictionary, 2023). However, nothing can be shared effectively without a deep understanding of the receiver involved in the process. Additionally, the most recent trends in Strategic Communication practices lead to adopting two-way pseudo-symmetric communication models (Grunig & Hunt, 1984), where target publics are involved not only as mere receivers of messages, but also as participants in the strategic discussion.

In this sense, adoption and acceptance studies are considered the consumers-to-company stream of communication and the fundamental step to acquiring knowledge to set any communicative strategy. Coming to the specific case, given that by the time this study is conducted, L4 cars are still in the development phase, this predictive adoption analysis can bring the consumers’ perspective into the actual product design discussion. Moreover, as a consequence of the cited potential benefits deriving from the diffuse adoption of automated vehicles, the treated case unites the organisational and societal approaches to Strategic Communication (Falkheimer & Heide, 2018). A more efficient strategic communication of L4 self-driving cars will bring superior productive results for companies, but also a more safe and sustainable way of travel for all road users.

1.3 Background

This section contains an overview of the essential design concepts and current development of automated cars. Although this study focuses on the topic within an acceptance framework, a basic knowledge of the product is necessary to fully understand how the research is carried out.

1.3.1 Functioning and Automation Levels

Automated cars are defined as vehicles capable of performing driving activities without the intervention of a human driver (Panagiotopoulos & Dimitrakopoulos, 2018). To different extents, AVs analyse the surrounding environment through multiple and advanced sensors and use detected data to make safe driving decisions on different levels. Although there are no fully self-driving cars on the streets yet, the process of automating individual private vehicles has already accomplished advanced steps. The process is carried out by implementing several Advanced Driver Assistance Systems (ADAS), devices and technologies which assist the driver in enhancing vehicle safety. This group includes adaptive cruise control, automatic emergency braking, lane departure warning, forward collision warning, blind-spot monitoring, rear cross-traffic alert, traffic sign recognition and similar.

Based on the extensivity of the integration of ADAS in the car, the International Society of Automotive Engineers (SAE) defined six levels of automation related to driving (Lee et al., 2022). Level 0 vehicles do not have any type of automation. In level 1 samples, ADAS help the car to accelerate and decelerate (i.e. adaptive cruise control). Level 2 introduces partial steering automation, although the driver remains responsible for operating the vehicle. Level 3 vehicles are defined as 'conditionally automated', considering their capability to travel independently in limited situations like highways. Starting from level 4, cars can properly be defined as 'self-driving', due to the high automation that allows them to travel without human intervention in the majority of contexts, including urban traffic and adverse weather conditions.

Fully automation is guaranteed in level 5 vehicles, inside which none is considered the ‘driver’ anymore and human control tools are absent (SAE International, 2014).

1.3.2 Legal Framework

In 2022 the European Union revised the General Safety Regulation (GSR) by making compulsory the presence of several ADAS on all the new cars produced after July 2024 (General Safety Regulation, 2022). Hence, complete automation is expected to be reached through implementing a broad and various complexity of ADAS which can completely substitute the driver in all their activities.

By the time this thesis is written, SAE level 2 vehicles are largely available on the market and their use is allowed in every European country, while the situation for upper levels is more complex. Regarding level 3 and superior vehicles, the European Union set a favourable legal framework through the latest updates of the previously cited GSR, released between 2019 and 2022 (General Safety Regulation, 2022). However, the regulation does not directly impose on the Member States the legalisation of level 3+ automation, which leads to a heterogeneous situation which varies from State to State.

Advocated by local automotive producers like BMW, Mercedes and Volkswagen (GreyB, 2021), in 2021 Germany approved the use of automated cars up to level 4 on public streets under specific conditions, becoming one of the world leaders in automation drive (German Federal Ministry for Digital and Transportation, 2021). In Italy, where this study is conducted, the current legal framework does not allow the registration and use of any vehicle not specifically driven by humans (Decreto Legislativo Del 28/02/2018, N. 70, 2018). This is practically translatable in the prohibition of registering and using a car belonging to SAE L3 and superior. Despite the heterogeneous and complex situation from the legal point of view, there is room to believe that, thanks to the favourable intervention of the European Union and the automotive majors, automated cars will be allowed in the whole continent in two or three years (Traton, 2024).

1.3.3 Economic Profitability

By the time this thesis is written, the market of autonomous driving is expected to be one of the most fruitfully growing in the next ten years. The latest specialised reports forecast a commercial revenue of between 300 and 400 USD by 2035 (McKinsey, 2023). However, the same article points out the necessity of designing new specific advertising and selling strategies which address the most valuable consumer groups and take into account safety concerns and other adoption barriers. Evidence of this sector's profitability also resides in the quantity and the variety of the companies which are, with a protagonist or a partnership role, involved in the development of AI-based vehicles. Among those, a group of the automotive sector majors like BMW, Mercedes, Toyota, and Hyundai could be found, but also some corporations coming from other high-tech sectors like Google, the smartphone-production giant Xiaomi and the absolute leader of computing components Nvidia (GreyB, 2021; Xiaomi, 2023; BMW 2020). This heterogeneous group of automakers and technology & component producers is studded by a galaxy of innovative start-ups and platforms which already provide the use of services like automated taxis in limited urban contexts (Cruise, n.d.).

1.4 Disposition

This Master thesis is developed through five chapters. This is the end of the introduction, which provides an overview of the treated topic and presents the aim of the study, together with its main features. In the following chapter, Literature Review and Theoretical Framework, some previous studies are summarized to show the process which led to the definition of the AVA model introduced in this thesis. The third chapter illustrates the details of the methodology through which the empirical analysis of this research is carried out. The results of the analysis are presented in the fourth chapter and finally, some conclusions about the developed hypotheses are presented in chapter five. Appendices show some technical material which was used during this study development.

2. Literature Review and Theoretical Framework

The following section synthesises the cornerstones of the previous research about consumers' attitudes towards Artificial Intelligence and Automated Vehicles acceptance. This review endeavours to portray the journey which leads to this present thesis and foremost to the novel Automated Vehicles Acceptance model which is likewise presented in this chapter.

2.1 Technology Acceptance Studies

2.1.1 Artificial Intelligence General Acceptance Studies Overview

Although the application of Artificial Intelligence in most aspects of our lives is a recent phenomenon, studies about people's attitudes towards it fall into the pre-existing field of technology acceptance (Tan & Lim, 2018). Artificial Intelligence is defined as a computational machine which can emulate human behaviour from a physical and/or neural point of view (Huang & Rust, 2021). The general aim of this group of studies is to understand the impact on consumer practices of the integration of AI into different stages of the value production chain (Puntoni et al., 2020). Mariani et al. (2021) conduct a systematic literature review isolating several clusters referring to the eight major topics connected with AI and Marketing, reserving one for the acceptance and the adoption of new technologies.

Concerning the difference between acceptance and adoption concepts, the first is defined as the inclination or readiness to utilise, purchase, or experiment with a product or service (Kelly et al., 2022), while the second is the process through which individuals or groups decide to incorporate a new technology into their daily lives (Rogers, 1962/2003). As, by the time this study is conducted, Automated Vehicles are not available yet on the market, this thesis formally focuses on acceptance rather than on adoption. However, considering the strict similarity of the concepts, knowledge connected to both of them is acquired and used throughout the course of this thesis.

As AI can be involved in a considerable number of sectors, acceptance and adoption studies target a wide group of different and heterogeneous products. Chuah et al. (2016) study the drivers correlated with the adoption of smartwatches wearable AI-based devices. Danieli et al. (2021) focus on AI taking into account the capability of AI to, partially, imitate human behaviour and human tasks. In this sense, some research has been conducted about the adoption of conversational agents in mental health issues cases (Ling et al., 2021) and in other practices belonging to the healthcare sector (Kwak et al., 2022; Reddy, 2024). Acceptance of AI-based new forms of pre-existing products is studied also in Journalism and the news market (Lindén et al., 2019; Lim & Zhang, 2022) introducing news personalisation algorithms and natural language processed articles, which show higher levels of impartiality perception (Gutiérrez-Caneda et al., 2023). Other examples come from the educational field (Fathema et al., 2015; Cukurova et al., 2019; Kizilcec, 2023), customer services (Chatterjee et al., 2021; Seo & Lee, 2021) design (Lin & Xu, 2021; Zhang et al., 2022) and agriculture (Mohr & Kühl, 2021; Wakchaure et al., 2023).

Despite the diversity intrinsically connected with the differences between the products of each commercial sector, some common drivers are found to be redundant in a large number of studies. Among the most influential and widely applicable are perceived usefulness (Andrews et al., 2021; Pelau et al., 2021; Vu & Lim, 2021), perceived risk (Huang et al., 2019; Liang et al., 2019; Song & Kim, 2020), trust (Zarifis et al., 2020; Chatterjee et al., 2021; Prakash & Das, 2021) and a general attitude towards technology in general and AI in particular (Liang et al., 2019; Kim & Kim, 2020; Kelly et al., 2022).

2.1.2 Automated Vehicles Acceptance Studies Overview

Considering the novelty of the product itself, the research field connected with Automated Vehicles acceptance is considered wide and minimally explored (Bansal & Kockelman, 2017; Nastjuk et al., 2020). This is partially connected with the effective unavailability of AVs on the market, which forces the studies to investigate opinions and attitudes rather than effective purchasing behaviour. One of the consequences of the predictive nature of this group of studies is the variability of the technical information based on which people's opinions are gathered and acceptance is forecast. Generally, in the context of a social inquiry, answers about opinions are considered more volatile than those detecting behaviours. Bernardi (2005) deems this being due to a lower resistance of opinions, compared to facts, to social desirability bias which influences the data-gathering process. It is important to point out that opinions' volatility does not diminish the validity of this body of literature, but increases the necessity of additional studies which investigate the acceptance phenomenon in heterogeneous environmental conditions.

Another criterion which preventively influenced the acceptance of AVs is the level of automation the different studies were investigating. As previously mentioned in the *Background* section, the automation of cars is measured on a scale of 6 levels (0 to 5) based on the quantity and the quality of the actions which the vehicle can execute safely without any human intervention (SAE International, 2014). With respect to the aim of this thesis, the plethora of levels impacts the acceptance phenomenon in at least two different ways. The first and most obvious regards the level of automation which each individual study investigates. It actually makes a difference to ask a driver whether they would delegate to an L3 car driving for 30 km on a straight highway stretch or, instead, whether they would get into an L5 car, which does not have a steering wheel, to be driven through New York traffic jam. Rödel et al. (2014) point out that the level of acceptance tends to decrease steadily with increased automation levels.

The second way depends on the automation level people are experiencing while participating in the study inquiry. As automation is a step-by-step process based on ADAS, drivers are increasingly using them as time goes by. This reforms the automation development process into a "technology cluster" (Stella, 2012, p. 344), a conceptual structure where affinity bonds arise between being experienced with a technology and the fact of being capable of adopting the following one (Tichenor et al., 1970). In the treated case, the technology clusters phenomenon leads to heterogenous acceptance between drivers being able to substitute the private car every time an upper-level vehicle becomes available and those who are later forced to jump the technological gap.

In one of the first studies conducted in Europe, Payre et al. (2014) assert intention to use AV is predicted by an experiential factor as contextual acceptability as well as by personal feelings and general attitudes. However, scholars are generally agreeing on the idea that these types of conclusions are variable over time. As evidence of this inconsistency, the American Automobile Association ran general inquiries about people's perceptions of Self-Driving Cars between 2016 and 2019. In the first inquiry, 63% of respondents declared to be scared by SDCs arising on the streets. The percentage increased to 71 in 2019 (American Automobile Association 2016; Othman, 2023). Lienert (2018) agrees with the point underlying that uncomforting feelings towards SDCs are growing when more details about underlying technology become publicly known. Furthermore, on a more general level, curiosity seems to have a positive effect on attitude towards the involvement of AI in some parts of the product if compared to knowledge (Zhang et al., 2022).

However, studies concerning attitudes towards AVs and SDCs first focus on relatively fixed precursors like sociodemographic variables (Othman, 2023). Scholars seem to agree with the idea that males generally manifest a more positive attitude than females towards the general topic. A very broad paper conducted by Kyriakidis et al. (2015) gathering more than 5000 questionnaire respondents from 109 countries shows people identifying with male gender would feel more comfortable in riding a completely self-driving vehicle (in that cited study's survey, an L5 SDC), while an indirect correlation bonds male gender variable with a complete aversion to fully automated drive and concern for one's physical safety. A survey conducted some years afterwards, limited to Dublin urban area, highlights that female respondents are more doubtful about potential AVs' benefits (briefly summarisable in higher road safety, better ecological impact and improved accessibility for impaired people) while agreeing on the potential risks connected with the introduction of these new products, mostly connected with safety and security issues (Acheampong & Cugurullo, 2019). However, as evidence of the high variability of AV acceptance studies results, an inquiry conducted in the UK by Ruggeri et al. (2018) does not point out any significative difference between people identifying with different genders.

Another sociodemographic variable typically crossed with AV acceptance in the previous research is age. In general, younger people look more favourable to the adoption of AVs (Krueger et al., 2016). As generally hypothesised in the normal adoption curve of new technology, young consumers are more likely to constitute a large share of the early adopters (Rogers, 1962/2003). The age variable is normally combined with the fact of living in large cities, a condition which is associated with a positive adoption attitude (Cavoli et al., 2017). Another variable inertly connected to age is the number of children living in the family of the respondent. A recent study conducted in Australia points out that the habit of taking a home-school trip between 0 and 10 km by car every day, an activity connected with the presence of one or more children in the family, is a strong precursor for SDCs adoption (Faisal et al., 2023).

However, Ruggeri et al. (2018) insist on seeing these results as generational rather than purely connected to age. In other words, conclusions about people within the same age should be considered as connected to the specific age group at that specific historical time. Hence, Ruggeri et al. hypothesise positive attitudes to be driven by belonging to digital natives, a group specifically set in the historical timeline, rather than to a generic 18-30 age band in any timeframe. Therefore, the same authors suggest that adoption studies should not be conducted based on general assumptions, but by gathering data "by and for" (Ruggeri et al. 2018, p.41) the specific population in relation to the specific product.

2.2 The Previous Models

Apart from the sociodemographic variables, research about AV and SDC acceptance is largely influenced by the Technology Acceptance Model (TAM; Davis et al., 1989). Developed by F.D. Davis between 1985 and 1989, the TAM describes the *behavioural intention* of using or not using a new technology as a dependent variable anticipated by *perceived usefulness and perceived ease of use* (Davis et al., 1989). *Perceived usefulness* refers to the extent to which the potential accepter believes the new technology improves their performance in a given situation. *Perceived ease of use* conceptualises the effort the potential accepter believes is necessary to make use of the new technology (Sharp, 2007).

The TAM roots in the Psychology field, being described as a consequence of the adaptation to the acceptance studies of two fundamental psychological theories: the Theory of Reasoned Action and the Theory of Planned Behaviour (Marangunić & Granić, 2014). The Theory of Reasoned Action asserts that human behaviour is determined by intentions, which are influenced by attitudes, referring to each one's personal attitude towards the behaviour, and subjective norms, conceptualising the external pressure to perform it (Fishbein & Ajzen, 1975). Firstly published in 1975, the theory has become a keynote in the Psychology and the Social Sciences fields. The wide usage enhances also one of the main limits, concerning the absence of a variable conceptualising the control a person believes to have on his/her behaviour. As a consequence, the same Ajzen added the variable *perceived behavioural control* to the original theory, extending it to the Theory of Planned Behaviour (Ajzen, 1985; 1991). Thanks to its simplicity and wide adaptability, the TAM has been applied to a multitude of fields and commercial sectors including the one this thesis is about. Some scholars compare the model as part of the benefit-cost dichotomy in the field of behavioural decision studies (Payne et al., 1992). In this sense, *perceived usefulness* represents the benefit, while *perceived ease of use* corresponds to the cost of the effort that is necessary to adopt the new technology (Xu et al. 2018).

Bay et al. (2018) utilise an extended version of the TAM to analyse consumers' intentions to use AVs with (L3/L4) and without (L5) human controls resulting in a valid explanatory power of the model. In the AV acceptance case, scholars agree on the strong positive effect of *perceived usefulness* while the issue regarding the relevance of *perceived ease of use* is more complex. Baccarella et al. (2020) analyse L5 AV acceptance in Germany through TAM, highlighting a robust positive effect of the *perceived usefulness* variable on *behavioural intention*, while a positive relation between the latter and the *perceived ease of use* variable is very weakly detected. Choi and Ji (2015) and Xu et al. (2018) agree on the point suggesting that the variable fails to conceptualise all the details that influence each one's perceived behavioural control, from which it derives. (Marangunić & Granić, 2014).

If, as mentioned earlier, in the TAM context *perceived ease of use* is seen as the formulation of the costs of the given behaviour, in the AV case other potential downsides go beyond the mere driver's belief of being capable of performing the right actions inside the SD. These arise from the part of control conceded by the human to the AI governing the vehicle and from the integration into the road traffic environment (Kyriakidis et al., 2015). For this reason, both Choi and Ji (2015) and Xu et al. (2018) expand TAM with supplemental independent variables. In the first case the variable is called *perceived risk*, roughly definable as the expected probability of the occurrence of a negative situation (Numan, 1998). In the latter, it is named *perceived safety*, defined by the same authors as an atmosphere characterised by a sense of relaxation, safety and comfort for both drivers and passengers

(Xu et al. 2018). This habit of extending the model with other variables is widely spread in the use of TAM (Wu et al., 2011; Marangunić & Granić, 2014), confirming the previously mentioned necessity, supported by Ruggeri et al. (2018), of adapting general models to the specific case.

One of the most influential and widely appreciated extensions of the TAM is the Unified Theory of Acceptance and Use of Technology (UTAUT), at first proposed by Venkatesh et al. (2003). Based on eight previous acceptance/adoption models, including TAM, the UTAUT postulates *behavioural intention* being anticipated by *performance expectancy*, *effort expectancy*, *social influence*, *facilitating conditions* and by the key moderators *gender*, *age*, *experience*, *voluntariness of use* (Venkatesh et al., 2003, p.447). While the first two constructs define concepts similar to those involved in TAM, *social influence* represents the external pressure willingly or unwillingly exerted by the group of significant others (i.e. family, managers, etc.). *Facilitating conditions* refers to the perceived support and resources available to an individual that facilitate the use of a particular technology, those include technical assistance, training and other supports (Venkatesh et al., 2003).

As UTAUT is developed referring to the case of the adoption of new technologies by employees inside a working environment, Venkatesh et al. (2012) extend it to the consumer acceptance study field by adding *hedonic motivation*, *price value*, and *habit* constructs. *Hedonic motivation* conceptualises the enjoyment felt by the user while experiencing the new technology, *price value* refers to the perceived cost-benefit trade-off associated with the adoption of the given technology, while *habit* refers to the degree to which an individual learns to perform a certain behaviour automatically. Following what was previously said about technology clusters (Tichenor et al., 1970, Stella, 2012), this is normally due to its coincidence with a pre-existent behaviour, possibly towards a previous technology (Kim & Malhotra, 2005). The second version of the model by Venkatesh et al. (2012) is now largely called UTAUT2 and is a dominant paradigm in the context of consumer acceptance studies.

Specifically referring to the context of automated vehicles, the UTAUT2 model has been successfully applied in different studies. Nordhoff et al. (2020) apply the UTAUT2 model to L3s acceptance in the European market, pointing out the positive effects, on different levels, of all the independent variables of the model on the analysed behavioural intention. As the conclusion of a similar study Smyth et al.

(2021) highlight that among the plethora of relevant constructs of the model, *effort expectancy* is found to be the most influential one in the studied case. Considering this variable as a development of the TAM's *perceived ease of use* (Marangunić & Granić, 2014), these results are partially in opposition to those obtained by applying the TAM model, relegating *perceived ease of use* as a barely influential factor (Choi & Ji, 2015; Xu et al., 2018; Baccarella et al., 2020). This discordance proves once again the importance of considering the results of each as strictly related to the analysed population, as a consequence of the extreme variability of the outputs of this type of product acceptance (Bernardi, 2005; Ruggeri et al. 2018).

Considering the general domain of technologies and products the model refers to, in the UTAUT2 case, as in the TAM's one, the number of extended versions is vast. Panagiotopoulos et al. (2023) analyse the acceptance of SAE L3+ AVs by European adults through an extended version of the original UTAUT model adding *perceived financial cost*, *perceived reliability/trust* and *driving enjoyment*. The first extended variable represents a more expenditure-oriented, rather than a conceptualization of the trade-off monetary benefit vs cost. The other two new variables represent two largely treated concepts in the automotive market sector.

Perceived reliability/trust refers here to the extent to which treated AVs are capable of carrying the passenger safely, protecting them by unappropriated uses of the technology and other kind of problems (Panagiotopoulos et al. 2023). As previously mentioned for the TAM, the trust in automation issue is a recurrent topic in both general AI adoption (Hoff & Bashir, 2015; Choung et al., 2022) and specific AV acceptance studies (Man et al., 2024; Zhang et al., 2024). As an independent variable concerning trust and safety is included in the new model presented in this thesis, this concept will be deeply treated in the following pages.

The other construct added by Panagiotopoulos et al. (2023) is *driving enjoyment* which conceptualises the amount of pleasure that the respondent gets from driving an automated vehicle. Although it partially represents a contextual adaptation of the *hedonic motivation* construct present in the original UTAUT2 model (Venkatesh et al., 2012), this variable gives the chance to introduce a new view which too often gets ignored in the acceptance and adoption studies of products firstly perceived as utilitarian: the symbolic and enjoyment perspective. Despite referring to traditional non-automated cars, Kaufmann (2000) shows that analysing consumption only focusing on utilitarian and rational aspects leads to a biased and partially blind understanding of people's habits towards private vehicles.

Apart from social and symbolic meanings, which are not considered in Panagiotopoulos et al. (2023), evidence shows car consumption to be influenced by the sensory and emotional pleasure the driver feels from staying inside the cockpit, perceiving the vibrations from the steering wheel, blurring because of speed (Miller 2001, as cited in Sheller, 2004). In this sense, passing from a non-automated car to an SDC entails rediscussing the described sensory and emotional feelings, which are inevitably varied by the change in the physical performance requested by the driver. However, although this and other studies (Tan et al., 2022) include variables conceptualising the driver's pleasure derived from using an automated car, the field seems to lack in the consideration of the usual feelings, connected with the use of the traditional car, which the driver has to give up on when passing to an automated one. In other words, AV acceptance studies fail to consider the emotional cost of modifying habits and feelings derived from possessing a traditional car.

In general, both TAM and UTAUT are founded on a synchronically understanding of acceptance, which analyses the process in a single time stage, without considering the situation before the introduction of the new technology. A partial solution to this issue is represented by Gursoy et al.'s (2019) Artificially intelligent device use acceptance (AIDUA) model, built upon Lazarus' (1991) cognition-emotion-motivation framework. The model determines acceptance through three timeframes: primary appraisal, where consumers understand AI relevance to themselves based on *hedonic motivation*, *social influence* and *anthropomorphism*; secondary appraisal, where outputs of the first one are considered in a sort of benefit-cost evaluation which the authors conceptualise similarly to the TAM, resulting in the generation of several emotions towards AI use in the given context; and outcome stage where willingness to accept or refuse AI-based product is determined (Gursoy et al. 2019). The authors strongly highlight that consumers tend to minimize the cognitive dissonance (Festinger, 1957) which arises between the stages of the process. This normally happens by adapting the process of each stage to the previous one, ending up with a strong influence on the initial emotions considered in the primary appraisal stage.

2.3 The New Conceptual Idea

Although AIDUA signifies a step toward a more comprehensive understanding of the acceptance phenomenon from a diachronic point of view, the three stages introduced with the model investigate how feelings and attitudes towards the new technology arise (Gursoy et al., 2019). However, again, the model does not consider the previous situation in which the AI-based product is installed. This trait unites AIDUA, which is anyway more specifically designed for AI, to TAM and UTAUT2. What these models share is to be designed around acceptance phenomena involving products which are already available by the time the data gathering is conducted (Baccarella et al., 2020). For this reason, the models tend to focus on a snapshot of the phenomenon once it happened, rather than investigating the situation in which this occurs. As Level 4 cars are not available yet, the efficiency of these previous theories, however valuable, is considered partial.

Another critique comes from the fact that the three present models are designed to be applicable to a large domain of different products and services (Davis et al., 1989; Venkatesh et al., 2012; Gursoy et al., 2019). Despite making them useful general keystones for acceptance studies, the general nature inevitably influences how specifically the models can comprehend all the features of each particular adoption case. Furthermore, the TAM and the original UTAUT are theorized around acceptance phenomena involving technologies which entirely create new markets, like informatics, where the influence of the previous context is marginal. Moreover, in the case of UTAUT, the model is firstly destined for working contexts, where the adoption of a new technology is a decision of the top management (Venkatesh et al., 2003).

Neither of these specifications adapts to the case this thesis takes in exam. Automated cars, and even more self-driving ones, constitute a disruptive change in a market that already exists (Meyer-Waarden & Cloarec, 2021) and which presents, for this reason, a wide range of habits, feelings, consuming practices, ideas, beliefs and other internal phenomena (Sheller, 2004). Furthermore, as previously discussed, the introduction of automated vehicles is a long-term process already in the act with the introduction of ADAS (SAE International, 2014). The first consequence of the long-lasting nature of this process is a continuous variability in the information and the experiences possessed by consumers. As firstly and most famously affirmed by Akerlof (1970) in his lemon market problem case, the knowledge possessed by the two sides of a transaction, in this case assimilable to car manufacturers and consumers, has a fundamental effect on the success of the operation. Furthermore, problems arise in the case of a possible inequality in the amount of the notions possessed by the sides, typical in the distribution of such a technologically complex product as SDC. In this sense, comprehending consumers' understanding of the studied product signifies a fundamental step in overcoming the resistance form which inevitably arises considering the wideness of the consumers involved (Othman, 2023).

Another evidence of the importance of extending interpretation models with construct aiming to comprehend the contextual background of the target group is brought by Stuart Hall's encoding/decoding model, the fundamental theory of Cultural Studies and one of the most influential paradigms in the Mass Communication field. Active in the 80s England, Hall reinterprets classic communication conception based on sender, message and receiver, where the comprehension of the meaning by the latter results in a mere dichotomy of success/failure (Stella, 2012). Hall (1996) introduces the concept of the message-decoding process, based on the idea that the receiver has the chance to renegotiate the understanding of the message based on its experiences and its culture. Consequently, Hall describes the negotiated reading, throughout which the receiver acquires an active role in the definition of the meaning of the message. With Hall's theory as a manifesto, Cultural Studies begin a reinterpretation of Mass Communication which goes beyond the mere sender perspective which had been the dominant point of view until the 80s. From that moment on, a deep comprehension of the experiences, culture and features of the target becomes a basic element in most of the disciplines connected to Communication, with the peak of Marketing and Public Relations which are primarily based on the understanding of the designed consumer/public (Kotler et al., 2019). Considering the wideness and the variety of the AV case, taking a step to stand from the consumer's point of view is necessary.

After these short excerpts coming from other neighbouring areas in the Communication field, it has to be cited how the evaluation of the previous context is seen as a cornerstone also in the masterpiece which sets the beginning of the adoption studies as a tradition. Indeed, the importance of the "past experiences" and "existing values" of potential adopters is considered crucial also by Rogers

(1962/2003, p.15), perhaps the most influential scholar in technology adoption studies, who builds upon these concepts in his definition of *compatibility* as a core characteristic of innovation. However, after this initial consideration, the involvement of these factors in the main acceptance model, especially those presented in the previous lines, is limited.

Hence, this thesis and the new model here presented aim to analyse acceptance of AV, and more specifically SAE Level 4 cars, from a consumer point of view. The objective is switching the focus, as Cultural Studies did in Mass Communication, to the information and the knowledge possessed by the "receiving side" of the transaction, because it is through this literacy that the product is understood and its purchase evaluated, decoding it as a message. Considering the complexity of AVs, consumers do not understand the large majority of the devices on which automated drive is based. There is room to believe that lots of people do not even have a practical understanding of what ADAS do, apart from reading it in the introduction of the social inquiries. This very limited knowledge forces potential adopters to evaluate AVs based on the criteria proper of traditional cars and, even more, seeing them as an evolution of non-automated cars. Even from a linguistic point of view, the expression 'automated cars'[2] is literally made up of something everyone is used to like cars and a new, unknown, mysterious to someone, attribute. Following this reasoning, the Automated Vehicles Acceptance (AVA) model is made up of constructs conceptualising the features of the pre-existing automotive sector and its consumers as well as others concerning the development of the new largely used AI technology and the automation of the driving functions.

Another general pillar lying underneath the AVA model is the awareness that AVs are entering a market that already exists, an element that the previous model tends to overlook. The presence of non-automated cars radically changes the meaning of non-acceptance behaviour, which is normally defined as the complete refrain from the new sector/field/practice that the disruptive technology is creating. In the treated case, refusing the acceptance does not mean staying away from driving in general, but means maintaining the use of the traditional car to fulfil the goal of going from A to B. Furthermore, a comparison between data about the Italian

[2] The Italian translation of this expression is 'auto autonome', which equally works in this analysis.

private car fleet and the number of people with a driving licence (ANFIA, 2024) points out that Italians, in general, do not possess more than one car. Hence, in the large majority of cases, acceptance of AV will include giving back the previous non-automated car. This scenario aligns with Schumpeter's vision of innovation as the deletion of existing habits and well-known practices, the willingness to maintain which can concretize in a form of resistance to AV diffusion (Ziemnowicz, 2013; König & Neumayr, 2017).

2.4 The Automated Vehicles Acceptance Model

Considering the overall scenario described in the previous lines, the model assumes the consumer's point of view by decoding automated cars in two fundamental meaning groups:

a) a known product category with its pre-existing products.
b) a new technology which is, to different extents, modifying and automating the cars the user is used to.

Both of these meaning groups impact, individually and together, the understanding of the final AV product in the eyes of the potential accepter. Each one presents factors and motivations which pull the consumer to acceptance or push him away to resistance.

From a conceptual point of view, the AVA model can then be divided into two sections or sides: an *in-market side* and an *automation side*. The *in-market side* includes several theoretical constructs framing reasons, motivations and feelings coming from the previous experience of the consumer as a driver of the traditional non-automated car. The idea here is that some drivers could be positively inclined towards AV due to their willingness to find an alternative to traditional driving. Reasons for this could be the preference of not having the steering wheel responsibility and the belief that traditional driving is becoming unsafe. Vice-versa some motivations still related to the well-known automotive world, like the pleasure of manual driving or the appreciation for a particular type of vintage cars, could lead to a form of AV acceptance resistance. The *automation side* is instead focused on capturing the key variables deriving from the novelty of the application of Artificial Intelligence and automation in this category. The main highlights focus on the perception of the ease of use of the new means of transport and on the perceived safety that AV cars express, which is considered one of the main selling points (Fagnant and Kockelman, 2015). This side also conceptualises the extent to which the potential accepter considers acceptable, or trusts, to deprive themselves the control of the car and concede it to AI.

The fact that the model is presented on different sides does not mean that the mental process which guides the possible acceptance must be analysed into two totally separate components. Reading the following paragraphs, in which the variables are presented one by one, it is clear how much the items through which the variables of one side are detected also consider concepts, ideas and prevision for the others. However, the choice of the two sides is due to the attempt to create a model which analyses the acceptance imitating the mental process which occurs in consumers' minds, with a particular focus on the quantity and the quality of the knowledge in their possession.

2.4.1 In-Market Side: Relative Utilitarian Performance Expectancy

The *in-market side* contains the constructs *relative utilitarian performance expectancy* and *current hedonic performance*, which conceptualises what from the current experience of driving can increase or reduce the chance that the consumer will have a positive behavioural intention towards the purchase of a level 4 self-driving car. *Relative utilitarian performance expectancy* (RUPE) is defined as the extent to which the respondent believes he or she will benefit from the use of L4 SDC compared to his or her current main private means of transport from a strictly utilitarian point of view. This variable partially recalls the concept of performance expectancy present in acceptance models both in TAM (Davis et al. 1989) and UTAUT (and UTAUT2) (Venkatesh et al. 2012). However, compared to these concepts, the AVA's variable builds more upon the consideration the driver has of the current situation of their driving experience.

The concept of relative advantage in this field of study is first introduced by Rogers (1962/2003) in the Diffusion of Innovation model (DOI), mostly known for the influential curve-shaped innovation adoption lifecycle, as the extent to which the new technology improves the performances of the one it substitutes (Baccarella et al., 2020). For what concerns the previous acceptance models, the focus on the relativity of the advantage comes out mainly from the theory of planned behaviour

(Ajzen, 1985; 1991) which, as mentioned in the previous sections, converges into the TAM (Davis et al., 1989). The concept is then considered in several studies about AV topic. Gkartzonikas et al. (2022) analyse the behavioural intention to adopt AVs in three American metropolitan areas by applying relativity through a redefinition of the theory of planned behaviour (Ajzen 1985; 1991) as a precursor of attitudes towards use variable.

As regards the present study, the concept of relativity is invested in a wider meaning, considering the importance given to the detection of the respondents' attitudes towards the current non-automated driving experience. Indeed, part of the items converging in this variable (n. 5, 6, 7, 8; a display of all the items is presented in *Appendix A*) are subgrouped in a second-level variable called *matter-related risk.* The connection between first and second-level variables is explained in the Methodology chapter. *Matter-related risk* is here defined as the concern the respondent has about the driving safety level at the current, mostly not automated, stage on the streets. The inclusion of this second-level construct of the overall *relative utilitarian performance expectancy* (RUPE) builds upon the need-benefit correspondence, extremely eradicated in Marketing studies (Kotler et al., 2019). As the safety gain is one of the main selling propositions of AVs (Fagnant and Kockelman, 2015), it is reasonable to believe that the effectiveness of this benefit will be higher for those consumers who perceive a higher need for safety in the current situation. It also justifies the presence of RUPE on the in-category side. Although this variable refers to the improvements brought by automation, this disposition highlights the nature of perceived benefit as interrelated with the understanding of the current situation.

H1: Relative utilitarian performance expectancy has a statistically significant positive influence on the behavioural intention (BI) to adopt the use of an L4 self-driving car.

2.4.2 In-Market Side: Current Hedonic Performance

Since the production of the very first models, cars have not been perceived just as a new way of going from A to B more quickly and safely, but also as a new leisure product which, year after year, model after model, became the centre of the new cultural world (Martin, 2019). This process results in a true car culture made up of deep emotional relations between people, vehicles and places. Among others, Miller (2001) argues car consumption extends beyond mere rational economic decisions; it encompasses aesthetic, emotional, and sensory experiences related to driving. Additionally, it involves social dynamics, including patterns of kinship, social status, living arrangements and employment. Previous studies find several themes as the basis of this phenomenon, those include stress reduction, social activities, history revival and personal knowledge increase (Martin, 2019).

A car enthusiast is a person having a strong passion, interest and hobby related to cars, both by owning or not owning one. The car enthusiast should not be intended only as the wealthy collector of cars who claims the ownership of three Ferraris and an Aston Martin DB5. Car enthusiasm is a heterogeneous phenomenon which occurs in plenty of different ways. From the simple pleasure feeling of driving, maybe without the use of modern electronic controls, to the making of cars the main topic of every discussion. From the participation in a car rally as a curious observer, to the possession of a historical Toyota MR2, one of the enthusiasts' favourite autos.

For what concerns this study, it is crucial to comprehend which feelings and connections car enthusiasts invest in their current vehicles. Analysing consumers' attitudes towards AI products in general, Zhang et al. (2022) already point out that AI enthusiasm is lower when corns products are destined for leisure and hedonic practices. Furthermore, highlighting the results of the previous research material about car enthusiasm, Sheller (2004) points out that, to different extents, the car has a role in the ego-formation process of the owner. Being able to comprehend what motivations and feelings connect an interplay between a car and its owner could add a new and essential theoretical driver to the acceptance or the refusal of the innovation of AV. Evidence shows that the analysis of the choice of the vehicle based on pure utilitarian and rational reasons overlooks the wide and decisive emotional and irrational side of the process. Scholars agree on the point that a deeper understanding of car enthusiasm can lead to better-designed policies and marketing strategies (Kaufman, 2000; Sheller, 2004), also oriented to fulfil important societal goals like those connected with AV.

The previous discoveries are supported also by the magnitude of the car enthusiasm phenomenon. The 2022 report by Hears Autos states car enthusiasts own around 50% of the global vehicle fleet (Hears Autos, 2022). Furthermore, despite the lack of a study which maps out the diffusion of car enthusiasm in Italy, where the data gathering of this thesis is conducted, the World 1st Historical Auto Report by Automobile Club Italia states the presence of more than 4,3 million historical autos in the country (roughly 10% of the whole national fleet), while 10 million cars are aged 10 or more years (25% of the fleet) (ACI, 2023). These numbers suggest the presence of a diffused car enthusiasm in Italy, which justifies the inclusion of a variable conceptualising this phenomenon in the AVA model.

The *current hedonic performance* variable (CHP) is defined as the extent to which the respondents identify themselves as car enthusiasts. The construct is built upon a group of items measuring the level of non-rational connection between the respondent and their current private vehicle, or the one they drive more frequently. Despite the similar name, The AVA's CHP should not be confused with UTAUT2's hedonic motivation. The variable proposed in the latter refers to the pleasure or excitement felt by the respondent in the use of the technology which is the object of the acceptance study (Venkatesh et al., 2012). Contra, CHP refers to the degree of excitement and personal/emotional connection between the respondent and the car they are using *before* passing to the technology analysed by the AVA model. Considering this difference, as well as the largely cited Schumpeter's concept of innovation as previous habits and practices deletion (Ziemnowicz, 2013; König & Neumayr, 2017), the emotional aura connecting a driver to its current vehicle is expected to act as a resistance towards the acceptance of a new extremely developed car.

H2: Current hedonic performance has a statistically significant negative influence on the behavioural intention (BI) to adopt the use of an L4 self-driving car.

2.4.3 Automation Side: Perceived Ease of Use

The *automation side* contains the constructs *perceived ease of use* and *automation trust*, conceptualising which elements deriving from the use of the new automation technology in vehicles can increase or reduce the chance that the consumer will have a positive behavioural intention towards the purchase of an L4 SDC. *Perceived ease of use* is defined as the extent to which the respondent believes the new AV is simple to use. Differently from the previous cases, this variable overlaps with the one presented by Venkatesh et al. (2012) in UTAUT2. However, since the very first appearance in acceptance studies as part of the TAM, the perceived ease of use variable constitutes a readaptation of the perceived behavioural control construct introduced within the theory of planned behaviour (Ajzen, 1985), a clarification about the meaning the variable assumes in the AVA model context is necessary. Both perceived behavioural control and perceived ease of use aim to conceptualise a shared psychological instance. However, despite their similarity, the perspectives assumed by these concepts are opposite. Indeed, the target of the analyses conceptualised through perceived ease of use is the studied technology, while perceived behavioural control invites respondents to reflect on their own abilities. Based on this distinction, it has been decided to include *perceived ease of use* in the AVA considering perceived behavioural control as more sensible to social desirability bias during the data-gathering phase. The choice of this perspective also justifies the inclusion of this variable within this side of the model.

H3: Perceived ease of use has a statistically significant positive influence on the behavioural intention (BI) to adopt the use of an L4 self-driving car.

2.4.4 Automation Side: Automation Trust

The involvement of constructs summarizing trust in AV acceptance and adoption studies is wide. Hajiheydari and Ashkani (2018) demonstrate that consumer who trusts a specific technology tends to show a more positive attitude towards it. Zhang et al. (2024) reinforce this assumption by showing the relevance of the trust variable in the context of an extended UTAUT2 model. With a specific connection to the treated topic, Panagiotopoulos et al. (2023) define trust as the extent to which AVs are capable of carrying passengers safely, protecting them by unappropriated uses of the technology and other kinds of problems. However, considering that the most developed models of SDCs are not available yet, the exploration of the trust construct needs to take into account the different factors which can contribute to the overall trustability perception of L4 SDCs. Also from a general point of view, the word trust labels a heterogeneous and differently-originated group of feelings and emotions. Aiming to map the wideness of trust in automation, Hoff and Bashir (2015) analyse the previous studies by identifying three factors contributing to variability in trust between humans and automation: the operator, the situation where the interaction happens and the automated system. The three are respectively connected with three interdependent trust layers: dispositional trust, learned trust and contextual trust. Dispositional trust refers to the respondent's general trust in automation, no matter the context or the specific product. Situational trust refers to the level of trust that the user feels towards a specific product in a specific context, in this case, L4 SDC. Learned trust refers to the past experiences the user had with the specific product (Hoff and Bashir, 2015).

Wide is the plethora of factors which can influence dispositional trust. The same authors who defined the 3-layer structure list sociodemographic variables like age, gender, education and personality. However, considering the worldwide interest in the SDC topic, studies reveal an important impact of negative, rather than positive, news about automation failures during both tests and ordinary situations on people's intention to accept and adopt SDC (Bazilinskyy et al., 2015). As in the case treated in this thesis, any L4 SDC is not available yet, little contribution can be brought by the learned trust layer. However, considering the level-by-level development of automation in the vehicle sector (SAE International, 2014), owning an L1 or L2 automated car could act as a partial experience of the more advanced models. This dynamic also finds support in the previously explained technology cluster theory (Tichenor et al., 1970; Stella, 2012) and in empirical evidence revealing drivers currently experiencing the use of four or more ADAS in their daily driving is predicted to be SDC early adopters (Faisal et al., 2023). Nevertheless, experiencing L1/2 automation as a trial of L4/5 should not be seen as a true learning phase, but rather contributes to a general attitude towards a broad and large innovation. Hence, in the context of the AVA model, learned trust is assimilated to *dispositional trust* (DT), which is listed as a second-level contributor to the first-level variable *automation trust*.

For what concerns *contextual trust* (CT), the layer conceptualises, in the AV case, the perceived safety and reliability of the automation system of the specific L4 SDC. Differently from *matter-related safety* presented on the other side of the model, this construct refers to the risk deriving from a potential failure of the automation system. Although following this reasoning a possible name for this variable could be *automation-related safety*, to maintain consistency with Hoff and Bashir's (2015) work, *contextual trust* is included in the AVA model as a second-level contributor to first-level variable *automation trust*. In the context of the AVA model, the *automated trust* variable refers to the attitude of the respondent towards ceding the control of the vehicle to artificial intelligence, with a particular focus on safety concerns deriving from a potential failure of the latter. Hence, *automated trust* finds a place in the automation side of the AVA model.

H4: Automation trust has a statistically significant positive influence on the behavioural intention (BI) to adopt the use of an L4 self-driving car.

2.4.5 Behavioural Intention and the AVA Model Presented

Behavioural intention is the dependent variable of the AVA model and is generally defined as the measure of the respondent's readiness and willingness to perform a specific behaviour (Ajzen, 1991). This variable, first presented by Ajzen (1985) in the TPB, is proposed by Venkatesh et al. (2012) in the UTAUT2 model as a direct precursor of use behaviour. Considering what was previously stated about the predictive nature of this study, AVA's *behavioural intention* is defined as the measure of the respondent's acceptance of L4 self-driving cars.

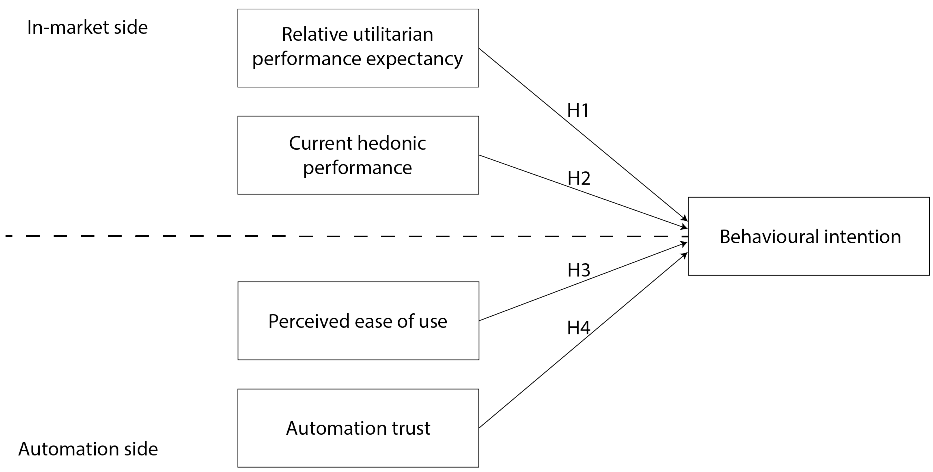

Figure 1. The Automated Vehicle Acceptance model

Considering L4 SDCs to be still in the development phase, some constructs are voluntarily excluded by the AVA model. The first of this group is a variable summarizing the impact of the price of the new vehicle on the acceptance process. This parameter, present for example in UTAUT2 (Venkatesh et al., 2012) is not taken into consideration due to the impossibility of determining an indicative price range for L4 SDC. Furthermore, whether this was possible, it would not be precise to ask respondents to make a decision based on a predicted price compared to unknown living conditions and purchasing power they could reach in the following 5 years.

Another construct excluded due to the scares validity to make respondents predict others' opinions is *social influence*. Largely included in previous models like UTAUT2 (Venkatesh et al., 2012) and AIDUA (Gursoy et al., 2019), social influence captures the positive or negative effect of respondents' significant others on the acceptance process. However, investigating this influence means asking people to imagine their response to someone else's potential thoughts; something extremely hard and exposed to biases from a statistical inquiry perspective (Bernardi, 2005).

3. Methodology

The following chapter focuses on the techniques and instruments that have been used in this study. The first part concentrates on the research design process with a focus on the structurization of the survey, the sampling method and the data gathering process. The second part illustrates how the data analysis is conducted and reflects on reliability and validity, as well as on the ethical issues of this study.

3.1 Research Design

The present study mainly leverages on a quantitative approach to verify the hypothesis displayed in the previous chapter. The choice is due to the commonality with the large majority of previous studies in this field, based on the same approach (Acheampong & Cugurullo, 2019; Park et al., 2021; Baccarella et al., 2020) Faisal et al., 2023), and oriented to produce numeric-data-based knowledge, particularly suited for today's personalized advertising communication practices (Lombardi & Mindshare, 2022). Being the hypothesis based on a re-modulation and conjunction of previous theories coming from various fields, the approach used in this piece of research can be defined as deductive. From a philosophical point of view, this study is rooted in a positivistic paradigm, considering the character of objectivity which is attributed to the results (Bryman, 2004/2016).

The goal of this study is to understand the precursors of the acceptance of not-yet-available SAE level 4 self-driving cars. The selection of this specific automation level is predicated on the prioritization of autonomous driving mode over human control, with Level 4 vehicles being the initial focus in this regard. Consequently, Levels 3 and below may be viewed as incremental safety enhancements rather than representing a fundamental paradigm shift in the conceptualisation of mobility. On the other side, Level 5 automation is considered to be insufficiently developed, thereby lacking the requisite conditions for conducting perception studies with minimal validity (BMW, 2020). The analysis results can be relevant to better tailor a communication campaign to emphasize the distribution of this product. Considering the potential benefits of the mass adoption of SDCs, including the reduction of accidents, pollution and massive urban traffic as well as a major accessibility for physically impaired people (Foroughi et al., 2023), the topic treated in this thesis is relevant for both private organisational and public societal goals (Falkheimer & Heide, 2018).

3.2 Survey Design

Data are gathered through an online survey answered by 322 Italian drivers aged 18+. The survey is designed in Italian, considering the sample and the country the study is conducted in, and in English, for a larger comprehensibility into the scientific community. The correspondence between the two versions is assessed by a group of common observers and by a proficient evaluator who graduated in Language studies at a Master's level claiming more than 40 years of experience in English teaching to Italian students.

The survey is composed of 37 items, distributed between a control variable (how long have you had your driving licence?), the sociodemographic variables (age, gender, education, family dimension), one yes/no question (previous accidents) and 31 questions based on a based on the Likert scale (Leavy, 2022) in which the respondent has to specify his position towards a sentence on a 5-point scale between 1 (strongly disagree) to 5 (strongly agree). Revilla et al. (2013) indicate the Likert scale as the optimal choice to avoid biases a confusion in the eyes of respondents. The choice is utterly justified by the use of this same scale in most of the previous studies concerning acceptance and adoption (Haboucha et al., 2017; Shabanpour et al., 2018, Meyer-Waarden & Cloarec, 2021; Irannezhad & Mahadevan, 2022). Finally, the Likert scale inertly contains the conversion of the answers into numeric scores, which simplifies the following creation of summative indexes reflecting the AVA model's variables.

The plethora of items is the result of a union of pre-tested scales from previous studies and some novelty designed to conceptualise the innovative constructs of the AVA model; the complete list of items and their origin is available in *Appendix A*. Plus, the group of questions conceptualising the *current hedonic performance* variable are based on a qualitative interview. As this variable has the scope of measuring to what extent each respondent is a car enthusiast, a car enthusiast was interviewed as an expert observer of the car enthusiasm phenomenon. The interviewee was conveniently chosen among the participants of the Midnight Club Toscana Rally of Historical & Sports Car held in Pisa, Italy on February 16th 2024. The interview was conducted to map out the features of car enthusiasts and to define the Likert scale-based items which are included in the online survey. The interview lasted 16 minutes and was conducted in Italian based on a semi-structured script available in *Appendix C* of this document. The recording of the interview was manually transcribed, and translated into English and the data were treated anonymously on the base of the informed consensus of the interviewee (see *Appendix D*).

Considering the willingness to focus on the future majority of accepters/adopters (Rogers, 1962/2003), the proposed items aim to capture the respondents' personality traits, which normally distinguish the early adopters, as well as a wide group of experiences, feelings and thoughts. For this reason, questions defining the *relative utilitarian performance expectancy* variable score largely require a reflection on previous experience and traditional driving safety perception. One of the questions belonging to the *automation* (*dispositional*) *trust* group is based on a slightly different scale. Question n.22 asks the respondents about the number of ADAS equipped in the car they mostly drive. Being impossible to readapt this stimulus on a Likert scale, answering options are tailored on a 1 to 5 scale as follows: 1 - It has no ADAS; 2 It has one ADAS; 3 – It has some ADAS; 4 – It has the main ADAS; 5 – It has most of the ADAS. The choice of this scale is justified by the compatibility with the Likert one in the summative index calculation process.

Besides the items forming the variable indexes, sociodemographic variables are gathered. Apart from a general evaluation of the actual sampling, the relevance of these variables in the study is given due to comparison with previous research (Kyriakidis et al., 2015; Faisal et al., 2023; Othman, 2023). Furthermore, considering the importance of evaluating age not as a mere life-phase indicator, but as an index of the generation to which the respondent belongs (Ruggeri et al., 2018), mapping out demographical variables is essential. Finally, reflecting on the possible applications of this study's knowledge as the basis for a communication campaign and considering the tools of targeted advertising through which campaigns are nowadays conducted, the availability of specific numeric sociodemographic data is precious for more precise targeting. For the same reason, the yes/no variable for previous accidents is gathered. Although not included in the AVA model, due to the struggle of evaluating the details of the event with a quantitative survey, the experience of a previous car crash can influence a user's need for improved safety (Shabanpour et al., 2018). Furthermore, this data is easily available, considering the databases of public administration and insurance companies, which can be involved in societal campaigns promoting the acceptance of SDCs.

Differently from the list presented in *Appendix A*, the items are presented in the survey ordered in meaning groups, no matter the reference variable. Also, as suggested in Bernardi (2005), the questions are presented starting from the less sensitive to the more personal ones, concluding with the sociodemographic group. The survey begins with an introductory text and a GDPR-compliant explanation of the procedures and scopes of the data treatment (both available in *Appendix B*). To continue beyond the first page, it is necessary to fill out the control variable "age of driving licence". SDCs development and SAE level system are explained in a brief text before the first relevant question.

The survey is realised through Sunet Survey, a software officially provided and suggested by Lund University. Sunet Survey allows a developed design, both functional and practical, of each part of the questionnaire and automatically orders the answer recordings in Microsoft Office Excel and IBM Statistical Package for the Social Sciences (SPSS). Sunet Survey connects the survey to an online URL which can easily be shared across the internet. The data gathering process is carried out by publishing the survey link shared online on the Facebook, Instagram and LinkedIn profiles of the researcher as well as in a plethora of blogs, forums and social media groups regarding cars and car enthusiasm. Plus, some posters bearing a QR code leading to the survey are attached around the country. The data are gathered for a month between March 18th 2024 and April 18th 2024.

3.3 Sampling

The present study is based and conducted in Italy, due to the technical and financial resources in possession of the researcher. The choice is mainly connected with a linguistic issue. Expanding the research to a pan-European level would require providing a translation of the data-gathering instrument in all the spoken languages spoken on the continent. Considering English proficiency is not guaranteed in all countries (Statista, 2019), providing the survey only in this language would lead to an implicit reduction of the sampling to the most educated people. Furthermore, extending the target population to which the sample refers without increasing the sample dimension would compromise the overall validity of the study. In the case of a mono-country study, the sampling ratio is higher, resulting in a higher generalizability and validity of the study. Additionally, considering this is a quantitative study based on a structured survey, in the case of high relevance of the findings, the research could be easily reproduced and exported to other countries, using supplementary resources like additional funds, expertise in other countries' automotive sector and multiple language proficiency. The sample is limited to people owning a B-type driving license (conventional vehicles up to 8 seats, destinated to passengers), which further limits the group to 18+ age, the minimum to obtain the license in Italy. Furthermore, considering that participation in the inquiry requires a computer or a mobile phone connected to the internet, the sample is also reduced to people able to use these devices.

Hence, the group of respondents is obtained through convenience sampling, which means people are selected under their accessibility (Bryman, 2004/2016). Considering this is a non-probability sampling method, the sampling error, concerning the differences between the sample and the population from which it is extracted, is expected to be higher. This is partially compensated by the performing of a pilot study with the chosen sampling method, useful to verify the avoidance of excessive polarization in any of the variables, and to correct small errors and imprecisions in the questionnaire. As suggested by Wrench et al. (2019) the pilot study consists of 5-10% of the final sample, meaning in this case 15 to 30 respondents, not included in the final inquiry. In the present case, the pilot study gathered answers from 30 respondents, resulting in some small changes concerning how the items were presented and minor wording mistakes. Furthermore, the statistical significance of the findings is assured by additional tests carried out during the analysis process of the gathered data (Pallant, 2020).

Many ways are suggested to determine the sample size. Considering the main analysis performed in this study is the testing of a multiple regression model, Tabachnick & Fidell (2013) propose the general rule of sample size being more than 50 + 8p, where p represents the number of predictors (independent variables) of the tested model. In the treated case, this results in 82 respondents. However, due to the novelty of the AVA model, a confirmative factor analysis is considered necessary to evaluate the consistency of the designed constructs. Again, Tabachnick & Fidell (2013) suggest a minimum number of 300 answers for a valid performance of factor analysis. On this basis, the sample size for this study is determined by a minimum of 300 respondents, ending up with 321 valid recordings.

3.4 Analysis Procedure

The data analysis is performed through the IBM Statistical Package for the Social Sciences (SPSS). The first step is to check the gathered data looking for possible mistakes or outliers. These are already limited by the fact that all the survey questions are structured in a defined number of answers, not including the "other" option and that the respondent is required to type something only in the "year of birth" question. However, a general screening of the data is executed through descriptive statistics and frequency functions on the data (Pallant, 2020).

The answer variables are then grouped into the indexes of the AVA model, as presented in *Appendix A*, through the sum of the points resulting from the Likert scale of each question. Second-level variables are added to the respective first-level indexes. The internal reliability of the proposed indexes is verified through the evaluation of Cronbach's α parameter, which marks the index as reliable when the value is above 0,7 (Pallant, 2020). At this point, some of the formed indexes are included in the bi-variate analysis with the variables which do not participate in the multiple regression model (previous accident, age, gender family dimension, education). The analyses are performed in different ways (compare means, correlation) depending on the type of variables involved.

After that, a confirmatory factor analysis is carried out on all the indexes corresponding to the constructs of the AVA model. The goal of this analysis is to verify that the new set of variables is consistent, valid and does not need to be reduced or further aggregated, i.e. due to the presence of a hidden underlying variable (Pallant, 2020). This test also helps to prevent the rise of the multicollinearity phenomenon in the following multiple regression analysis. Finally, multiple regression analysis is performed as illustrated in the AVA model. The goal of the analysis is to evaluate the variance explanatory power of the model and which factors contribute the most to the variability of the dependent variable behavioural intention. These properties are evaluated through the analysis of the multiple outputs of the multilinear regression, with a specific focus on homoscedasticity and β coefficients. Results are presented in the following chapter.

3.5 Reliability and Validity

Although various mentions of this topic are present in the previous lines, a brief excerpt is here necessary. Reliability concerns the consistency of the measurement performed in a study under three major aspects: temporal stability, internal reliability and inter-rater reliability. Being impossible, due to temporal resources, to repeat this study in the context of this thesis, stability is enhanced by providing numerous details in the methodology and analysis part of this document, giving the chance to other scholars to verify the same hypothesis in the future. Concerning the consistency of the scales used in the study, internal reliability is assessed through the continuous evaluation of Cronbach's α during the data elaboration process and through the confirmative factor analysis. Inter-rater reliability refers to the potential subjectivity bias which can intervene in the gathering or the analysis of the data. In this sense, the online anonymous survey guarantees to diminish the arising of these distortions (Bryman, 2004/2016). Furthermore, each step of the conceptual path which led to the hypothesis development is widely explained in *Chapter 2* and so available for critical readings and verification by other scholars.

Validity refers to the extent to which an indicator aiming to measure a concept actually succeeds in measuring it and it is improved in various ways (Bryman, 2004/2016). Regarding the inquiry instrument, the present questionnaire is made up of the union of new scales, necessary to introduce the new AVA model, and of pre-existing scales, whose efficiency is largely assessed in previous studies (see *Appendix A*). The brand-new scales are defined using the one name, one adjective, one verb per question rule of thumb (Bernardi, 2005). Finally, once again the validity of the constructs is verifiable through the analysis of the mental process which brought to their definition (see *Chapter 2*).

3.6 Ethical Reflections

The present study is performed maintaining the participants' well-being as a key guideline. Every step of the data gathering and analysis process strictly complies with the norms of the General Data Protection Regulation, active in the EU since 2018. All the data are gathered anonymously, and the few sociodemographic data requested do not permit the identification of the respondent. The survey starts with an informative text explaining the details and the goals of this study and the respondent cannot continue without reading and accepting it (*see Appendix B*). Although it is reasonable to believe that no question about any sensible topic is asked in the survey, the respondent can, at any moment, interrupt the filling out of the process, resulting in a total deletion of the data gathered during the interruption. The data are processed through Sunet Survey, Microsoft Office Excel and IBM SPSS, all officially provided by Lund University.

The main purpose of this study and the relative data treatment is research and the enrichment of the knowledge on the topic. The respondents are informed that their data could be published anonymously, and the knowledge of this study applied to both private and societal scopes. Also, the interview with the privileged observer is conducted on the basis of an informed consent form based on the same principles (see *Appendix D*). The researcher is aware that the knowledge of this study could be acquired by private organizations to improve their profit. However, considering the widely explained advantages for all the street users deriving from the mass adoption of AVs and SDCs, it is reasonable to believe that each step in the acceptance, adoption and distribution of these products will signify a step ahead for public safety and mankind's sustainability.

4. Analysis

This section illustrates the main results of the analyses displayed in the previous sections. These are presented starting with univariate analysis and a short extract from bivariate. Then, the reliability test leads to the index formation, which is supplementary confirmed by factor analysis. Finally, the results of the AVA model multiple regression analysis are presented.

4.1 Univariate Screening

A general screening of the sociodemographic variables of the 321 gathered answers reveals the sample to be composed of 132 women (41,1%), 186 men (57,9%) and 3 others (0,9%). The mean age is 35,96 years, while the mode for this variable is 25. This indicates a quite young group of respondents, understandable considering the digital nature of the utilized instruments. Considering the family dimension, 34 respondents declare to live alone (10,6%) and 73 to live with another person (22,7%). 86 and 84 respondents live respectively with other 3 (26,8%) and 4 (26,2%) people, while the rest belong to larger families (13,7%). Coming to education, 137 (42,7%) respondents claim an academic title (Bachelor, Master or PhD), while 184 (57,3%) express another level of education. Finally, the variable previous accidents splits into 157 yes (48,9%) and 164 no (51,1%). *Table 1* presents a wide overview of the sociodemographic variables.

All the other variables of the survey are inspected verifying that no category polarizes too many hits (Bernardi, 2005), apart from the case of variables 6 and 7, both belonging to the second-level index MRR and to the first-level RUPE, where the distribution is extremely skewed to the left (n.6: -1,364; n.7: -1,361). Extreme polarization in one or more independent variables can impact the explanatory power of the multiple regression model in which these are collocated. A supplementary screening is executed looking for outliers and missing values. However, as mentioned before, the internal structure of the survey only requires respondents to select structured options not giving the chance of skipping any of the questions, resulting in the impossibility of producing missing values and outliers. As a consequence of these cited elaborations, at a univariate stage, the gathered data are complete and solid.

Variable	Category	Frequency	Percentage
Gender	Female	132	41.1%
	Male	186	58.0%
	Other	2	0,6%
	Prefer not to answer	1	0,3%
Age	18-24	95	29,6%
	25-34	105	32,7%
	35-44	28	8,7%
	45-59	55	17,2%
	60-74	34	10,6%
	75 and more	4	1,2%
Educational level	Middle school diploma	10	3,1%
	High-school diploma	165	51,4%
	Bachelor's degree	65	20,2%
	Master's degree	58	18,1%
	PhD or after-graduate master	14	4,4%
	Other profess. diploma/cert.	5	1,6%
	Prefer not to answer	4	1,2%
Family dimension (respondent included)	1 person	34	10,6%
	2 people	73	22,7%
	3 people	86	26,8%
	4 people	84	26,2%
	5 people	31	9,7%
	6 people or more	13	4,0%
Years of driving licence	1-3	70	21,8%
	4-5	51	15,9%
	6-10	68	21,2%
	11-15	15	4,7%
	16-30	42	13,0%
	More than 30	75	23,4%
Involved in an accident	Yes	164	51,1%
	No	157	48,9%

Table 1. Overview of the sociodemographic variables

4.2 Index Formation and Confirmative Factor Analysis

After this stage, indexes reflecting the variables of the AVA model are created summing the Likert scale outputs of the questions grouped as shown in *Appendix A*. The reliability of the indexes is assessed through the evaluation of Cronbach's α parameter (Pallant, 2020) as shown in *Table 2*.

Index	N. of items	Cronbach's α
RUPE (Including MRR)	8	,793
CHP	6	,897
PEOU	3	,867
AT (DT + CT)	9	,832
BI	5	,941

Table 2. Reliability test on the variables of the AVA model

The test is deepened through the use of SPSS's item-total-statistic tool which gives the chance to check what happens to Cronbach's α if one of the variables included in the index is deleted. The maximum improvement that the exclusions can guarantee for all the created indexes is 0,025 which, taking into account also the already satisfactory level of Cronbach's α, leads to the decision not to modify the index groups. *Table 3* summarizes the central tendency of the created indexes.

Index	Mean	Mode	Median
RUPE	25,86	26	26
CHP	16,48	12	15
PEOU	10,60	12	11
AT	27,56	31	28
BI	14,96	5	15

Table 3. Central tendency of the created indexes

However, as previously mentioned in the methodology chapter, the novelty of the AVA model as well as the new scales proposed in large part of the survey the study is based on require a stronger confirmation of the structure underlying the set of defined variables (Pallant, 2020). The factor analysis is divided into three stages. The first stage focuses on the items forming the indexes corresponding to the variables of the *in-market* side of the AVA model. The second stage focuses, instead, on the variables presented in the *automation side* of the model, while the third stage only concerns the dependent variable *behavioural intention*. This stage-based procedure is adopted by Park et al. (2021) and enhances readability and understandability compromising the chance to reduce even more the factors analysed. However, considering the confirmatory purpose of this analysis, the trade-off is acceptable.

4.2.1 In-Market Side Factor Analysis

The first stage focuses on the *in-market side* of the AVA model, including variables r*elative utilitarian performance expectancy* (RUPE) and *current hedonic performance* (CHP). The factor analysis starts with an inspection of the Correlation matrix to check the values between the items within the same index are above 0,3. Tabachnick and Fidell (2013) argue values not to be suited for factor analysis whether this condition is not fulfilled in the majority of the cases. In the present stage, the groups of variables strongly succeed in the test, with a limited exception of the MRR group, which shows some 0,2 correlations. However, considering the overall results of the

RUPE variable in which MRR converges, and taking into account once again the reasons which lead to combining this large set of thematically different variables (see *Paragraphs 2.*3-*2.4*), the correlation condition is considered achieved. The quality of the elaboration is further assessed by checking the Kaiser-Meyer-Olkin (KMO) Measure of Sampling Adequacy which results in a 0,826 (Tabachnick and Fidell suggest a minimum of 0,6) statistically significant at a < 0,001 level according to Bartlett's Test of Sphericity (Pallant, 2020). The Communalities table does not present any value below 0,4. The Scree plot relative to this stage of the FA is presented in *Figure 2*.

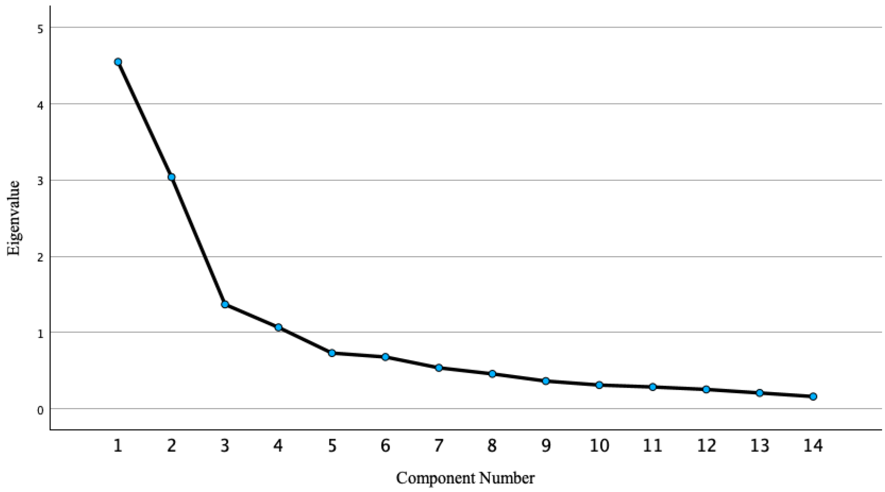

Figure 2. In-market side factor analysis Scree plot

The final step of the factor analysis consists of the inspection of the Pattern matrix, where SPSS optionally suggest a possible way of re-grouping the proposed items. A satisfactory result consists of a matrix where factors overlap the structure of hypothesized variables and the loadings of the grouped items are above 0,4. The Pattern matrix presents a rotated four-factor solution, where factor 1 perfectly overlaps the structure of the CHP variable, factor 2 includes the first four items of the RUPE variable (item numeration always refers to *Appendix A*); all the loadings are above 0,4 except item 9 in factor 1, which loads a 0,33. More complex is the situation of factors 3 and 4, which strongly couples respectively items 6 with 7 and 5 with 8. A possible explanation of this division concerns the orientation these items present: 6 and 7 concern the perception of the overall driving safety while 5 and 8 introduce a more reflexive perspective. Furthermore, as cited in the univariate part of the analysis, items 6 and 7 answer distributions are particularly skewed to the left (see *Paragraph 4.1*). Everything considered, the first stage of the factor analysis confirms the structure of the variables of the *in-market side* of the AVA model.

4.2.2 Automation Side Factor Analysis

The second stage of factor analysis regards the automation side of the AVA model, which includes variables *perceived ease of use* (PEOU) and *automation trust* (AT). AT is preceded by the two second-level variables *dispositional trust* (DT) and *contextual trust* (CT). This stage reflects the same procedure as the previous one. The Correlation matrix presents all values above 0,3 for PEOU and CT variables. Slightly more complex is the situation of the DT items where two correlations concerning item 21 do not reach the benchmark level. Item 21 concerns the number of ADAS equipped on the car the respondent is currently driving and it is based on a different scale than the Likert one (see *Paragraph 3.2*) which maintains the same scoring system. However, no critical outcome results from this table. For this stage, KMO is 0,86 and significant on the < 0,001 level according to Bartlett's Test. Looking at Communalities, the majority of items present values largely above 0,4 while only n. 21 and 26 respectively show extractions of 0,36 and 0,374. To evaluate how improvable this side of the model is, a supplementary of this factor analysis is run without the two items without evidencing any considerable upgrading (KMO is 0,843). *Figure 3* presents the Scree plot of this stage of the factor analysis.

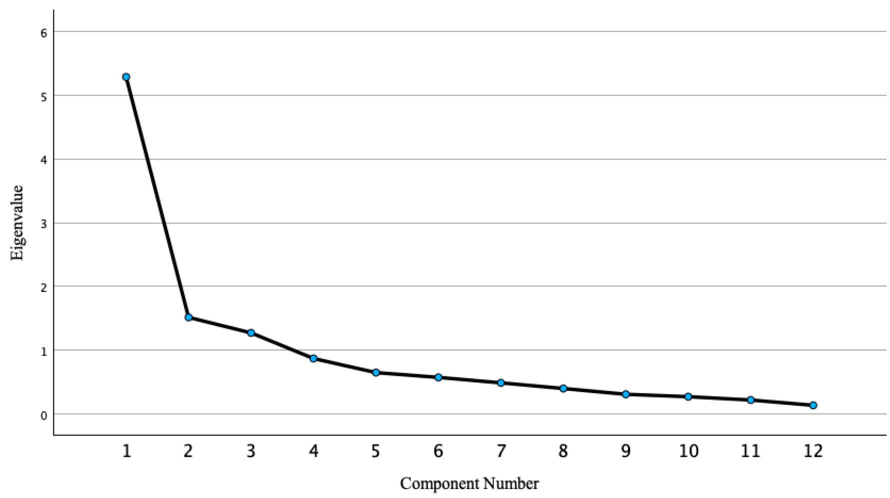

Figure 3. Automation side factor analysis Scree plot

The Pattern matrix extracts three factors. Factor number 3 perfectly overlaps the structure of the PEOU variable and factor 2 groups all the items of the DT group, including n.21, with the exception of n.22 which only loads for 0,148 (SPSS is set to automatically exclude items loading less than 0.1). According to the matrix, this last item seems to better fit into the CT group, which is faithfully reproduced by extracted factor 1 with the addition of items 22 and 20. The latter item shows anyway a superior loading parameter in factor 2 (DT): 0,505 vs 0,543. Despite these small inaccuracies and with the support of the alternative test conducted excluding items 21 and 26, the second stage of the factor analysis confirms the structure of the variables of the *automation side* of the AVA model.

4.2.3 Behavioural Intention Factor Analysis

The third stage of factor analysis focuses on the AVA model's dependent variable *behavioural intention* (BI). In the correlation table, all the values are largely above 0,3 and KMO test results in 0,909 significant at the < 0,001 level looking at Bartlett's Test. In the Communalities table, all the values are by far superior to 0,4. Eventually, the Pattern matrix only extracts one factor which perfectly overlaps with the structure of the (BI) variable loading all the items for way more than 0,4. Also this last stage of the factor analysis confirms the structure of the investigated variable. Overall, the confirmative factor analysis validates the whole structure of the AVA model and the items involved in the survey this study is based on.

4.3 Bivariate Analysis

The analysis proceeds with several bivariate tests, where especially variables not included in the final multiple regression analysis (MRA) are variously crossed with the indexes. As gender is a categorical variable, the means of the scores in the indexes of the two groups female and male (other options frequencies are considered not relevant) are calculated. Important divergence arises in CHP where females score 13,26 and males 18,62 and in AT where females score 26,26 while the male mean is 28,34. Independent sample T-test reveals mean differences to be statistically significant at a < 0,01 level. The education level variable is recoded in a dummy variable distinguishing people with an academic education (Bachelor, Master or PhD) from people claiming a different qualification. The first score on average higher in AT (28,99) and BI (16,37), while the latter score respectively 26,49 and 13,87 in the same indexes. Independent sample T-test reveals mean differences to be statistically significant at a < 0,01 level. Other differences in the means scored by the various category groups of sociodemographic variables are minor or not statistically significant. Also, no statistically significant correlation between age and any of the indexes is found. Considering the different scale (*see Paragraph 3.2*) on which the item is based, a correlation analysis is performed between item 21 (concerning ADAS in the current car) and BI; the result is a statically significant (< 0,001) 0,213 value in the Pearson correlation parameter. The following table illustrates the individual correlation (Pearson) between each of the indexes and the BI variable.

Index	Correlation with BI	Statistical significance
Relative utilitarian performance expectancy (RUPE)	,78	< ,001
Current hedonic performance (CHP)	-,13	,018
Perceived ease of use (PEOU)	,54	< ,001
Automation trust (AT)	,76	< ,001

Table 4. Correlations between independent variables and the dependent one

4.4 Multiple Regression Analysis

The main statistical test of this thesis is the test of the AVA model in multiple regression analysis (MRA). Pallant (2020) recognises this type of test as the best one to verify how a group of variables is able to explain the variance of a certain outcome. The type of MRA used in this thesis is the standard multiple regression, where all the expected predictors enter the model at the same time. The predictors included in this test are RUPE, CHP, PEOU and AT; the outcome is the variable BI.

The Correlations table displays the correlation level between each of the variables, both dependent and independent, included in the analysis. The optimum for this inspection is the absence of any value above 0,7 among the scores between the independent variables. Values above 0,7 evidence the potential presence of multicollinearity, defined as a situation in which two or more predictors are highly correlated biasing the contribution of each of them and impacting on the overall validity of the model (Pallant, 2020). In the case of this analysis, no value above 0,7 is detected and multicollinearity absence is statistically significant in almost all the cases, as explained in *Table 5*.

		Behavioural Intention	Relative Utilitarian Performance Expectancy	Current Hedonic Performance	Perceived Ease of Use	Automated Trust
Pearson Correlation	BI	1,000	,780	-,132	,539	,760
	RUPE	,780	1,000	-,213	,453	,625
	CHP	-,132	-,213	1,000	,102	,062
	PEOU	,539	,453	,102	1,000	,583
	AT	,760	,625	,062	,583	1,000
Sig. (1-tailed)	BI	.	<,001	,009	<,001	<,001
	RUPE	,000	.	,000	,000	,000
	CHP	,009	,000	.	,033	,135
	PEOU	,000	,000	,033	.	,000
	AT	,000	,000	,135	,000	.

Table 5. Correlations between involved variables

The overall capability of explaining the variance of the dependent variable of the model is expressed by the R^2 parameter and by the Adjusted R^2. Pallant (2020) suggests using the adjusted value when, as in this case, the model is tested on a relatively small sample. The R^2 for the present model is 0,738 (R is 0,859), while the adjusted version is 0,735 and the Standard error of the estimate is 3,001 (*Table 6*).

	R	R^2	Adjusted R^2	Std. Error of the Estimate
AVA model	,859	,738	,735	3,00808

Table 6. Model summary

This means that the AVA model is, in this case, able to explain the 73,5% of the variance of the *behavioural intention* of using an L4 self-driving car. The statistical significance of the model is assessed through the inspection of the One-way Analysis of Variance (Anova) table, presented below (*Table 7*).

	Sum of Squares	df	Mean Square	F	Sig.
Regression	8066,536	4	2016,634	222,868	< ,001
Residual	2859,339	316	9,049		
Total	10925,875	320			

Table 7. Anova table

As the overall quality of the model is assessed to be satisfactory, the analysis proceeds by checking the performance of each of the independent variables. The Coefficients table shows the most important parameters in this sense. The Standardized β coefficient shows the contribution of each predictor. RUPE is the one having the highest contribution scoring 0,459. AT shows the second highest impact with 0,424. Another positive relation with BI regards PEOU, which scores 0,09 in this parameter. A negative contribution is given, as hypothesized by CHP, whose Standardized β coefficient is -0,069. As shown in *Table 8*, all these contributions are statically significant at least at the < 0,05 level. Hence, all four hypotheses presented in the previous chapter about the AVA model are confirmed.

						95,0% Confidence Interval for β		Correlations			Collinearity Statistics	
	Unstandardized Coefficients β	Std. Error	Standardized Coefficients β	t	Sig.	Lower Bound	Upper Bound	Zero-order	Partial	Part	Tolerance	VIF
(Constant)	-7,128	,959		-7,430	< ,001	-9,016	-5,421					
RUPE	,450	,039	,459	11,610	< ,001	,373	,526	,780	,547	,334	,529	1,890
CHP	-,061	,027	-,069	-2,253	,025	-,113	-,008	-,132	-,126	-,065	,876	1,141
PEOU	,166	,067	,090	2,499	,013	,035	,297	,539	,139	,072	,635	1,575
AT	,351	,034	,424	10,217	< ,001	,283	,418	,760	,498	,294	,480	2,082

Table 8. Coefficients table

Looking at the previous table, the Part column shows the unique contributions of each variable. Squaring the Part value, it is possible to obtain the percentage of the unique contribution of each variable to the model. Once again, this parameter is higher for RUPE (0,334) and AT (0,294), while it is set on a lower level for PEOU (0,072) and CHP (-0,065). Although the unique contributions are unbalanced, it is interesting to focus on the extent to which each overall contribution is unique. In other words, by dividing each Part value for the respective Standardized β coefficients, the result shows how much uniqueness resides in each contribution. From this perspective, CHP highlights the highest value of 0,94 among the independent variables. Hence, despite a low general impact on the model in this case, data show CHP to provide a very new and unique contribution to the L4 SDC acceptance phenomenon. Taking into account the skewed distribution of the CHP index (0,490) and the novelty features of this group of variables (normally not involved in acceptance studies, based on one interview), evidence opens up for a deeper and more developed study of irrational and emotional motivations in acceptance and adoption studies.

The graphical representation of the model is provided in two different graphs. The Normal probability plot shows the distribution of the residuals (BI $value_n$ – AVA predicted $value_n$) of the analysed multiple regression model. A satisfactory Normal P-P plot displays residuals to be approximately aligned on a straight diagonal line from the bottom left corner to the top right one, which translates into the normality and linearity conditions, features of a well-performing model. *Figure 4* illustrates the Normal P-P plot of this case.

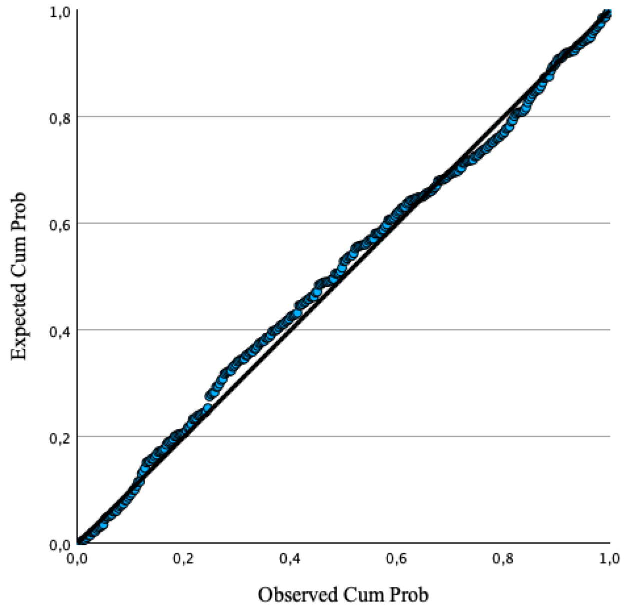

Figure 4. Normal P-P plot of regression standardized residual

The same positive result is visible on the Scatterplot, which presents the regression standardized predicted value on the X axis and the regression standardized residuals on the Y axis. Pallant (2020) and Tabachnick and Fidell (2013) consider the condition of homoscedasticity, graphically expressed as the dots to be distributed in a sort of rectangle on the Scatterplot, as the benchmark for a well-performed model. *Figure 5* displays the Scatterplot for the present model, which

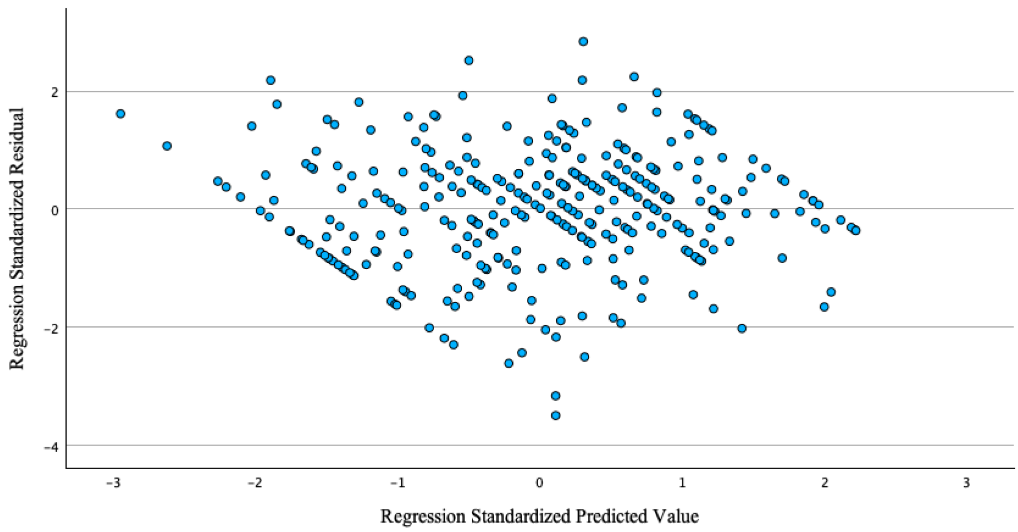

Figure 5. Scatterplot

reveals a sufficient homoscedasticity grade, being the variance of the residuals around the predicted values placed in a parallelogram.

Taking into account all the previously presented outputs as well as the significance of the Anova test and the Adjusted R^2, the present multiple regression analysis of the first level 4 self-driving cars acceptance survey based on the AVA model is considered well-performed and satisfactory. However, reflecting on the small inaccuracies in some of the previous stages of the analysis as well as the contributions of several previous studies on this topic, some supplementary versions of MRA are performed involving more and slightly different variables. The second MRA includes all the predictors of the first one plus the variables age, dummy_academic and gender (recoded in the dummy variable dummy_male), but no considerable improvement results in the outputs (Adjusted R^2 is 0,736). A third attempt is performed including the predictors of the AVA model plus the dummy variable conceptualising the previous accident experience (1: yes; 0: no). Once again, no relevant improvement in the Adjusted R^2 (0,735) and in the other outputs. The fourth attempt of MRA includes precursors RUPE, CHP, PEOU and a new version of the AT index which does not contain the contribution of items 21 and 26, as suggested in factor analysis (second stage), where these items do not reach the 0,4 benchmark score in the communalities table. However, considering the slightly different scale (ADAS), variable 21 is included in this MRA as a stand-alone variable. The results do not show any important improvement in the adjusted R^2 (0,736) and the other outputs. All in all, the first and largely displayed multiple regression analysis, strictly based on the AVA model which is presented in *Paragraph 2.4.4*, remains the most satisfactory and so the definitive one.

5. Discussion and Conclusion

The last chapter of this thesis displays the most important discoveries of the previous parts, as well as the theoretical and practical implications through which this piece of research contributes to the topic. Eventually, limitations and future development suggestions are provided.

Of the four hypotheses presented in the previous chapters, all of them were confirmed during the analysis. Tested on the data gathered among 321 Italian drivers, the AVA model is able to explain roughly 73% of the total variance of the independent variable *behavioural intention* of accepting the use a SAE level 4 self-driving car. Among the four precursors presented, *relative utilitarian performance expectancy* results to be the most influential one (Std. β 0,459), slightly superior to *automated trust* (Std. β 0,424). The other two parameters: *perceived ease of use* (Std. β 0,09) and *current hedonic performance* (Std. β -0,069) are still influential, but with a minor contribution to the variance explanation. Nevertheless, this last variable result possesses the highest degree of uniqueness (Std. β / Part) in its contribution. All the contributions are statistically significant.

At a bivariate stage of analysis, the fact of using a car equipped with ADAS (SAE level 1 or 2) emerges to be correlated with acceptance with a 0,213 Pearson's coefficient (Tichenor et al., 1970; Stella, 2012). The respondents claiming the possession of an academic title show a slightly higher *behavioural intention*, while males in general are moderately more inclined to trust the automation system, with no significative difference on the dependent variable (Kyriakidis et al., 2015; Ruggeri et al., 2018). No relevant difference is found between the people who have and have not experienced an accident. However, the dichotomic way yes/no through which this information is gathered does not allow a deep and complete diversification between the minor accidents and the most traumatic car crushes, which could impact the acceptance process in different ways.

5.1 Theoretical Contributions

The success of the first test of the AVA model provides a new perspective in the study of the acceptance of AVs and SDCs. According to Ruggeri et al. (2018), the model is specifically tailored around this product category, having the chance to better encapsulate the typical features of such a complicated sector (Martin, 2019). Recalling a common trend from Cultural Studies (Hall, 1996), Economics (Akerlof, 1970) and early adoption studies (Rogers, 1962/2003), the AVA model enhances the importance of the consumer's perspective for what concerns information possessed, needs, feelings and current competitive situation. The AVA model deconstructs the new product acceptance process into two meaning flows, the *in-market side* and *automation side*, respectively regarding the known sector where SDCs are released and the unknown/new part of the innovation, leading to a wider and more complete acceptance prevision.

According to some previous studies, the importance of mere utilitarian performance increasing continues to be the most important parameter in the prevision (Bay et al., 2018; Baccarella et al., 2020). However, a partial novelty element is constituted by a deep application of the concept or relativity, previously introduced by Ajzen, (1985; 1991) but not completely included in TAM (Davis, 1989) and UTAUT (Venkatesh et al., 2003). In this sense, much attention was given to detecting a potential need for greater safety due to a reflection on the current situation on the streets (MRR).

Considering scholars are countered about the importance of *perceived ease of use* in the acceptance process (Choi & Ji, 2015; Xu et al., 2018; Baccarella et al., 2020; Smyth et al., 2021) the analysis performed in this study reveals this variable contribution not to be extremely determinant into the model. Although care was taken to focus the items making up this variable both on the ease-of-use perception as well as on the belief of each respondent to be able to perform the necessary behaviour, the importance of this predictor is secondary compared to RUPE and AT. The variability of PEOU's importance in several studies could be due to the amount of expertise and knowledge possessed by the responding subjects (Zhang et al., 2022; Querci et al., 2022).

Agreeing with several previous contributions (Hajiheydari and Ashkani 2018; Panagiotopoulos & Dimitrakopoulos, 2018; Zarifis et al., 2020; Chatterjee et al., 2021; Prakash & Das, 2021) this study deepens the understanding of the impact of technology (automation) trust on *behavioural intention*. The AVA model *automation trust* construct is rooted in Hoff and Bashir's (2015) deconstruction in attitudinal dispositional trust and in the specific scenario-related contextual trust. This substructure aims to highlight the different sources from where the trust sensation can be generated, including the chance of transferring a positive attitude from the familiarity with other products of the AI cluster (Tichenor et al., 1970; Stella, 2012). The analysis affirms once again the importance of *automation trust* on the technology acceptance issue, pointing out it to be the second most influential factor after *relative utilitarian performance expectancy*.

Eventually, the success of the AVA model leads the way to a major consideration of the irrational and hedonic understanding in the acceptance process of new L4 SDCs. As suggested by Miller (2001) any analysis of the acceptance or distribution process of any car which does not take into account the non-utilitarian meaning connected to the product is partial and incomplete. This study contemplates the hedonic and sentimental values of the current vehicle possessed by the potential SDC accepter by mapping out the extent to which the respondent is a car enthusiast. Despite the hedonic motivation towards the new product already present in UTAUT2 (Venkatesh et al., 2012), the AVA model concentrates on the emotional attachment of the drivers to the product they should substitute for an AV. In this sense, *current hedonic performance* negative influence roots in Schumpeter's concept of innovation as a change in previous habits and practices, arguing that people could resist L4 SDC acceptance not to give up on the emotional and irrational connection to their current vehicles (Ziemnowicz, 2013; König & Neumayr, 2017). CHP variable gives the AVA model the chance not only to capture a snapshot of the acceptance as it happens, but to consider the long-term situational environment in which AVs are released. Despite CHP results in a weak impact in the AVA model multiple regression analysis, the high uniqueness degree which distinguishes this variable suggests the need for a deeper and more developed understanding of the irrational side of the acceptance issue.

5.2 Practical Contributions

The contributions of this study fall into the practical Strategic Communication and related fields too. Considering what is explained (see *Paragraph 2.3*) about the AVA model taking into account the consumer experiences before the AV launch, the adaptability of this theoretical model to the most recent applied communication and personalised advertising techniques (Lombardi & Mindshare, 2022) can maximise the importance of the individual consumers profiled data, which reflect their past behaviour. From an applied perspective, the variables making up the AVA model are designed to be simply reconstructed with a large amount of data available for producers, advertisers, and, considering the societal relevance of the topic (European Parliament, 2019), National States.

Considering the result of the MRA, advertising and PR campaigns should focus on the relative utilitarian advantage that new SAE L4 SDCs can offer in terms of safety, comfort and time management. Additionally, the campaigns' narrative could insist on comparing the new automated vehicles with the previous ones, presenting them primarily as a solution to improve drivers' (and drivers' families) personal safety. Furthermore, the analysis performed in the present study highlights the importance of maximising trust in the automation system. Reflecting on the fundamental ideas on which the AVA model is based (see *Paragraph 2.3*), ceding the control of the car, and so of the passengers' safety, to an unknown and incomprehensible for the most in-human artificial intelligence-based algorithm can represent a consistent obstacle to the adoption. In this sense, concentrating on people already using ADAS-equipped cars, so already involved in the automation cluster, in a primary phase to leverage them as advocates in a second phase of the campaign can be a winning strategy.

The model demonstrates the relevance of both contextual and dispositional trust, reflecting the importance of enhancing the awareness of the safety level guaranteed by the automation systems both specifically related to the driving context and on a wider and more general conception. In other words, the performed analysis points out that people already experienced in the use of AI-based products, also belonging to other market categories, have a more positive attitude towards automation trust and SDCs acceptance. Moreover, the use of any AI-based products (personal assistants, chatbots…) entails the production of a large quantity of personal data about the users. Hence, segmenting and reaching this category of people should not be too complicated.

Little importance should instead be given to increasing the perceived ease of use concept penetration, considering the scarce contribution this variable demonstrates in the performed multiple regression analysis. Furthermore, the necessity of investing on this point is expected to decrease naturally as the acceptance and adoption go by, due to its simplicity and adaptability to the spontaneous organic buzz flow. Furthermore, considering one of the main selling points of general AI-based products to be the very low mental and physical required effort to perform even complex tasks, the ease-of-use concept could be transmitted as an intrinsic part of the automation system.

Finally, the AVA model underpins a wider reflection on the car enthusiasts' world. Although not very impactful in the analysis performed in the present thesis, the negative influence on the acceptance phenomenon allows the formation of several resistant car enthusiasts clusters. Taking into account that the societal benefit, in terms of safety and sustainability, will be achieved only when almost all the car fleet of a given area is highly automated, the found negative influence, despite the weakness of its intensity, requires major and deeper investigation, especially involving supplementary resources. Far from being limited to the specific case, the *current hedonic performance* results in the analysis suggest the need to consider the impact of the previous habits and experiences in any acceptance process, as well as a major consideration of the non-utilitarian and irrational relationship which bonds a car and its driver.

5.3 Limitations and Future Research

The limitations of this research reside primarily in the lack of involved resources and in the dimension of the sample the analysis is based on. Gathering 321 respondents for an online form without a monetary investment in ads or panels is considered a satisfactory result, but inevitably not sufficient to generalize the findings of this thesis. Furthermore, distributing the survey in Italian limited the sample to this language speakers, but no specific criteria were adopted to gain a uniform distribution of the respondents from a geographical point of view (North, Centre, South). The use of the structured questionnaire was determinant to perform the multiple regression analysis, but at the expense of a monodimensional conceptualisation of the variables. As mentioned before, the scale used for measuring ADAS familiarity did not take into account the intrusiveness that some of these systems can present more than others, being limited to asking a not precise numerical answer. In the same way, the variable previous accident was structured in a yes/no choice, not having the chance to evaluate the impact of the crash on the drivers' experiences and feelings. The structuration of these variables was due to the limited attention span that is on average dedicated by a respondent to an online survey. The study would surely have benefited from the addition of more items, but in this case, more questionnaires would have been left incomplete due to a longer configuration. Furthermore, considering the previous accident experience as a very sensitive and private one, asking for further details about it would have hurt the sensibility and well-being of several participants.

The lack of resources impacted also the hybrid methodology which affected the part of the survey dedicated to car enthusiasm. Due to the lack of temporal, human and financial resources, the items of this section were built upon just one interview with an expert observer chosen on convenience. Despite the double effort to study this part of the issue and the precious contribution conceded by the interviewee, a deeper investigation is necessary to improve the knowledge of the hedonic and emotional vehicle consumption on the acceptance of new SDCs.

Coming to the analysis part, the AVA model was tested involving univariate, bivariate and multiple regression analysis. This means that only the relation between the independent variables and the dependent variable was verified, without any inspection aiming to detect a potential moderating effect or second/third level correlation between the independent variables or by the sociodemographic ones. In this sense, a supplemental analysis involving structural equations and other more advanced tests is suggestable to expand the understanding of the plethora of relations interspersed between the constructs.

The future research could in first place test the functioning of the AVA model on a larger sample and beyond the borders of Italy. In second place, considering the limitations widely explained in the previous lines, investing further resources in these details can improve the knowledge of this field. For example, further investigations around the potential moderating effect of car crush experience on relative utilitarian performance expectancy could be researched with a more detailed mapping out method for the accidents.

Moreover, as several times mentioned during this text, the fluctuating quality of information about AVs and SDCs, united with their continuous development and step-by-step availability, will inevitably impact acceptance and adoption processes, making constant revelations and studies necessary. Considering the independent variables, each one of them represents a meaning group which summarizes one aspect of the mental process which guides the acceptance of SDCs. However, further research can be conducted to discover several second-level precursors of the four individuated constructs. Where does relative utilitarian performance expectancy come from? What about automation trust, what leads to it? In the same way, the involvement of the car enthusiasm phenomenon as a driver of acceptance is a new element in the field, but of course, it needs to be explored with more precise and heterogeneous methods. Enthusiasm is a wide phenomenon and there is room to believe that it will become more impacting when drivers have to choose between their current car and a new self-driving model. Furthermore, as mentioned in the Methodology chapter, acceptance contributions of price and social motivations were excluded by the model considering that the studied products are not available on the market yet.

Finally, despite the just presented limitations and beyond the positive analysis results, the AVA model was built to introduce a new way of understanding acceptance studies. Rather than focusing on a snapshot of the process from the producer's position, this study aims to switch perspective aligning with the consumer's point of view. Standing at the side of final users it is essential to comprehend what drives their decision and their potential resistance, to design the best communication strategies and achieve the great societal benefits of self-driving cars.

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7. Appendices

Appendix A. Survey Items

Variable	N.	Item	Scale origin
Relative utilitarian performance expectancy	1	I would generally benefit from the daily use of a self-driving car	(Nordhoff et al., 2020)
	2	If I used a self-driving car my life quality would be improved	(Nordhoff et al., 2020)
	3	I would use the time on a self-driving car for other activities	(Nordhoff et al., 2020)
	4	Riding a self-driving car fits in well with my travel habits	New
	5	I do not feel completely safe when I am driving my traditional car	New
	6	I believe most of the road accidents are caused by people mistakes/distractions	New
	7	I believe safety on the streets should be improved	New
	8	I would prefer not to have the responsability of driving	(Acheampong & Cugurullo, 2019)
Current hedonic performance	9	I like driving	New (interview)
	10	I often talk about cars with my peers	New (interview)
	11	I consider my car not just as a means of transport, but as something more	New (interview)
	12	I modified one of my cars (estically or functionally)	New (interview)
	13	I often participate in car-related events	New (interview)
	14	I am a car enthusiast	New (interview)
Perceived ease of use	15	Interacting with a self-driving car would not require much mental effort	(Foroughi et al., 2023)
	16	Learning how to use a self-driving car would be easy for me	(Nordhoff et al., 2020)
	17	It would be easy for me to become proficient in the use of a self-driving car	(Nordhoff et al., 2020)
Automation (dispositional) trust	18	I often adopt new techonologies before my peers	(Gkartzonikas et al., 2022)
	19	I normally use AI-based products (voice assistent, connected appliances)	New
	20	I look favorably upon the arrival of Artificial Intelligence in various fields	New
	21	My current car is equipped with advanced driver assistance systems (ADAS) (e.g. adaptive cruise control…)	New
	22	My trust in self-driving cars is based on the reliability of the underlying technologies	(Foroughi et al., 2023)
Automation (contextual) trust	23	I do believe self-driving car will be safe	New
	24	I believe self-driving cars will be more accurate than humans in driving	(Gursoy et al., 2019)
	25	Self-driving cars will make me reach my destionation safer than traditional cars	(Foroughi et al., 2023)
	26	I am not concerned about someone taking control of my self-driving car	(Acheampong & Cugurullo, 2019)
Behavioural intention	27	I like the thought of riding a self-driving car	New
	28	I intend to use a self-driving car in the future	(Nordhoff et al., 2020)
	29	I would use a self-driving car in controlled situations (highways)	New
	30	I would use a self-driving car during my everyday trips	(Nordhoff et al., 2020)
	31	I would change my car with a self-driving car, if it was available for a suitable price	(Nordhoff et al., 2020)
Previous accidents	32	I was previously involved in an accident	New
Sociodemo-graphics	33	Age	Largely used
	34	Gender	Largely used
	35	Education level	Largely used
	36	Family dimension	Largely used

Appendix B. Survey Introductory Texts

Both the texts are here provided in the English translation.

B.1 Cover Page

Hello, I am Filippo Lorenzelli, a student of Strategic Communication at Lund University (Sweden).

For my **master thesis** I am conducting a study on how people perceive **self-driving cars**, which will be available on our market in a few years. If the topic seems complicated to you, don't worry, the necessary information will be provided in the questionnaire. Please only participate **if you have a B driving licence** (normal car licence).

The completion will only take **5 minutes**.

The processing and protection of personal data is regulated in accordance with EU Regulation 2016/679.
By continuing with the questionnaire you declare that:
- Be of legal age.
- Consent, in accordance with EU Regulation 2016/679, to this data being recorded and submitted, in anonymous form, to academic staff for examination, for research purposes and within the legal limits of the aforementioned Authorisation.
- I also consent to their being analysed, archived and published in anonymous form.

If you have any questions, you can contact me, as data controller, at filippo.lorenzelli.2787@student.lu.se.

Thank you for your time

B.2 Introduction Page

Self-driving cars are vehicles that can, under various circumstances, **drive themselves** without the need for human intervention. These cars use sensors, cameras and **artificial intelligence** software to see the road, recognise traffic signs, other vehicles and pedestrians, and **make** safe **driving decisions**. In more advanced models, the driver will only have to set the chosen destination and **relax**.

Self-driving cars will be less polluting, reduce traffic congestion, and **decrease traffic accidents** by up to almost 90%, potentially eliminating all human error.

The types of self-driving cars have been organised into 6 levels:

Level 0: no automation, the car that you probably drive every day.
Level 1: car that has adaptive cruise control or lane-departure warning.
Level 2: has at least 2 advanced driver assistance systems (like those in level 1) that can be used simultaneously. If you have recently purchased a car, it is probably of this type.
Level 3: the car can drive itself in controlled contexts (e.g. motorway), but driver intervention is still important.
Level 4: the car can drive itself even in complex contexts, like urban traffic jam. It still has the traditional controls in case of emergency. The driver can do other activities while the car moves.
Level 5: complete automation (there is no steering wheel).

THIS SURVEY IS ABOUT LEVEL 4 CARS EVERY TIME THAT “SELF DRIVING CARS" ARE MENTIONED. Driver control is possible, but automation is the primary mode.

Some questions refer to traditional cars or other themes.

Appendix C. Interview Script

Aim of the interview: crafting a group of quantitative structured scales (4/5 questions) to map out, in the survey which will be conducted afterwards, to what extent the respondent is a car enthusiast. Questions will be based on the Likert scale.

Stage 1: Presentation, introduction of the topic and legal information.

- "Hi welcome"…
- Mention why he/she was selected, but not the final goal of the interview
- Compliance to GDPR (R. 679, 2016 EU). Try to explain it simply so the respondent trusts you more.

Stage 2: "You and the car". This section aims to make the respondent feel comfortable and let them talk about what he/she loves.

- "What is your car for you?"
- "How many cars do you have? What do you use them for?"

Stage 3: "Car enthusiasm, the beginning". Let him/her talk about how they became close to the world of cars. How it started and how it developed over time.

- Pay attention to every time the respondent builds a new group of sentences. They will probably tend to concentrate around a pillar or something, which can be useful to become a question in the survey.
- "How was your enthusiasm born?"
- "How do you live it now?"
- At least once ask for details about one of the "enthusiasm development stages"
- What do you do now to maintain it?

Stage 4: Define a car enthusiast. The goal of this part is to make the respondent give details on how to identify, to different extents, a car enthusiast. The more details, the merrier, since more than one question is needed in the survey.

- "How do you identify a car enthusiast"
- Try to make him/her define a sort of scale.
- "What is the minimal condition to be a car enthusiast?"

- Lastly, ask what distinguishes a car enthusiast from a utilitaristic driver.

Stage 5: Thank you and goodbye.

Appendix D. Interview Consent Form

LUND UNIVERSITY

Initials _________ Date _______________

Project Title	Filippo Lorenzelli. Master thesis in Strategic Communication. Lund University. (By the time this form is filled out, the thesis does not have a title yet)
Purpose of the Study	This research is being conducted by Filippo Lorenzelli at Lund University, Sweden. You have been invited to participate in this research project as a privileged observer and participant in the Italian car enthusiast movement. The purpose of this interview is contributing to a larger study about SAE level 4 self-driving cars acceptance in the Italian market.
Procedures	The procedures involve individual interview, conducted face to face. The interview is recorded with the unique goal of transcribing it. After this process, the recording will be destroyed.
Potential Risks and Discomforts	There is not any relevant risk from participating in this research study.
Potential Benefits	There are no direct benefits to participants.
Confidentiality	Any potential loss of confidentiality will be minimized by pseudonymization. Furthermore, the whole research is conducted with a personal computer protected by password and ID print. Whether a report or article about this research project is written, your identity will be protected to the maximum extent possible. Your information may be shared with representatives of Lund University or governmental authorities if you or someone else is in danger or if we are required to do so by law.
Medical Treatment	Lund University does not provide any medical, hospitalization or other insurance for participants in this research study, nor will Lund University provide any medical treatment or compensation for any injury sustained as a result of participation in this research study, except as required by law.
Right to Withdraw and Questions	Your participation in this research is completely voluntary. You may choose not to take part at all. If you decide to participate in this research, you may stop participating at any time. If you decide not to participate in this study or if you stop participating at any time, you will not be penalized or lose any benefits to which you otherwise qualify.

	If, after the conclusion of this interview, you decide to stop taking part in the study, if you have questions, concerns, or complaints, or if you need to report an injury related to the research, please contact the researcher: Filippo Lorenzelli e-mail: fi2787lo-s@student.lu.se phone number: +393925181178
Participant Rights	If you have questions about your rights as a research participant or wish to report a research-related injury, please contact: Lund University, Campus Helsingborg, Sweden Institutional Review Board Office Universitetsplatsen 2, 252 25 Helsingborg E-mail: info@ch.lu.se Telephone: 042-35 65 15 This research has been reviewed according to Lund University procedures for research involving human subjects.
Statement of Consent	Your signature indicates that you are at least 18 years of age; you have read this consent form or have had it read to you; your questions have been answered to your satisfaction and you voluntarily agree to participate in this research study. You will receive a copy of this signed consent form. If you agree to participate, please sign your name below.

Signature and Date	**Subject name**	
	Subject signature	
	Date	