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Analysing the Acceptance of Vehicles With Assisted Driving Technologies: The TAM Approach

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ABSTRACT

Autonomous vehicles (AVs) are positioned as the next major innovation in the automotive industry, with the release of some prototypes being expected in the coming months. While the technology is undoubtedly promising, it is essential to analyse public opinion regarding its acceptance. This study seeks to analyse consumer acceptance using the Technology Acceptance Model (TAM), expanded with relevant external variables.

To analyse them, a quantitative research method was applied through an online questionnaire. The survey gathered over 500 answers, from which 269 valid responses were retained for analysis. The data were analysed using a partial least squares structural model (PLS-SEM).

The results confirmed all 11 research hypotheses. For the latent variable perceived ease of use (PEOU), the external variables social influence and facilitating conditions were found to have a statistically significant positive influence on PEOU, while the variable anxiety had a negative influence. Regarding PU predictors, both social influence and self-efficacy had a statistically significant positive impact on PU. The core TAM relations (PEOU → PU, PEOU → Attitude, PU → Attitude, PU → Behavioural Intention, and Attitude → Behavioural Intention) were all statistically significant and demonstrated good explanatory power. Additionally, the variable ethical concerns had a statistically significant negative impact on attitude. The model explained 64.7% of the variance (R^2) in Behavioural Intention (BI).

At the academic level, this study contributed with more knowledge about the acceptance of vehicles with assisted driving technologies, proposing new relations (Ethical Concerns → Attitude) and reinforcing other tested relations. In practice, the study offers value not only to the automotive developers but also to policymakers, highlighting the importance of addressing ethical and emotional questions as well as the technical ones.

Keywords: TAM, consumer behaviour, ethical concerns, autonomous vehicles

RESUMO

Os veículos autónomos são a perspetiva futura do setor automóvel, estando prevista a apresentação de alguns protótipos nos próximos meses.

Embora esta tecnologia tenha um grande potencial, torna-se essencial analisar a opinião do consumidor relativamente à sua aceitação. O presente estudo tem como objetivo analisar a aceitação, ou não, através do modelo *Technology Acceptance Model* (TAM) por parte dos consumidores, considerando uma versão ampliada do modelo com a inclusão de variáveis externas relevantes.

Para tal, foi aplicado um método de investigação quantitativa, através de um questionário online. O inquérito recolheu mais de 500 respostas, das quais 269 eram válidas para análise. Os dados foram analisados recorrendo ao modelo *partial least squares structural model* (PLS-SEM).

Os resultados corroboram as 11 hipóteses propostas. Em relação à variável latente *perceived ease of use* (PEOU), as variáveis externas "influência social" e "condições facilitadoras" revelaram ter uma influência positiva estatisticamente significativa sobre a PEOU, enquanto a variável "ansiedade" demonstrou uma influência negativa. No que diz respeito aos preditores da *perceived usefulness* (PU), tanto a variável "influência social" como a variável "autoeficácia" apresentaram um impacto positivo estatisticamente significativo sobre a PU. As relações do TAM (PEOU → PU, PU → Atitude, PEOU → Atitude, PU → Intenção Comportamental e Atitude → Intenção Comportamental) revelaram-se todas estatisticamente significativas, com um bom poder explicativo. Adicionalmente, a variável "preocupações éticas" teve um impacto negativo estatisticamente significativo sobre a variável atitude. O modelo explicou 64,7% da variância (R^2) da *behavourial intention to use* (BI), indicando um nível substancial de precisão preditiva.

A nível académico, este estudo forneceu novos dados para a compreensão da aceitação, por parte do consumidor, de veículos com tecnologias de condução assistida, propondo novas relações (Preocupações Éticas → Atitude) e reforçando outras já testadas. Em termos práticos, o estudo oferece valor tanto para o mercado da indústria automóvel como para a opinião pública e política, salientando a importância de abordar não apenas as questões técnicas, mas também as preocupações socioculturais, éticas e emocionais.

Palavras-Chave: TAM, preocupações éticas, carros autónomos, comportamento do consumidor

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ABBREVIATIONS

AV – Autonomous Vehicle

BI – Behavioural Intention

BIU – Behavioural Intention to Use

EE – Effort Expectancy

EV – Electric Vehicle

FC – Facilitating Conditions

OICA – International Organization of Motor Vehicles Manufacturers

PEOU - Perceived Ease of Use

PE – Performance Expectancy

PU – Perceived Usefulness

SI – Social Influence

TAM – Technology Acceptance Model

UTAUT – Unified Theory of Acceptance and Use of Technology

1. INTRODUCTION

1.1 Contextualization

The automotive industry continues to be one of the largest and most influential economies of the world, experiencing significant transformations driven by technological evolution and shifting customer preferences. In 2024, the market recovered and surpassed pre-COVID-19 levels, with almost 95.5 million cars sold. In terms of production, China led the market with 32% of global production in 2023. Combined with other Asian countries, this percentage goes up to 54%, while the remaining market share belongs mainly to Europe and America (OICA, 2024).

As a technology-driven market, every car brand is actively exploring alternative sources of energy and autonomous vehicles (AVs) to stay competitive. Countries and companies are investing heavily in R&D to create the most advanced and efficient prototypes. For instance, in Germany in 2023, the automotive industry represented the largest R&D expenditure of any sector, accounting for 34% of total R&D investment.

Although the path to fully autonomous driving is still underway, semi-autonomous vehicles, which still require some human oversight, are becoming increasingly common. Being the main focus of this dissertation, cars with driving assistance technologies are experiencing growing demand and desire from the public. Leading AV manufacturers are reporting rapid growth, in contrast to the stagnation of traditional vehicle models. For example, Tesla and its main Chinese competitor, BYD, sold 1.77 million and 2.68 million vehicles in 2023, respectively, representing an annual growth of 32% and 47%, respectively. This exceeds the overall automotive market growth of 12% during the same period, which dictates the incredible market growth of both electric and driverless cars.

Regarding this rapid growth is important to analyse consumers' sentiment and acceptance of the technology. This perception is not only affected by technology performance but also by consumer acceptance and trust. Understanding what really drives customers to buy a car with assisted driving technologies is crucial for the market.

Several studies on AVs have demonstrated that TAM assumptions effectively explain customer acceptance of these technologies (Rahman et al., 2017; Xiao and Goulias, 2022; Huang, T., 2023). In addition to TAM, research suggests that some external variables are explanatory, such as self-efficacy (Faqih, 2013), facilitating conditions (Tian and Wang, 2022), and social influence (Sutarto et al., 2023). Therefore, this study proposes a hybrid model, maintaining the TAM core while incorporating selected external predictors. Moreover, to reflect social and emotional dimensions of technology adoption, the model also analyses consumers' ethical concerns and anxiety, which are relevant in the context of emerging autonomous driving.

Given the exponential growth of this technology and its potential impact on mobility, safety, and the environment, the importance of understanding its acceptance becomes increasingly relevant.

1.2 The main objective and research questions

The main objective of this research is to understand the factors that influence consumers' adoption of vehicles equipped with assisted and autonomous driving technologies. The research focuses on analysing a TAM model with five external variables to understand the behavioural intention of the public.

Besides the main objective, a number of specific objectives were formulated: to find out what externalities affect the adoption of technology, to learn if consumers' ethical concerns make them worried about the technology, and to determine how ready people are to adopt the technology.

Based on these objectives, the research seeks to answer the following questions:

1. Which factors impact the adoption of vehicles with assisted driving technologies, and what is the extent of their impact?
2. Do consumers' ethical concerns have an impact on their decision to adopt advanced assisted driving technologies?
3. What concerns or expectations do consumers express as it comes to automated mobility? Are they ready to adopt it?

1.3 Dissertation Structure

The structure of this research is in six chapters that are in line with the traditional organizational pattern of a dissertation. Chapter 1 describes the market context, the relevance of the research, the objectives of the research, and also the dissertation structure.

Chapter 2 is a literature review that discusses the important issues on which the research is guided, starting with consumer attitude toward the technology, the theory of technology acceptance, and the environmental, ethical and economic issues involved with implementing technology. Chapter 3 provides the conceptual model and the research that underpinned its development.

Chapter 4 describes the research methodology, such as research design, sample, and data collection tools (survey). Chapter 5 reports the results and discussion by examining the sample, the conceptual model, the measurement model, the structural model, the hypotheses, and the overall analysis of findings. Lastly, Chapter 6 presents the conclusion, discusses the limitations of the study, and gives future research recommendations.

2. LITERATURE REVIEW

2.1 Consumer Behaviour in Automotive Markets

Currently, the interest in electric and autonomous vehicles is growing, yet consumers still have concerns. According to Deloitte's 2025 Global Automotive Consumer Study, the average consumer shows curiosity about new technologies, but more than half of US consumers remain hesitant about full autonomy (Appendix A & B).

2.1.1 Consumer Attitudes Toward Assisted Driving Technologies

Consumer attitude has long been recognized as a key concept in marketing and psychology, defined as a psychological tendency that is expressed by evaluating a particular entity with some degree of favour or disfavour (Eagly & Chaiken, 1993).

Research on consumer attitudes towards autonomous vehicles (AVs) has been conducted by a number of authors. The potential safety improvements, the ease of not needing to search for parking, the convenience of doing other activities (Howard & Dai, 2014), greater efficiency and environmental friendliness (Quartulli et al., 2013) are hypothesized as the most appealing incentives that people may have towards AV.

Conversely, personal issues that have been found in the literature are liability, affordability of the technology, fear of system failure, data privacy and data security, communication with non-autonomous vehicles, performance in harsh weather conditions, and the possibility of software misapplication or hacking (Howard & Dai, 2014; Kyriakidis et al., 2015; Schoettle & Sivak, 2014).

Early adopters of technology see the advantages of driverless cars in the reduction of driver fatigue, the facilitation of multitasking, and a reduction in environmental footprint, though they are seen to be less safe. However, such adopters perceive autonomous cars as even better than ordinary ones (Hardman, Berliner, & Tal, 2019).

Demographic differences impact technology acceptance. For example, people who are enthusiastic about autonomous vehicles are typically male, young, highly educated, and living in rural areas, whereas sceptics are older, car reliant, and live in less densely populated areas (Nielsen & Haustein, 2018). Concerning the interest in AVs, Bansal et al. (2018) recorded that Texans with more annual vehicle miles travelled were more interested and willing to pay (WTP) more to fit automation technology to their cars. Additionally, Liu et al., (2019) concluded that younger and more educated participants with higher incomes were more willing to pay. According to Daziano et al. (2017), households were willing to pay 3500$ for partial automation and 4900$ for full automation.

Some authors consider trust the most important predictor of consumer acceptance, influencing their attitude towards AV technology. Results from a study by Zhang et al. (2019) revealed that initial trust was the most critical factor in promoting a positive attitude towards AVs. Similarly, results from a study by Choi and Ji (2015) corroborated that trust is a major determinant of intention to use AVs. Their work added that system transparency, technical competence, and situation management positively impact user trust in AVs.

2.1.2 Generational Differences in Attitudes Toward Assisted and Autonomous Driving

Age can play a role in the perception and opinion forming of autonomous vehicles (AVs). Rahimi et al. (2020) investigated generational disparities in attitudes toward autonomous vehicles and other mobility options. Based on their model results, which computed attitude scores for each parameter, they identified significant generation gaps across all mobility attitudes. Younger generations showed more positive attitudes toward shared mobility, transit, driving assistance and full automation, while the older generation exhibited a higher inclination towards private vehicles.

This contrast aligns with findings by Owens et al. (2015), who suggested that older generations tend to be more hesitant to engage with advanced technology, because they find it more distracting than useful. Interestingly, those who owned advanced vehicle technologies rated similarly to the younger generation, indicating that adoption barriers may lie more in perception than actual functionality.

Further reinforcing this generational divide, Calvo-Porral et al. (2020) found that one of the reasons why generation X is the most technology interested generation is information seeking motivation and entertainment motivation, which have the strongest influence on technology engagement.

2.1.3 Consumer Safety Concerns

The perception of safety weighs on public opinion regarding the acceptance of autonomous vehicles. As Othman et al. (2021) emphasizes when vehicles are perceived as not safe, they become less desirable, regardless of their benefits. Additionally, according to Kenesei et al. (2025), user acceptance of AVs does not necessarily depend on the real benefits and risks of the technology, but rather on their perceptions. These two quotes establish a fundamental link: safety perception directly influences public acceptance, which in turn is essential for the widespread adoption of AVs.

Additionally, the public perception of safety is often negatively impacted by accidents involving AVs. Currently, when a crash occurs due to system failures, the event is rapidly disseminated across all news channels and social media, rapidly influencing public opinion. To investigate this phenomenon, Jefferson and McDonald (2019) did a semantic analysis of Twitter data about a Tesla autopilot crash in 2019.

After analysing more than 11,000 tweets related to the Tesla Autopilot crash over six days, their semantic analysis revealed interesting conclusions. Firstly, the most used words were “Tesla”, “Autopilot”, and “crash”, which indicated a focus on brand, technology, and failure. Additionally, they found that the number of tweets increased significantly after the news. This shows that, in this industry, incidents can rapidly reshape public opinion as trust is lost.

In conclusion, consumer perceptions towards AVs are susceptible to negative but not positive news regarding the technology. The technology is initially viewed as unreliable, and consumers would have to rely on it over time by slowly gaining trust in it, which is a critical aspect of their decision-making process Jefferson and McDonald (2019).

2.2 Technology Acceptance Theories

The introduction of a new technology always raises questions. To better understand these questions, this study applies technology adoption theories to analyse the factors that influence the acceptance or rejection of a new technology, specifically assisted driving technologies.

Technology acceptance theories have been applied in a wide range of domains to understand and predict users’ behaviour. Acceptance occurs when the individual has a positive decision to use an innovation (Taherdoost, 2018).

2.2.1 Technology Acceptance Model (TAM)

The Technology Acceptance Model (TAM), developed by Davis (1989), is one of the most cited models. This model has two main components: Perceived Usefulness (PU) and Perceived Ease of Use (PEOU). PU symbolizes the utility of a technology (by using the technology, could I perform better?), while PEOU represents the ease of using the technology (Davis, 1989). TAM has shown broad applicability across various areas, allowing researchers to predict technology acceptance based on these core constructs (Appendix C).

Regarding assisted driving technologies, TAM has been used by renowned authors to understand user adoption, and the results were significant. Rahman et al. (2017) applied TAM to advanced driver assistance systems (ADAS) and found that PU and PEOU significantly predicted Behavioural Intention to Use (BI). Their model explained 73% of the variance in BI, confirming TAM applicability. Xiao and Goulias (2022) used the model to test the AV adoption intention of U.S. consumers and reported that PU was the most influential factor. Also, Huang (2023) found a novel relationship: perceived ease of use (PEOU) has an established impact on behavioural intention (BI) through its impact on perceived usefulness (PU). It was also demonstrated in the study that emotional factors strengthen the explanatory value of the technology acceptance model (TAM) as external variables. Regarding attitude, Leich et al. (2018) confirmed that PU and PEOU significantly predict attitude and BI.

Nonetheless, the assumptions of the Technology Acceptance Model (TAM) are not consistent across all research on autonomous vehicles (AVs). As an example, Herrenkind et al. (2019) concluded that PU played a significant role in determining the behavioural intention of autonomous shuttle services, but PEOU did not exhibit a significant direct effect. This implies that in public transport situations, users could be driven by perceived benefit rather than convenience. On another note, Lee et al. (2019) identified that neither PU nor PEOU had strong direct effects on AV adoption intention. Other issues, like self-efficacy and relative advantage, had a greater effect instead, which points towards the idea that contextual and emotional factors can supersede functional expectations.

The TAM model, initially developed by Davis (1989), had two more versions; firstly, TAM2, proposed by Venkatesh and Davis (2000), which incorporates social influence processes and cognitive instrumental processes as predictors of perceived usefulness. Later, TAM3 was introduced, proposed by Venkatesh and Bala (2008). This new model uses TAM2 as a base and adds predictors of perceived ease of use, such as perceptions of external control, anxiety, and playfulness.

For example, self-efficacy has shown an impact on influencing technology acceptance. According to Faqih (2013), internet self-efficacy positively influences both perceived ease of use and perceived usefulness. Those findings suggest that individuals with higher confidence in their technical ability are more likely to perceive a system as easier to use and more beneficial.

Also, the external variable anxiety was tested in a study about the intention to use mobile learning among university students in Yemen. Results from this study by Alrajawy et al. (2018) indicated that anxiety directly affects negatively PEOU and PU. Similarly, Turan and Kir (2019) studied about the introduction of anxiety as an external variable in TAM and observed that it has a medium effect on PEOU while just a small effect on PU. Both variables were included in this study.

The present study adopts the Technology Acceptance Model (TAM) as its conceptual model. TAM main advantage lies in its clarity, focusing on two central constructs: PU and PEOU, that predict attitudes and behavioural intention across contexts (Davis, 1989). Another benefit is its strong predictive power, with prior meta-analyses showing that TAM is a valid and robust model that has been widely used (King & He, 2006). Furthermore, TAM is flexible and extensible, as it allows the inclusion of external variables that may influence PU and PEOU, making it adaptable to specific contexts such as assisted driving technologies (Faqih, 2013; Alrajawy et al., 2018).

2.2.2 Unified Theory of Acceptance and Use of Technology (UTAUT)

The Unified Theory of Acceptance and Use of Technology (UTAUT), introduced by Venkatesh et al. (2003), integrates elements from eight established models, including TAM, to explain user acceptance and usage behaviour (Appendix D).

The Unified Theory of Acceptance and Use of Technology (UTAUT) is based on four main variables: performance expectancy (PE), effort expectancy (EE), social influence (SI), and facilitating conditions (FC) with four moderators: age, gender, experience, and voluntariness of use. Performance expectancy (PE) refers to the individual belief that the use of a system will assist in gains in work. The ease of use of the system is called effort expectancy (EE). Social influence (SI) refers to the extent to which a person has a perception that important people think he or she must utilize the new system. Facilitating conditions (FC) is a term used to define how strong an individual feels that there is an organizational and technical infrastructure that supports the use of systems (Venkatesh et al., 2003).

This model demonstrated that it could explain up to 70% of the variance in user intentions to adopt a technology, outperforming previous models in empirical accuracy (Venkatesh et al., 2003).

UTAUT has been widely used in various contexts. Kijsanayotin et al. (2009) used UTAUT to analyse health information technology adoption in developing countries. Their findings revealed that the willingness to use health IT was determined by the perception that it is useful (performance expectancy, PE), simple to operate (effort expectancy, EE), recommended by significant people (social influence, SI), and based on the feeling of having a choice in using the technology (voluntariness of use). Among these four influencing factors, PE was by far the strongest predicting factor.

UTAUT has also been used in automotive applications to understand consumer acceptance of AVs. For instance, Sutarto et al. (2023) applied UTAUT to understand adoption intentions in Indonesia. They mention that PE plays a significant role in shaping adoption behaviour. Similarly, EE and hedonic motivation also significantly affected the UTAUT. They identified SI as a primary determinant but justified that the socio-cultural context of Indonesia could influence it.

Moreover, regarding AVs, Kaye et al. (2021) found that PE and EE were significant predictors of BI in France, although only PE was a significant predictor for participants residing in Australia and Sweden. Additionally, a study by Kettles et al. (2019) showed the adoption intention of AVs in South Africa and confirmed that PE, hedonic motivation, trust in safety, and SI were strong predictors of intention. Tian and Wang (2022) found that PE, EE, and FC have an indirect positive influence on intention to adopt AVs. Finally, in Thailand, PE and EE also proved to be good predictors (Chaveesuk et al., 2023).

Gunasinghe and Nanayakkara (2021) integrated the variable technology anxiety in the UTAUT model to assess the adoption intention of virtual learning environments. Their work proved that technology anxiety had a significant negative impact on technology adoption.

By quoting the papers above, it is easy to understand that the four key constructs have an impact on technology adoption. But Venkatesh et al. (2003) also integrated four moderating effects, which are as important as the other four constructs. For example, Gupta et al. (2008) examined the moderating effects of gender. Citing Gupta et al. (2008), partial support for Hypothesis 1 in this analysis is found, which states that the influence of PE on BI to use internet technologies is moderated by gender.

2.3 Triple E: Environmental, Ethical, and Economic Considerations

2.3.1 Sustainability and Environmental Impact of AVs

The integration of autonomous technology with sustainable driving systems, such as electric vehicles, can yield significant environmental benefits.

Automated vehicles (AVs) potentially optimize energy use by enabling smoother driving patterns, which reduces idle times and fuel consumption. As said by Greenblatt & Shaheen, (2015), researchers estimate that AVs could reduce energy use up to 80% from platooning, efficient traffic flow and parking, safety-induced light-weighting, and automated ridesharing.

Also, a study done by Miller & Heard, (2016) reiterates the idea that fuel economy improvements are likely to result from light-weighting vehicles due to reduced collisions, reduced traffic congestion due to optimized vehicle operation, "platooning" AVs together in proximity, and intelligent transportation systems that enable smart communication between vehicles and infrastructure.

Despite the advantages in fuel economy (fuel spent by km), Miller and Heard (2016) argue that a widespread adoption of AVs could increase the km travelled per car, and that occurs because of increased use by those currently unable to drive, increased numbers oftrips (both occupied and unoccupied), a shift away from public transit, additional km travelled due to self-parking and self-fuelling, and longer commutes.

2.3.2 Ethics in Autonomous Decision-Making

Some ethical challenges appear when we delegate the decision-making to algorithms, totally removing human decisions, which could lead to pragmatic/unethical outcomes. This is happening with autonomous vehicles (AVs), where the algorithm has full control over decisions. The question that arises here is: Is the AV algorithm capable of making ethical decisions?

While the adoption of AV's is expected to decrease the number of traffic incidents. Citing Fleetwood (2017) AVs could reduce traffic fatalities by up to 90% by eliminating accidents caused by human errors, representing more than 29000 lives saved per year in the United States alone. However, despite these optimistic projections, there are some cases where "human decisions" could be valuable. As Keeling (2019) argues, AVs should evaluate harm and risk of harm and must prioritize minimizing it while balancing other moral considerations, such as fairness and individual rights.

Several models have been considered to address these dilemmas. Geisslinger et al. (2021) evaluated whether normative ethics, such as Deontological, Utilitarian, Virtue, and Risk ethics, could be used to determine AV decision-making but concluded that all the theories are too broad or face some challenges when dealing with algorithm decision-making.

Among the many ethical dilemmas, the classic "trolley problem" causes the most discussion. In this problem, the person must choose between two harmful situations, as demonstrated in Appendix E.

Regarding AV's, the "trolley problem" is not merely hypothetical. A scenario where the vehicle must choose between colliding with a pedestrian/other vehicle or swerving and harming the passenger inside the vehicle could be common. Therefore, should the AV minimize harm, or should it make the best moral decision?

Bonnefon, Shariff, and Rahwan (2016) evaluated people's opinions about this ethical dilemma. Their study concluded that people generally support the idea of AVs minimizing total casualties (minimizing harm), but at the same time, they are less inclined to purchase a vehicle that doesn't first protect its passengers. Which means that people's ethical concerns have a negative impact on their attitude toward using a technology.

To tackle this challenge, some authors studied/developed theories to program the AV's algorithms. For instance, Evans et al (2020), developed the Ethical Valence Theory (EVT). The goal of EVT is the mitigation of moral claims, the theory states that every road user has a claim (vary in strength based on risk/vulnerability) and a valence (measures how socially acceptable is to prioritize a claim), and the algorithm must choose the action that minimizes moral claims. For example, in Appendix F, there are 3 actions for the AV (hit the wall, the pedestrian, and the other vehicle). The AV final decision will depend on valences, harm, and moral profile.

Yet, despite these concerns, some car manufacturers have publicly announced that their cars should prioritize the safety of those inside. For example, Mercedes-Benz announced that it would program its self-driving cars to prioritize the safety of people inside the car over pedestrians (Taylor, 2016). This position illustrates the ethical tension between individual safety and collective moral responsibility.

It becomes clear that ethics are complex in algorithm decision-making. Excluding the trolley problem, there are other, more mundane situations where ethical issues appear, for example, data protection, lack of transparency, jobless drivers, etc. To address this, a multidisciplinary approach to AV ethics is essential, leveraging the expertise of ethicists, engineers, and regulators to navigate complex moral landscapes (Geisslinger et al., 2021).

2.3.3 Economic Impact and Cost of Ownership

Regarding the cost of ownership, AVs will make it more affordable. As said before, these cars are more efficient in energy/fuel consumption, which reduces the number of times the owner needs to charge the car, making it more affordable. As said by Silberg (2013), platooning could reduce highway fuel use by up to 20% solely due to the decreased drag coefficient from drafting. Also, by excluding human errors from driving, it is expected that a lower number of car accidents will occur, thus the personal cost with insurance will reduce a lot. According to a report by KPMG, over 90% of accidents each year are caused by driver error, and accident frequency could drop as much as 80% with commercially viable Level 4 fully automated vehicles (Albright et al., 2015).

But the introduction of AVs will not only affect the owners, also it will affect several industries. According to Shapiro et al. (2023), their initial adoption could increase insurance industry revenues if the cost of coverage for AVs is higher during the initial period of adoption and certification. However, the expected reduction in accidents, severe collisions, should reduce premiums and lower industry revenues, a development that would be enhanced if AVs lead to fewer vehicles on the road. Furthermore, according to Clements et al. (2017), another industry that will lose business from the improved safety of AVs is the medical industry. In 2019–2020, in the US, the annual average emergency department (ED) visit rate for motor vehicle crash injuries was 11.6 visits per 1,000 people per year (data from CDC – National Center for Health Statistics, 2020).

With the expected reduction of crashes, other implicated industries will lose some work, for example legal and auto repair industries. According to Clements et al. (2017), as the level of automation increases and crashes fall, a large percentage of collision repair shops will lose revenues and be forced out of business. Regarding the legal industry, with a total number of around 1.3 million practicing attorneys in the United States, personal injury lawyers make up approximately 6% of the American lawyer population. Vehicle collisions are the most common type of tort case, accounting for around 35% of all civil trials (McCarthy 2008). So, it is expected lesser work for this type of attorneys.

Although, the real socio-economic problem will happen at the transportation industry, as AVs could contribute to an unemployment crisis. As stated by Wallace (2017), in the U.S., the transportation industry itself employs 3.2% of workers, but introduction of AVs threatens jobs in every sector of the economy. In total, AVs could affect the jobs of 15.5 million workers (1 in 9 workers).

3. CONCEPTUAL MODEL

The conceptual model of this study (Figure 1) is based on an adaptation of the Technology Acceptance Model (TAM) proposed by Davis (1989). The original TAM identifies two main constructs, Perceived Usefulness (PU) and Perceived Ease of Use (PEOU), that impact Attitude and the Behavioural Intention to use certain technology.

To address the objectives of this study, a model was developed using the core of TAM and five external variables defined in Table I:

Table I, Frame of Reference

Variable	Definition	Reference
Perceived Usefulness	The degree to which a person believes that using a particular system would enhance job performance.	Davis (1989)
Perceived Ease of Use	The degree to which a person believes that using a particular system would be free of effort.	Davis (1989)
Social Influence	The degree to which individuals perceive that important others believe they should use the new technology.	Venkatesh et al. (2003)
Facilitating Conditions	The degree to which an individual believes that organizational and technical infrastructure exists to support system use.	Venkatesh et al. (2003)
Self-Efficacy	A belief that one has the ability to perform certain behaviour.	Bandura (1989)
Anxiety	The degree of apprehension or fear individuals experience when considering or using a new technology.	Gunasinghe et al. (2021)
Ethical Concerns	The degree of concern users expresses regarding the ethical implications of a system's decision-making in critical scenarios.	Bonnefon et al. (2016)
Attitude Toward Use	A major determinant of whether the user will use or reject the system.	Davis et al. (1989)
Behavioural Intention	The degree to which a person has formulated conscious plans to use or adopt the system.	Davis (1989)

Source: Own elaboration

The external variables presented were backed by literature in chapter 2:

- **Social Influence** inspired by the UTAUT model (Venkatesh et al., 2003) and applied by Sutarto et.al (2023) and Kettles et al. (2019) in AV adoption studies
- **Facilitating Conditions**, present in the UTAUT model Venkatesh et al. (2003), and proved to be a good predictor by Tian and Wang (2022).
- **Self-efficacy**, as it was integrated in TAM3 developed by Venkatesh and Bala (2008) and had explanatory results in Faqih (2013), Teo (2007), and Hasan (2007) works.
- **Anxiety** regarding automation, as it had significant results in Gunasinghe and Nanayakkara (2021), Alrajawy et al. (2018), and Turan and Kir (2019) works.
- **Ethical Concerns**, due to the increasing relevance of ethical debates related to decision-making algorithms in AVs, as discussed by Bonnefon et al. (2016) and Keeling (2019).

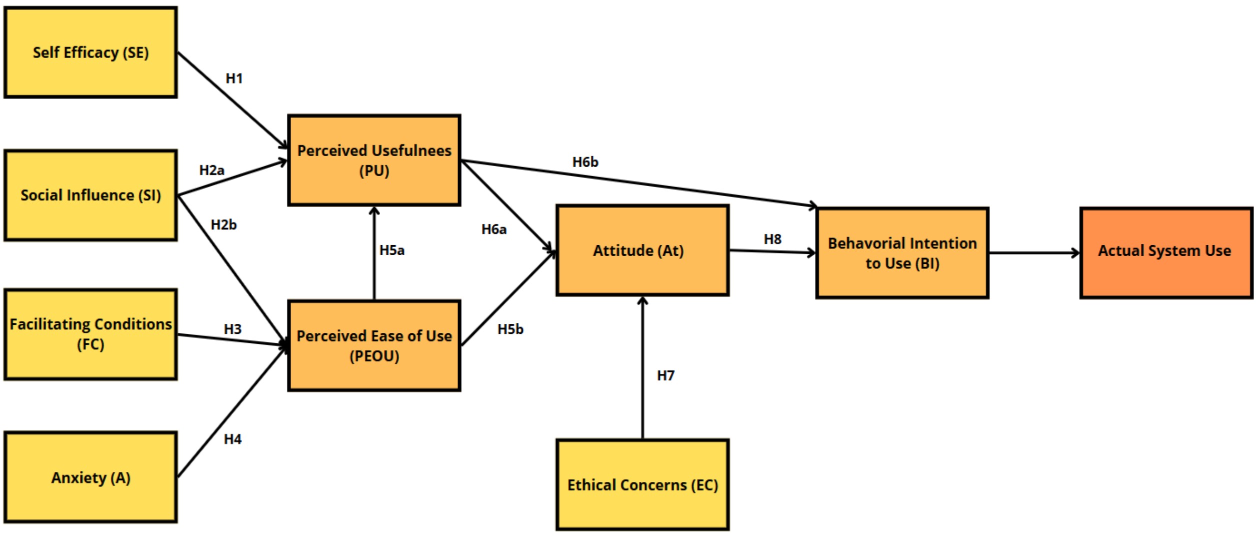

Figure 1 - Conceptual Model
Source: Own elaboration based on Davis (1989)

Figure 1 illustrates the conceptual model developed for this study, showing the relationships between the selected variables.

Hypothesis presentation:

Prior studies on technology acceptance have demonstrated that self-efficacy (the belief that one has the ability to perform certain behaviour) significantly influences perceived usefulness (Hasan, 2007; Teo, 2007; Faqih, 2013). Based on these findings, the variable was included in the model as a predictor of perceived usefulness.

Accordingly, the first research hypothesis is proposed (H1): *Self-efficacy has a positive impact on Perceived Usefulness.*

In TAM2, social influence was introduced as a predictor of perceived usefulness. The effect of it is described as people internalizing influences into their own usefulness perceptions, and also through using a system to gain status and influence within the group, which consequently improves job performance (Venkatesh and Davis, 2000).

Also, social influence was found to be one of the principal predictors of consumer adoption of AVs in Indonesia (Sutarto et al., (2023). Likewise, it was determined as a significant predictor of adoption intention of AVs in South Africa (Kettles et al., (2019). Moreover, the willingness to use health IT was determined by the recommendation from significant people.

In consequence, the following hypotheses were proposed:

H2b: *Social Influence has a positive impact on Perceived Usefulness*

H2b**:** *Social Influence has a positive impact on Perceived Ease of Use*

Facilitating conditions were described as an indirect positive influence on intention to adopt AVs (Tian and Wang, 2022). Additionally, regarding mobile-assisted language learning, facilitating conditions were described as a significant predictor of learners' perceived ease of use (Ebadi and Raygan, 2022).

Consequently, it is proposed the research hypothesis (H3): *Facilitating Conditions have a positive impact on Perceived Ease of Use*

Furthermore, in a study about the intention to use mobile learning among university students in Yemen, it was found that anxiety has a negative effect on perceived ease of use and perceived usefulness (Alrajawy et al., 2018). Similarly, when integrated in a UTAUT model to assess the adoption intentions of virtual learning environments, anxiety also had a negative impact on adoption. Once the variable is applied as an external variable of TAM, the effect on perceived ease of use was medium.

Accordingly, the following research hypothesis was proposed, (H4): Anxiety *has a negative impact on Perceived Ease of Use.*

The Technology Acceptance Model (TAM), introduced by Davis (1989) continues to be one of the most applied models to analyse technology acceptance. The model captures five relations: Perceived ease of use directly affects perceived usefulness, perceived usefulness directly affects attitude, perceived ease of use directly affects attitude, perceived usefulness directly affects behavioural intention to use, and attitude directly affects behavioural intention to use. These relations were tested severely in AV studies (Rahman et al. 2017; Xiao and Goulias 2022; Huang, 2023; and Leich et al. 2018).

Therefore, the following research hypotheses were proposed:

H5a: *Perceived Ease of Use has a positive impact on Perceived Usefulness*.

H5b: *Perceived Ease of Use has a positive impact on Attitude*.

H6a: *Perceived Usefulness has a positive impact on Attitude*.

H6b: *Perceived Usefulness has a positive impact on Behavioural Intention to Use*.

H8: *Attitude has a positive impact on Behavioural Intention to Use*.

Finally, the model presents a new relation between ethical concerns and attitude, because of the ethical dangers customers could perceive. Besides the trolley problem, issues like data protection, lack of transparency, and jobless drivers could appear (Geisslinger et al., 2021). These issues are already perceived by the consumer, and it makes them less inclined to purchase the technology (Bonnefon et al., (2016).

Consequently, the hypothesis was proposed (H7): *Ethical Concerns have a negative impact on Attitude*.

4. METHODOLOGY

4.1 Study Type

This study is quantitative, as it examines relations between variables (Saunders et al 2019). Being the goal to establish causality between variable relations, the purpose of the study is explanatory (Saunders et al. 2019). The research strategy used was the inquiry, through a survey to collect data, because of its simplicity to control, analyse, and interpret the results (Nunan et al. 2020) and because of the capacity to obtain a high number of responses (Sauders et al. 2019). Due to a time constraint, the study was realized in a certain period, thus, its time frame is cross-sectional (Sauders et al. 2019).

4.2 Sample Selection

The study population is composed of users and non-users of cars with assisted driving technologies who have an opinion (positive or negative) regarding the technology. As it was impossible to collect data from every person in the population, a sample was used (Sauders et al. 2019).

The sample technique was non-probabilistic of convenience, as the inquiries were selected by the investigator due to higher accessibility, cooperation, and also because it is a less time-consuming technique with lower costs (Nunan et al. 2020). Nevertheless, as it is a non-probabilistic sample, it is not possible to make projections and statistical generalizations of the population (Nunan et al. 2020, Sauders et al. 2019), and the probability of a certain convenience sample represent the population is very low (Nunan et al., 2020; Saunders et al., 2019). Additionally, the inquiries were requested to share the survey, so it was used also the snowball non-probabilistic sample technique (Nunan et al., 2020; Saunders et al., 2019).

4.3 Instruments used for data collection

A quantitative research strategy was adopted to study the proposed hypothesis and understand the relationships between the variables included in the conceptual model. Specifically, an online questionnaire was developed to collect data on key constructs of the extended TAM model.

The questionnaire, designed in Qualtrics, was firstly pre-tested with a sample of 30 participants to check if all the questions were well developed. After it was launched, being available in two language versions: Portuguese and English. It was published online on

24/11/2024 and remained open until 31/03/2025. The survey was distributed through several means, including social media, email, and academic groups. Participants were anonymous and completed the survey voluntarily without any incentives. At the beginning of the survey, all the participants were informed about the purpose and gave consent to use their input.

The questionnaire was structured in six main sections divided into groups of questions:

1. **Introduction questions** (4 questions)
2. **UTAUT questions**
   2.1. Performance Expectancy (4 questions)
   2.2. Effort Expectancy (4 questions)
   2.3. Attitude (4 questions)
   2.4. Social Influence (4 questions)
   2.5. Facilitating Conditions (4 questions)
   2.6. Self-Efficacy (4 questions)
   2.7. Anxiety (4 questions)
   2.8. Perceived Enjoyment (3 questions)
3. **TAM questions**
   3.1. Perceived Usefulness (4 questions)
   3.2. Perceived Ease of Use (3 questions)
   3.3. Behavioural Intention to use (5 questions)
   3.4. Intention to Use (3 questions)
4. **Resistance / Satisfaction questions**
   4.1. Usage Barrier (5 questions)
   4.2. Value Barrier (2 questions)
   4.3. Risk Barrier (3 questions)
   4.4. Traditional Barrier (5 questions)
   4.5. Image Barrier (2 questions)
   4.6. Satisfaction (4 questions)
   4.7. Search for alternatives (2 questions)
   4.8. Intention to recommend (2 questions)
5. **Ethics questions** (8 questions)
6. **Demographic questions** (7 questions)

The questions were adapted from previously tested measurement scales, as referenced in Table II. All items were measured using a 7-point Likert scale, ranging from 1 – Completely Disagree to 7 – Completely Agree, where 4 indicated Neutral.

Table II. Measurement Scales References

Construct	Reference Authors
Behavioural Intention to Use	Oliveira et al. (2016)
Attitude	Venkatesh et al. (2003)
Perceived Ease of Use	Abou-Shouk et al. (2021)
Perceived Usefulness	Abou-Shouk et al. (2021)
Performance Expectancy	Venkatesh et al. (2003)
Effort Expectancy	Venkatesh et al. (2003)
Anxiety	Venkatesh et al. (2003)
Social Influence	Venkatesh et al. (2003)
Ethical Concerns	Own elaboration

Source: Own elaboration

Certain survey groups were only displayed if some conditions were met in earlier responses. For example, only those with prior experience using a car with assistance technology could respond to the “Satisfaction” group of questions. This logic ensured that participants were only asked relevant questions, improving response accuracy and avoiding unnecessary or confusing items.

During the data collection period, more than 500 responses were collected. After cleaning the database by removing incomplete answers, a final sample of 269 fully completed answers was retained for analysis. These completed answers were coded using Excel and subsequently analysed using SmartPLS and SPSS.

5. ANALYSIS AND DISCUSSION OF RESULTS

5.1 Sample Characterization

This study sample is composed of 269 respondents. Among them, 59.1% identified as males, 39.8% as female, and 0.1% as non-binary or prefer not to say. The most common represented age group was 46-55, accounting for 35.23% of the participants, followed by the age groups of 17-25 (17.05%) and 56-65 (16.67%).

Regarding education, nearly half of the respondents (44.4%) held a bachelor’s degree, while 26.9% completed high school, 23.5% had a master’s degree, 3.4% a doctorate, and 1.9% selected “other”. In terms of employment status, 64.3% were full-time employed, followed by 18.6% who were self-employed, 11.9% who were students, and 1.9% each who were part-time employed or retired, and 1,5% that were unemployed.

Concerning income perception, 48.7% reported coping with present income, 39.3% stated they are living comfortably on present income, 8.2% were having difficulties, whilst 3.7% were going through very difficult times.

Almost every respondent is Portuguese (95.9%), as the study was conducted in a Portuguese Institute: ISEG. However, the sample also included 1 respondent from France, 2 from Germany, 1 from Italy, 1 from Poland, 4 from the USA, and 2 from other regions. Finally, regarding residence, 62.1% lived in big cities, 23.4% lived in suburban areas, and 14.5% lived in rural areas.

In terms of respondents' experience with cars equipped with assisted driving systems, 61% had already driven a car with these characteristics, while 29% had not but were interested in doing so, and 10% had not and were not interested.

Among those who had driven such vehicles, 55.5% had used a car with basic driving assistance tools, such as adaptive cruise control, lane-keeping assistance, and parking assistance. Additionally, 43.9% had driven cars with partial automation, for example, Tesla’s Autopilot, and only one respondent reported having driven a car with full automation (which currently exists only as a prototype). Furthermore, the majority of these respondents (59.8%) had been using such cars for more than two years. The most frequently mentioned car brands among these respondents were Mercedes (31 mentions), BMW (23 mentions), and Tesla (21 mentions), reflecting the popularity of premium brands in the early adoption of assisted driving technologies.

The respondents' main reasons for using or considering using a car with driving assistance features were Cost Savings (fuel/maintenance), Technological Interest, and Social Influence (recommendation from peers). However, their principal concerns about this type of car were Safety, Reliability, Cost of Purchase, Road Infrastructure Readiness, and Ethical Concerns in accident situations, for example.

As the evolution of the car industry is moving toward alternative energy sources, like electric or hydrogen, it is likely that future driverless cars will be powered by green energy. Because of this, respondents were also asked about their views on sustainability. In total, 48.7% expressed concerns about the environment, followed by 26.4% who had a neutral opinion, 13.8% who reported being very concerned, 6.3% who said they were not very concerned, and 4.8% who were not concerned at all.

5.2 Conceptual Model Validation

To test the conceptual model, the partial least squares structural equation modelling (PLS-SEM) was used through the software SmartPLS. PLS-SEM is a second-generation multivariate analysis technique that calculates relationships between latent constructs. This technique maximizes the explained variance of the dependent variables, which is suitable for predictive research and theory development (Hair et al. 2011). Also, it can handle small sample sizes, non-normal data, reflective and formative constructs, and high model complexity. Hair et al. (2017) described the technique as a “silver bullet” in business research contexts.

5.3 Measurement Model Evaluation

In PLS-SEM, the evaluation of the measurement model is essential to guarantee that the constructs are measured both reliably and validly. So, the indicator reliability, internal consistency, convergent validity, and discriminant validity must all be evaluated.

Concerning the indicator reliability, Hair et al. (2022) stated that the indicator’s outer loadings should be higher than 0.70. Indicators with outer loadings between 0.40 and 0.70 should be considered for removal only if the deletion leads to an increase in composite reliability and AVE above the suggested threshold value. Similarly, Sarstedt et al. (2017) emphasize that outer loadings below 0.40 are generally unacceptable and should be removed unless strong theoretical justification exists.

Consequently, only the construct E7 (Do you believe advanced autonomous systems should have transparent decision-making processes to guarantee responsibility in a crash?) was eliminated from the model because it presented an outer loading of 0.413. The outer loadings of the items that were integrated in the structural model can be found in Table III.

The traditional criterion for internal consistency is Cronbach’s alpha, which provides an estimate of the reliability based on the intercorrelations of the observed indicator variables (Hair et al., 2022). Other criteria to evaluate internal consistency is composite reliability, and it is generally preferred in PLS-SEM because it accounts for varying outer loadings of indicators. A third measure, rho_A, was introduced by Dijkstra and Henseler (2015) and is considered a more theoretically precise estimator of internal consistency reliability. Independent of the criteria chosen to evaluate the reliability, values above 0.7 are considered satisfactory in the first stages of research, and values above 0.8 or 0.9 are considered satisfactory in advanced stages of research (Nunnally & Bernstein, 1994).

In this study, every construct has adequate internal consistency, as seen through the indicators (Cronbach’s alpha, Rho_a, and Rho_c) in Table 2. The lowest value of 0.667 is the Cronbach's alpha of the Self-Efficacy construct.

To evaluate convergent validity, the average variance extracted (AVE) is observed. According to Hair et al. (2022), an AVE value of 0.50 or higher indicates adequate convergent validity. This rule is corroborated by almost every construct, only Self-Efficacy has an AVE of 0.499, which is below 0.5, but it will be considered acceptable for the study. Thus, all constructs explain on average 50% of the variance of the items.

Table III. Construct Reliability and Convergent Validity

Constructs	Items	Loadings	Cronbach's alpha	Rho_a	Rho_c	AVE
Anxiety	ANX1	0.911	0,932	0,939	0,951	0,830
	ANX2	0.892				
	ANX3	0.933				
	ANX4	0,908				
Self Efficacy	EE1	0,668	0,667	0,685	0,798	0,499
	EE2	0,705				
	EE3	0,615				
	EE4	0,822				
Ethical Concerns	E1	0,859	0,911	0,919	0,93	0,656
	E2	0,862				
	E3	0,905				
	E4	0,784				
	E5	0,641				
	E6	0,808				
	E8	0,786				
Social Influence	SI1	0,881	0,842	0,856	0,894	0,679
	SI2	0,881				
	SI3	0,766				
	SI4	0,760				
Facilitating Conditions	PE1	0,809	0,759	0,807	0,847	0,588
	PE2	0,851				
	PE3	0,829				
	PE4	0,534				
Perceived Ease of Use	PEOU1	0.982	0,965	0,966	0,978	0,936
	PEOU2	0.935				
	PEOU3	0.984				
Perceived Usefulness	PU1	0.929	0,936	0,936	0,954	0,839
	PU2	0.937				
	PU3	0.912				
	PU4	0.884				
Attitude	A1	0.875	0,887	0,910	0,921	0,744
	A2	0,847				
	A3	0,806				
	A4	0,919				
Behavourial Intention to Use	BI1	0.954	0,981	0,981	0,985	0,928
	BI2	0.967				
	BI3	0.969				
	BI4	0.960				
	BI5	0.964				

Source: Own Elaboration

Discriminant validity was assessed using the Cross-Loadings, Heterotrait-Monotrait (HTMT), and Fornell-Larcker ratios. Firstly, regarding HTMT criteria, all the HTMT values should be below 0.90 for conceptually similar constructs and below 0.85 for conceptually distinct constructs (Hair et al., 2022). Through Appendix G, it is shown that all the values are below 0.85. Also, to strengthen the discriminant validity of the model, was assessed the Fornell-Larcker criteria, which is positively passed when the square root of the AVE of each construct is greater than any with other latent variables in the model. Appendix H displays the perfect scenario, where every square root of AVE (bold value) is higher than the numbers below. To complete the discriminant validity test, the Cross-Loadings criteria should be met. It is met when an indicator’s loading on its assigned construct is higher than its loadings on any other construct (Henseler, Ringle, & Sinkovics, 2009). Appendix I shows that only the loading of FC4 has a value lower than its assigned loading on some constructs. Except for this minor validity problem, all the other tests suggest the existence of discriminant validity.

In the context of PLS-SEM, a tolerance value of 0.20 or lower and a VIF value of 5 or higher, respectively, indicate a potential collinearity problem (Hair et al., 2011). If the level of collinearity is very high, as indicated by a VIF value of 5 or higher, it should be considered for removing one of the corresponding indicators (Hair et al., 2022). By looking at Table IV, it is possible to conclude that there are no collinearity problems with the inner model, as the highest VIF value is 2.349 (Perceived Ease of Use and Attitude), which is lower than 5. Equally, the outer model has no collinearity problems, as the highest VIF is 3.623 (A3).

Table IV. Collinearity (inner model)

	Perceived Ease of Use	Perceived Usefulness	Attitude	Behavorial Intention to Use
Anxiety	1.239			
Attitude				2.063
Ethical Concerns			1.020	
Facilitating Conditions	1.381			
Perceived Ease of Use		1.244	2.349	
Perceived Usefulness			2.344	2.063
Self Efficacy		1.335		
Social Influence	1.158	1.193		

Source: Own Elaboration

5.4 Structural Model Evaluation

Below, in Figure 2, is an illustration of the model with the path coefficients (highlighted are the ones with higher absolute values), and the R^2 of the TAM variables (PU, PEOU, A, BIU).

The most commonly used measure to evaluate the structural model is the coefficient of determination (R^2 value). R^2 values of 0.75, 0.50, and 0.25 are considered substantial, moderate, and weak, respectively (Hair et al., 2022).

In this model, almost all of the TAM constructs exhibit good levels of explanatory power, as indicated by their R^2 values. The construct Perceived Usefulness (PU) has an R^2 of 0.631, meaning that 63.1% of its variance is explained by the model, a value that falls between moderate and substantial. Also, the R^2 value of the constructs Attitude (A) and Behavioural Intention to Use (BIU) sinks between moderate and substantial, with the values 0.557 and 0.647, respectively. The construct Perceived Ease of Use (PEOU) is the one with the lowest

R^2, with a result between weak and moderate, as 32.7% of the variance is explained by the model.

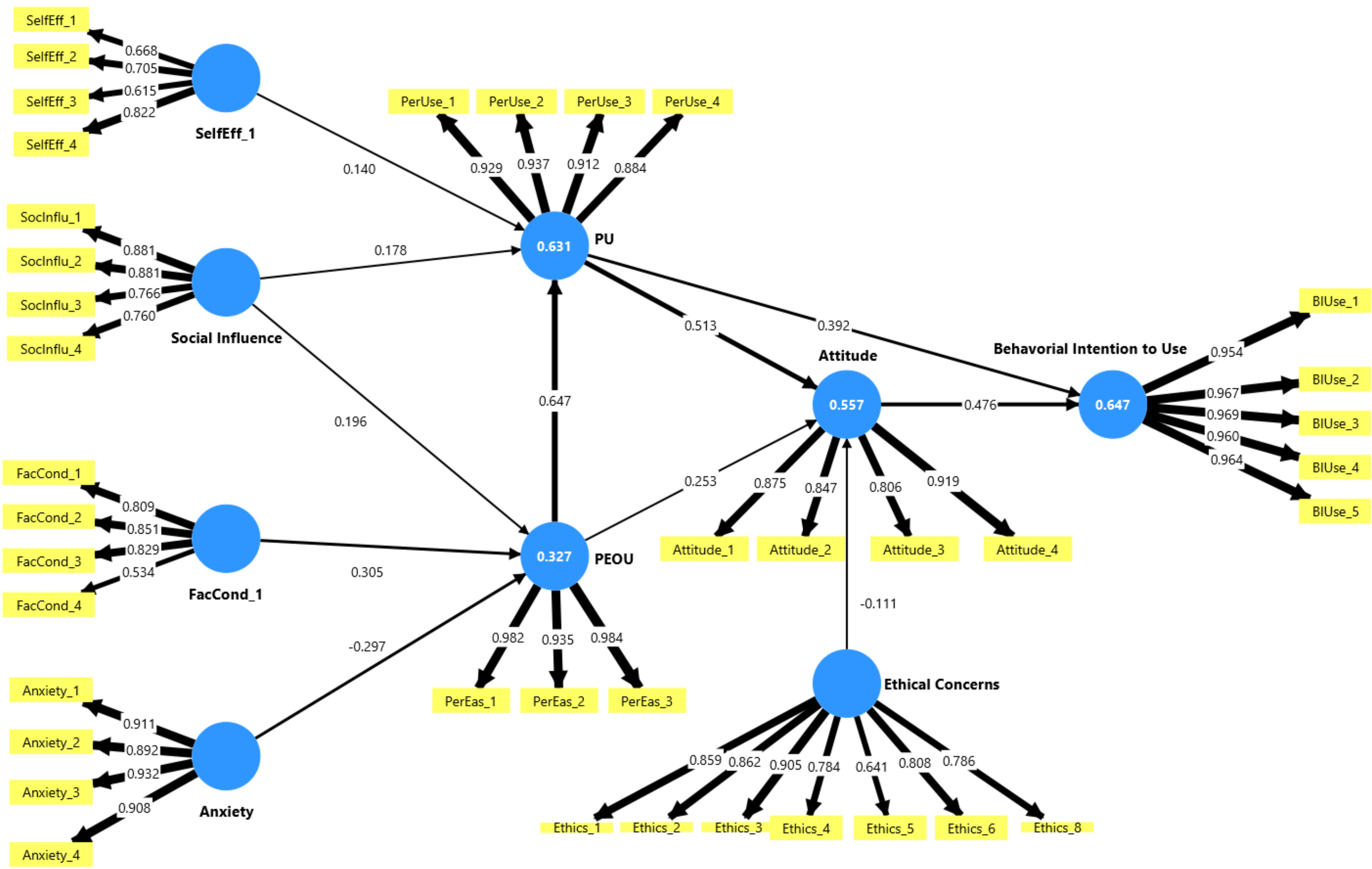

Figure 2 - Structural Model
Source: SmartPLS

Regarding the adequacy of the model, certain parameters were evaluated. Henseler et al. (2014) introduced the standardized root mean square residual (SRMR), which measures the squared discrepancy between the observed correlations and the model-implied correlations, as a means to validate a model. Hair et al. (2022) recommended that SRMR values below 0.08 indicate a good fit. In this model, the SRMR of 0.096 indicates an acceptable but not optimal fit.

Besides SRMR, the Normed Index (NFI) was evaluated. The Normed Fit Index (NFI), introduced by Bentler and Bonett (1980), is an incremental fit measure used in Structural Equation Modelling (SEM) to assess the goodness of fit between a hypothesized model and a null model (where all variables are uncorrelated). The values are situated between 0 and 1, and values above 0.9 are considered optimal. This model has an NFI of 0.787, which is acceptable but not optimal, as it can be seen in Table V. The model presents some adequacy "problems".

Table V. Adequacy of the model

Model Fit

	Saturated model	Estimated model
SRMR	0,077	0,096
d_ULS	4,614	7,261
d_G	1,73	7,82
Chi-square	2322,673	2385,418
NFI	0,792	0,787

R-Square

	R-square	R-square adjusted
Attitude	0,557	0,552
BIU	0,647	0,644
PU	0,631	0,627
PEOU	0,327	0,319

Source: Own Elaboration

5.5 Hypothesis Testing - Bootstrapping

As PLS-SEM does not assume data is normally distributed, the parametric tests used in regression analysis cannot be applied to test whether the outer loadings, outer weights, and path coefficients are significant. Instead, PLS-SEM relies on a nonparametric bootstrap procedure (Davison & Hinkley, 1997; Efron & Tibshirani, 1986) to test coefficients for their significance.

In this case, bootstrapping is used to evaluate path coefficients and test the hypothesis. When the paths are not significant or have an opposite sign, the hypothesis is not supported; in the other cases, the hypothesis is supported.

It was done using a bootstrapping procedure, with 5000 bootstrap samples. As the significance level chosen was 5%, the t-values should be higher than 1.96 (Hair et al., 2021).

Table VI is a summary of the hypothesis test. As can be observed, 11 of the 11 hypotheses were validated. All variables were validated.

Table VI. Hypothesis Testing Results

Hypotheis	Relation	Original sample (O)	T value	P values	Decision
H1	Self Efficacy-> Perceived Usefulness	0,140	3,182	0,001	Confirmed
H2a	Social Influence -> Perceived Usefulness	0,178	4,265	0,000	Confirmed
H2b	Social Influence -> Perceived Ease of Use	0,196	2,959	0,003	Confirmed
H3	Facilitating Conditions -> Perceived Ease of Use	0,305	5,015	0,000	Confirmed
H4	Anxiety -> Perceived Ease of Use	-0,297	5,181	0,000	Confirmed
H5a	Perceived Ease of Use -> Perceived Usefulness	0,647	12,897	0.000	Confirmed
H5b	Perceived Ease of Use -> Attitude	0,253	3,197	0.001	Confirmed
H6a	Perceives Usefulness-> Attitude	0,513	6,863	0.000	Confirmed
H6b	Perceived Usefulness -> Behavorial Intention to Use	0,392	5,867	0.000	Confirmed
H7	Ethical Concerns -> Attitude	-0,111	2,424	0,015	Confirmed
H8	Attitude -> Behavorial Intention to Use	0,476	6,846	0.000	Confirmed

Source: Own Elaboration

5.6 Discussion of Results

This chapter discusses the results of the tested structural model and compares the findings with the literature presented in Chapter 2. The discussion below interprets each tested hypothesis by identifying the impact and whether it is in line with expectations, and also the explanatory power of the model.

Concerning perceived usefulness (PU) external predictors, all hypotheses were confirmed. Firstly, H1, which proposed that self-efficacy has a positive impact on PU, was confirmed ($\beta = 0.140$, t-value > 1.96, p-value < 0.5). This result is in line with findings by Faqih (2013), who emphasized that individual with confidence in their technical skills may perceive the technology as more useful. In addition, H2a was also confirmed, stating that social influence has a positive impact on PU ($\beta = 0.178$, t-value > 1.96, p-value < 0.5), corroborating prior research of Kijsanayotin et al., (2009), Sutarto et al., (2023), and Kettles et al., (), who checked that social influence has a positive impact on users' attitude.

Moving to the external predictors of perceived ease of use (PEOU), all hypotheses were also supported. H2b, which proposed that social influence positively affects PEOU, was confirmed ($\beta = 0.196$, t-value > 1.96, p-value < 0.5), strengthening findings from Kijsanayotin et al., (2009), Sutarto et al., (2023), and Kettles et al., (2019). Additionally, H3, which stated that facilitating conditions had a positive impact on PEOU was validated ($\beta = 0.305$, t-value > 1.96, p-value < 0.5). This result aligns with Tian and Wang (2022) and Ebadi and Raygan (2022) work, confirming that users valuate an organizational and technical infrastructure to support system use. Finally, H4, which predicted that anxiety has a negative impact on PEOU was also confirmed (β = - 0.297, t-value > 1.96, p-value < 0.5), in line with the study by Alrajawy et al. (2018) and Turan and Kir (2019).

Regarding the core TAM relationships, every hypothesis passed the test. Firstly, H5a which posits that PEOU has a positive impact on PU was validated (β = 0.647, t-value > 1.96, p-value < 0.5), supporting Wang et al.,(2023) hypothesis, that perceived ease of use has an indirect effect on attitude by influencing perceived usefulness. Furthermore, H5b: PEOU has a positive impact on attitude, was also confirmed (β = 0.253, t-value > 1.96, p-value < 0.5). This shows that ease of use contributes to shaping attitudes both directly and indirectly, although the direct impact is lighter. Both H6a and H6b, were also confirmed, which state that PU has a positive impact on attitude (β = 0.513, t-value > 1.96, p-value < 0.5), and PU has a positive impact on behavioural intention to use (β = 0.392, t-value > 1.96, p-value < 0.5).

On one hand, these findings align with a study by Rahman et al. (2017), who show that both PU and PEOU are strong predictors of AV adoption, and Xiao and Goulias (2022), who report PU as the most influential factor (0.392 vs 0.253). They also confirm findings from a study by Leich et al. (2018), who observed that PU and PEOU significantly impacted attitude and behavioural intention to use. On the other hand, these results contrast with Herrenkind et al. (2019) results that reported PEOU had no significant direct effect on attitude, and results from Lee et al.'s study in 2019, who found that neither PU nor PEOU had a strong direct impact on AV adoption.

In this study, the variable ethical concerns was introduced to assess whether individuals' moral considerations of the probable outcomes of vehicles with advanced assistance driving technologies may influence their attitude toward partial or full automated vehicles. Accordingly, H7, which proposed that ethical concerns have a negative impact on attitude, was confirmed (β = - 0.111, t-value > 1.96, p-value < 0.5), confirming the work by Bonnefon et al. (2016), which connected purchase intentions and ethics.

Finally, H8, which examined whether attitude has a positive impact on behavioural intention to use, was also confirmed (β = 0.476, t-value > 1.96, p-value < 0.5). This result confirms the predictive power of the TAM model (Davis, 1989) and shows that attitude is determinant in shaping consumers' willingness to adopt a car with assisted driving technologies.

Not only does the hypothesis function alone, but also the model as a whole demonstrated good explanatory power, making it possible to draw conclusions from it. In particular, the model explains 64.7% of the variance in behavioural intention to use, primarily through its direct predictors, attitude and PU. Showing that users' usefulness perception of assisted driving technologies and their attitude toward the technology explain their intention to use it. This result is in line with other authors, for example, studies by Rahman et al. (2017) and Huang (2023) reached the R^2 of 0.73 and 0.49, respectively.

Regarding the latent variable attitude, this study introduced a new relationship by including ethical concerns as a predictor. One of the research objectives was to analyse whether consumers' moral considerations regarding advanced assisted driving technologies could negatively influence their attitude toward adoption: a hypothesis that was confirmed. 55.7% of the variance in Attitude was explained by its predictors (PU, PEOU, and Ethical Concerns), meaning that consumers' perception of utility, ease of use, and their ethical considerations mold their sentiment about assisted driving technology. The first two have a positive impact on attitude, as the last one has a negative impact.

The variance of the latent variable PU was also well explained by its predictors (R^2 = 63.1%). Among these, PEOU was the strongest predictor, ensuring that individuals' perception of a technology's ease strongly impacts the utility they see in it. Here, the indirect effect of PEOU by PU on attitude is clear, because it is a really strong predictor of PU.

Additionally, self-efficacy and social influence contributed meaningfully to explain PU variance. These findings suggest that users value social opinion (peers, news, influential people) and their capacity to succeed by using the technology to adopt it.

Lastly, PEOU had the lowest R^2, yet its predictor relations still demonstrated statistically significant effects. The three predictors (Social Influence, Facilitating Conditions and Anxiety) explained 32.7 % of PEOU variance. Which means that assisted driving ease of use is influenced positively by social opinion and the existence of a help department that could help them efficiently in case of malfunction or mistake, and PEOU is negatively affected by individuals' technology anxiety.

To conclude, all hypotheses were validated, and the model worked as a whole, which reinforces the robustness of the constructs and the model. The impact of these findings will be explored in the next chapter.

6. CONCLUSIONS, LIMITATIONS, AND FUTURE RESEARCH

6.1 Conclusions

This study investigated the factors that affected consumers' acceptance of cars equipped with assisted driving technologies. At the beginning, both general and specific objectives were traced, and by the end of the research, these objectives were successfully achieved. As a result, it is now possible to answer the research questions.

Concerning the first question, a Technology Acceptance Model (TAM) approach was used to explore the factors influencing adoption. All variables in the model were validated, indicating that all have a significant impact on consumers' behavioural intention to use (BI). Among these, some exhibit a stronger effect than others, becoming the variables that better explain BI.

The TAM model demonstrated good explanatory power within this study. In particular, three relations were notable. First, perceived ease of use (PEOU) strongly predicted perceived usefulness (PU), suggesting that when consumers find assisted driving technologies easy to use, they are more likely to comprehend that with the technology, they will perform better. Second, PU had a strong effect on attitude, and this relation also captures the indirect influence of PEOU on attitude through PU. This supports the idea that if a consumer believes that by using the technology, he will perform better, then his likelihood of developing a positive attitude is higher. Third, attitude significantly predicted BI, showing that the more favourable a consumer’s attitude toward the technology, the higher their likelihood of adopting it in the future.

Additional variables were included to predict PEOU and PU. All were found to be explanatory, although some had a more substantial effect. Facilitating conditions proved to be a strong predictor of PEOU, indicating that the perceived ease of a technology increases when consumers are aware of the existence of support mechanisms. Conversely, anxiety had a strong negative effect on PEOU, highlighting that consumers who experienced greater anxiety about assisted driving technologies were less likely to find them easy to use. Concerning PU predictors, both social influence and self-efficacy positively impacted it, supporting the evidence that consumers who feel confident in their ability to use the technology and who perceive that important others support its use are more likely to view the technology as useful. Also, in this study, the variable Ethical Concerns was included as a predictor of consumers' attitude, and it was explanatory; the results will be addressed in the next paragraph.

Regarding the second research question, the study concluded that ethical concerns do impact consumers' attitudes on adopting cars with advanced assisted driving technologies. In the survey, participants were asked to evaluate a range of ethical issues, including the decisions autonomous vehicles (AVs) might make in life-threatening situations, whether passenger safety should be prioritized, concerns about the fairness of the algorithm, the need to implement new regulations adapted to these type of vehicles, potential joblessness, data privacy, the importance of transparent decision-making processes and accountability in case of incident. Among these concerns, only “transparent decision-making” was not validated; thus, it wasn’t a predictor of the ethical concerns' latent variable.

This suggests that while transparency is often emphasized in public discussions, it may not be a decisive factor in shaping consumers' attitudes at this stage. All other ethical concerns were shown to have an impact on consumers' attitudes, although their absolute impact was lower than other predictors, PU and PEOU. Concluding, ethical concerns, particularly those related to accountability, algorithmic decisions, data privacy, and fairness, negatively influence consumer attitudes and, as a result, indirectly affect BI. These findings reinforce the importance of addressing the ethical dimension alongside the technical one to increase public acceptance.

Answering the last research question, respondents were mainly interested about autonomous driving technologies, because of features like cost savings (fuel, maintenance), technological interest and easiness of driving. However, respondents also expressed concerns regarding safety, reliability, cost of purchase, road infrastructure and ethical questions. In this sample, only 10% were not interested in using a car with such capabilities, which shows that, at this time, the perceived benefits surpass perceived concerns displaying the readiness of the average consumer to adopt AVs.

6.2 Study Implications

This study contributes to both theoretical and practical areas. From a theoretical standpoint, the study extends the TAM by integrating five external variables, four that are predictors of perceived ease of use or perceived usefulness, and one that is a predictor of attitude, offering an adapted outline to understand consumer attitudes toward assisted driving technologies. The validation of the model supports its applicability to emerging mobility contexts, where traditional TAM variables could interact with moral and emotional considerations.

From a practical perspective, the study offers valuable insights for automotive manufacturers, technology developers, and policymakers. By identifying which factors influence consumer acceptance, it provides guidance for designing more user-centred and socially acceptable driving systems. These insights are especially relevant at a time when industry and governments are actively shaping the future of mobility.

6.3 Study Limitations

While the findings of this study offer meaningful insights, some limitations should be acknowledged. Regarding the survey, the first limitation is the use of a non-probabilistic sample of convenience, which may be subject to some bias or misinterpretation. Secondly, the sample may not fully capture the population, especially in terms of geographic distribution (as it was made in Portugal), age, or technology familiarity, which could influence the results. Also, the study collects responses at a specific point in time, although the consumer acceptance of vehicles with assisted driving technologies is dynamic and could change as the technology becomes more exposed.

Finally, while ethical concerns were incorporated as a latent construct, the complexity of ethics in autonomous driving may require a more in-depth qualitative investigation to better understand public sentiment.

6.4 Suggestions for future research

As assisted and autonomous driving technologies exponentially evolve, future research should try to track how consumers' acceptance changes over time. The recent announcement of Tesla’s robotaxi is a concrete example of a research opportunity. This real-world implementation of a fully autonomous vehicle could be the object of a case study to examine consumer perceptions.

Moreover, future research could expand the theoretical model by testing other external variables that could also impact behavioural intention, such as environmental issues, trust, and perceived risk.

Additionally, qualitative methods, such as interviews or focus groups, could provide better responses about emotional and ethical variables, which may not be fully captured through quantitative models. Finally, to strengthen the research, a cross-cultural study could be done to perceive the variance of acceptance across countries with different cultures.

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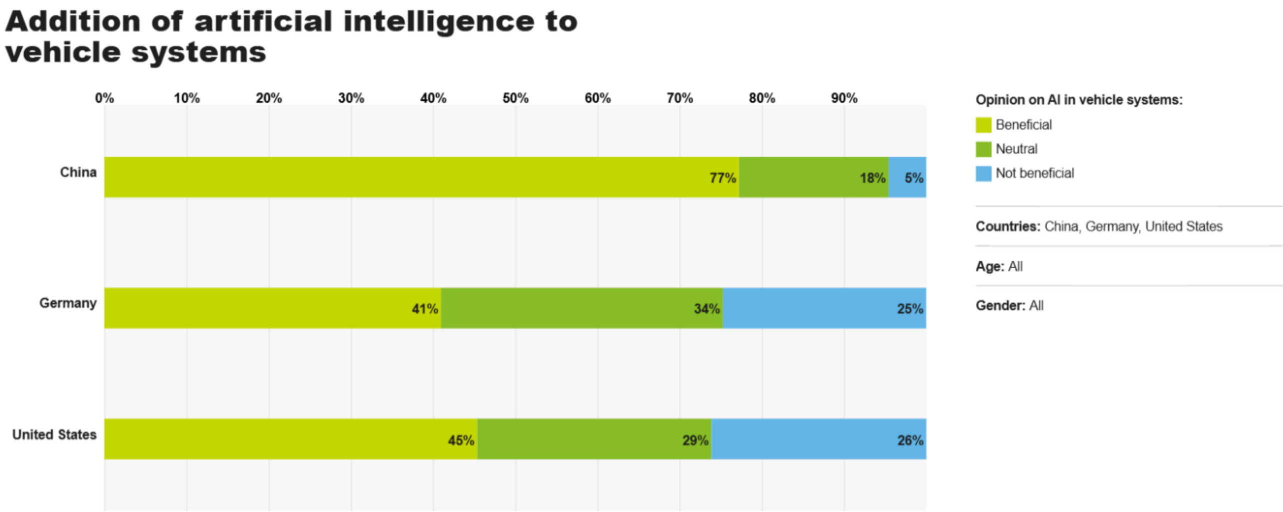
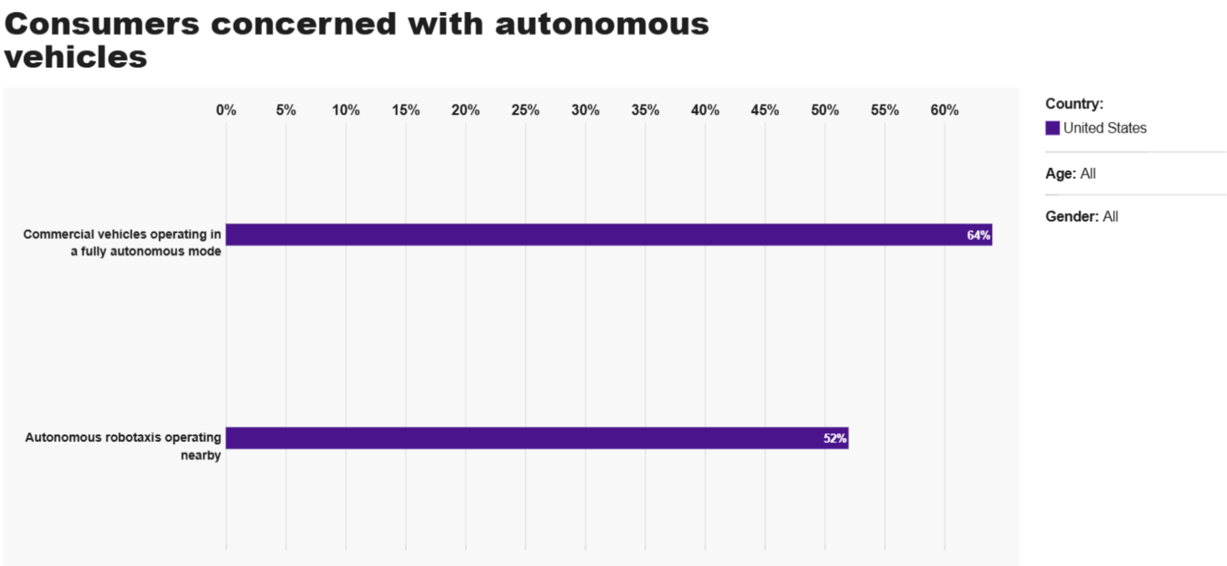
8. APPENDICES

Appendix A – AI in vehicle systems (Deloitte, 2025)

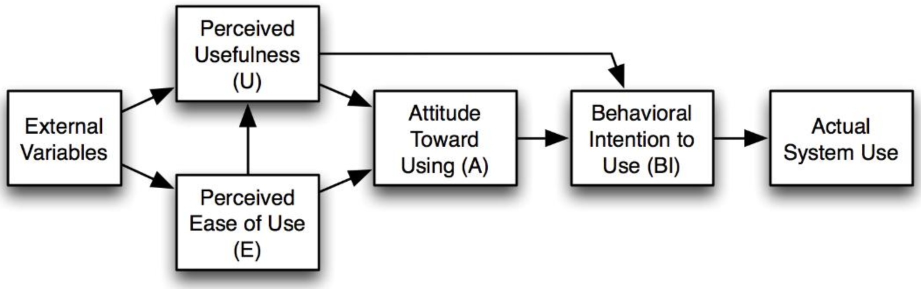


Appendix B – Consumer concerned with autonomous vehicles (Deloitte, 2025)

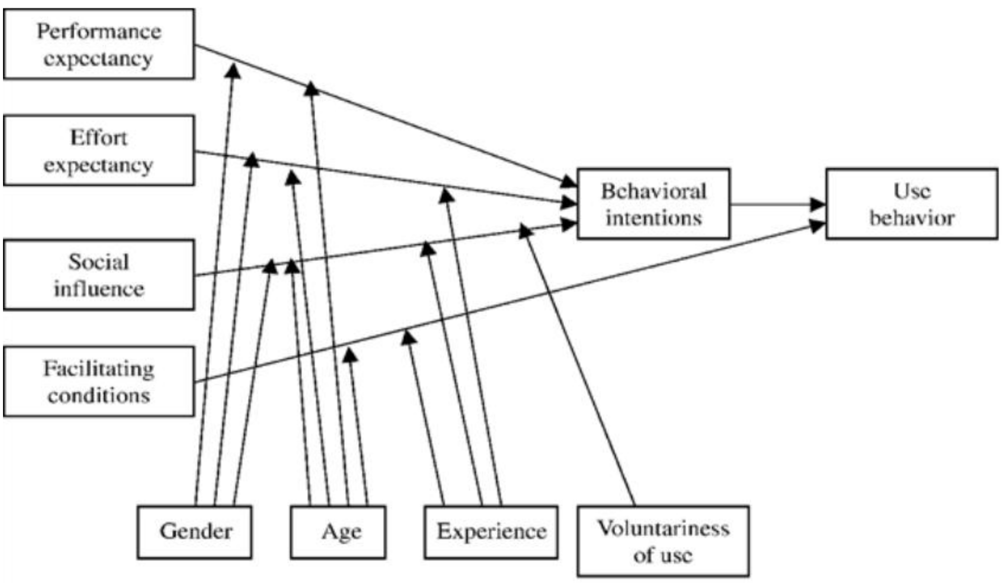


https://www.deloitte.com/global/en/Industries/automotive/perspectives/global-automotive-consumer-study.html
Consulted in 30/05/2025

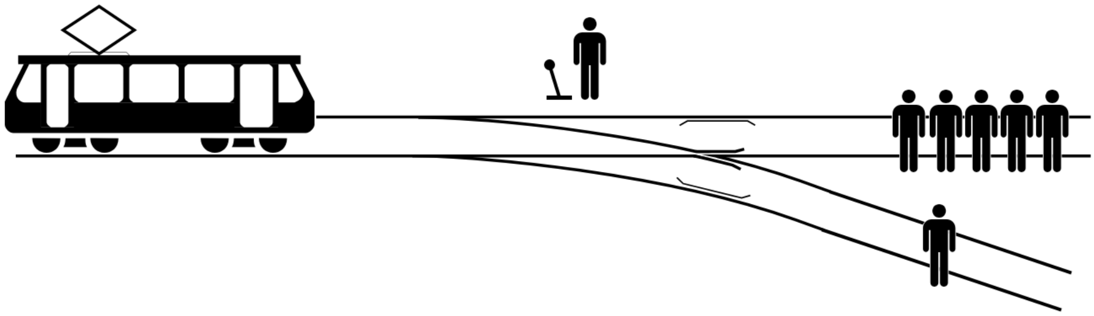
Appendix C – TAM Model (Davis, 1989)



Appendix D – UTAUT Model (Venkatesh et al., 2003)

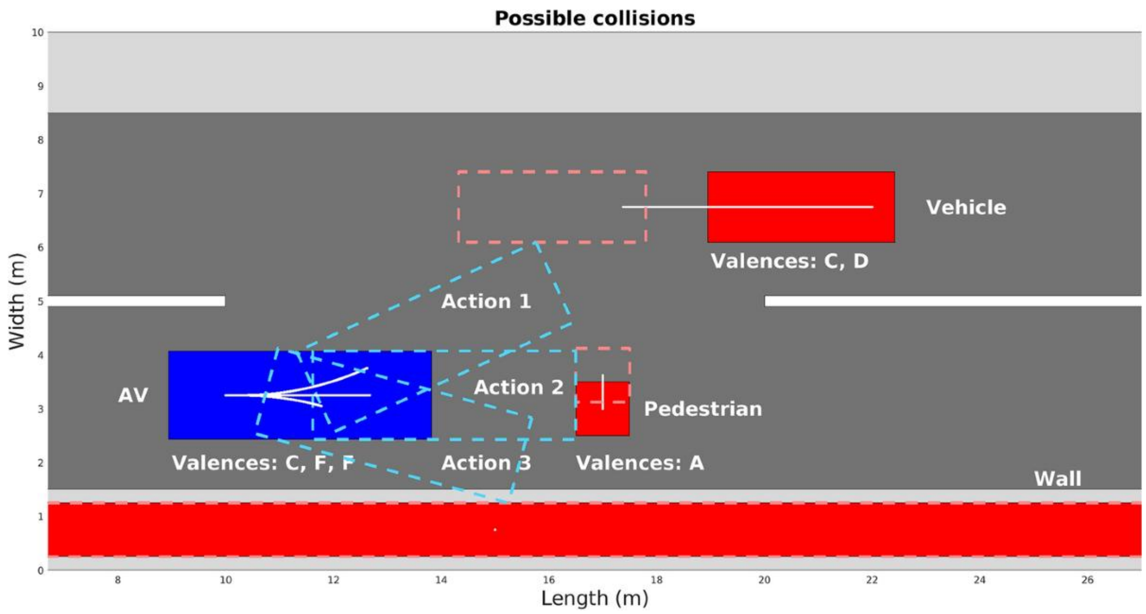


Appendix E– Trolley Problem



Source: https://en.wikipedia.org/wiki/Trolley_problem
Consulted in 30/05/2025

Appendix F – EVT Hypothetical Situation (Evans et al., 2020)



Appendix G – Heterotrait-Monotrait Results

	ANX	ATT	BIU	EC	FC	PEOU	PU	SE	SI
Anxiety									
Attitude	0,326								
BIU	0,506	0,790							
Ethical Concerns	0.,448	0,234	0,190						
Facilitating Conditions	0,446	0,526	0,649	0,092					
PEOU	0,432	0,686	0,694	0,144	0,557				
PU	0,375	0,776	0,764	0,134	0,589	0,796			
Self Efficacy	0,398	0,643	0,593	0,271	0,711	0,506	0,594		
Social	0,060	0.586	0.444	0,086	0,436	0,310	0,461	0,510	

Appendix H – Fornell-Larcker Results

	ANX	ATT	BIU	EC	FC	PEOU	PU	SE	SI
Anxiety	**0,911**								
Attitude	-0,326	**0,863**							
Behavorial Intention to use	-0,487	0,757	**0,963**						
Ethical Concerns	0,409	-0,209	-0,178	**0,810**					
Facilitationg Conditions	-0,403	0,437	0,563	-0,066	**0,767**				
Perceived ease of use	-0,413	0,656	0,675	-0,135	0,488	**0,967**			
Perceived Usefulness	-0,354	0,718	0,733	-0,126	0,493	0,757	**0,916**		
Self Efficacy	-0,312	0,523	0,502	-0,091	0,523	0,423	0,481	**0,707**	
Social Influence	0,036	0,510	0,410	0,053	0,322	0,283	0,414	0,378	**0,824**

Appendix I – Cross-Loadings Results

	ANX	ATT	BIU	EC	FC	PEOU	PU	SE	SI
Anxiety_1	**0,911**	-0,37	-0,499	0,376	-0,362	-0,429	-0,367	-0,317	-0,001
Anxiety_2	**0,892**	-0,257	-0,408	0,41	-0,391	-0,34	-0,29	-0,258	0,008
Anxiety_3	**0,932**	-0,283	-0,443	0,374	-0,392	-0,357	-0,321	-0,309	0,055
Anxiety_4	**0,908**	-0,26	-0,414	0,331	-0,326	-0,367	-0,301	-0,245	0,076
Attitude_1	-0,432	**0,875**	0,738	-0,171	0,453	0,665	0,662	0,554	0,412
Attitude_2	-0,137	**0,847**	0,539	-0,216	0,305	0,438	0,562	0,346	0,504
Attitude_3	-0,097	**0,806**	0,495	-0,172	0,258	0,407	0,525	0,332	0,433
Attitude_4	-0,372	**0,919**	0,774	-0,172	0,445	0,682	0,697	0,518	0,435
BIUse_1	-0,461	0,709	**0,954**	-0,184	0,56	0,666	0,689	0,502	0,393
BIUse_2	-0,507	0,736	**0,967**	-0,167	0,57	0,658	0,71	0,512	0,393
BIUse_3	-0,452	0,739	**0,969**	-0,177	0,527	0,615	0,703	0,473	0,409
BIUse_4	-0,459	0,726	**0,96**	-0,179	0,544	0,648	0,705	0,468	0,401
BIUse_5	-0,467	0,733	**0,964**	-0,152	0,511	0,665	0,722	0,466	0,381
Ethics_1	0,392	-0,16	-0,156	**0,859**	-0,054	-0,136	-0,117	-0,085	0,045
Ethics_2	0,375	-0,156	-0,107	**0,862**	-0,055	-0,101	-0,094	-0,043	0,037
Ethics_3	0,395	-0,201	-0,207	**0,905**	-0,138	-0,158	-0,148	-0,106	0,012
Ethics_4	0,262	-0,165	-0,082	**0,784**	-0,002	-0,035	-0,052	-0,084	-0,016
Ethics_5	0,358	-0,142	-0,213	**0,641**	-0,054	-0,111	-0,056	-0,041	0,096
Ethics_6	0,248	-0,189	-0,109	**0,808**	-0,037	-0,077	-0,099	-0,108	0,058
Ethics_8	0,298	-0,16	-0,139	**0,786**	-0,018	-0,143	-0,134	-0,03	0,083
FacCond_1	-0,302	0,294	0,438	-0,052	**0,809**	0,356	0,357	0,326	0,247
FacCond_2	-0,472	0,39	0,529	-0,113	**0,851**	0,464	0,417	0,469	0,195
FacCond_3	-0,284	0,325	0,402	-0,001	**0,829**	0,397	0,405	0,425	0,263
FacCond_4	-0,083	0,348	0,337	-0,017	**0,534**	0,238	0,335	0,392	0,353
PerEas_1	-0,417	0,626	0,662	-0,135	0,474	**0,982**	0,737	0,397	0,269
PerEas_2	-0,363	0,647	0,635	-0,129	0,469	**0,935**	0,717	0,421	0,289
PerEas_3	-0,418	0,628	0,662	-0,126	0,472	**0,984**	0,741	0,409	0,265
PerUse_1	-0,299	0,627	0,627	-0,112	0,43	0,678	**0,929**	0,444	0,388
PerUse_2	-0,284	0,681	0,67	-0,108	0,405	0,671	**0,937**	0,427	0,382
PerUse_3	-0,399	0,627	0,678	-0,132	0,501	0,726	**0,912**	0,455	0,365
PerUse_4	-0,312	0,69	0,706	-0,109	0,466	0,695	**0,884**	0,434	0,381
SelfEff_1	-0,494	0,343	0,444	-0,158	0,591	0,438	0,365	**0,668**	0,203
SelfEff_2	-0,012	0,318	0,287	0,049	0,264	0,22	0,287	**0,705**	0,332
SelfEff_3	0,061	0,291	0,177	0,158	0,159	0,166	0,265	**0,615**	0,255
SelfEff_4	-0,31	0,49	0,449	-0,206	0,393	0,324	0,412	**0,822**	0,294
SocInflu_1	0,05	0,484	0,372	0,021	0,224	0,225	0,356	0,304	**0,881**
SocInflu_2	0,002	0,491	0,395	-0,003	0,255	0,274	0,385	0,286	**0,881**
SocInflu_3	0,013	0,386	0,322	0,077	0,335	0,24	0,34	0,404	**0,766**
SocInflu_4	0,069	0,289	0,24	0,099	0,251	0,182	0,267	0,245	**0,76**

Appendix J – Sample

	Answer	Absolut Frequency	Relative Frequency
Gender	Male	159	59,1%
	Female	107	39,8%
	Other	3	1,1%
Age Gap	17-25	45	17,05%
	26-35	29	10,98%
	36-45	41	15,53%
	46-55	93	35,23%
	56-65	44	16,67%
	66-75	10	3,79%
	76-85	2	0,76%
Study Level	High school	72	26,9%
	Bachelor	119	44,4%
	Master	63	23,5%
	Doctorate	9	3,4%
	Other	5	1,9%
Income	Very difficult	10	3,7%
	Difficult	22	8,2%
	Coping	130	48,7%
	Living Comfortably	105	39,3%
Country of Origin	Portugal	258	95,9%
	France	1	0,4%
	Germany	2	0,7%
	Italy	1	0,4%
	Poland	1	0,4%
	USA	4	1,5%
	Other	2	0,7%
Type of City	Urban	167	62,1%
	Suburban	63	23,4%
	Rural	39	14,5%
Assisted Driving Experience	Yes	164	61,0%
	No, but interested	78	29,0%
	No, but not interested	27	10,0%
Type of assistance	Simple	91	55,5%
	Semi-autonomous	72	43,9%
	Autonomous	1	0,6%
Time using	Less than 6 months	20	12,2%

	6 months to 1 year	16	9,8%
	1 to 2 years	30	18,3%
	More than 2 years	98	59,8%
Employment status	Full-time	173	64,3%
	Part-time	5	1,9%
	Self-employed	50	18,6%
	Student	32	11,9%
	Retired	5	1,9%
	Unemployed	4	1,5%
Sustainability	Very Concerned	37	13,8%
	Concerned	131	48,7%
	Neutral	71	26,4%
	Not very concerned	17	6,3%
	Not concerned at all	13	4,8%