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The Relevance of Voice Assistants on Intention to Use: an Empirical Research on the Self-driving Industry

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October, 2022

BUSINESS
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Acknowledgements

The submission of this dissertation marks the end of my Master's in Marketing, at Iscte Business School, which is also a personal landmark for me because it is the end of many years invested in my personal education. Thus, the opportunity to share experiences inside classrooms and Zoom sessions with all my classmates and professors is undoubtedly a very enriching experience that will be in my memories forever and I definitely advise every student around the globe to do it.

Firstly, I would like to thank my thesis supervisor, Prof. Dr. Ricardo Godinho Bilro, for accepting this challenge and for all the guidance and support throughout the development of this master thesis. The success of this investigation would not have been possible without your valuable inputs, knowledge and experience.

Moreover, I would like to address a warm thank you to my family, especially my brother and my parents, for always reminding me to define my priorities and helping me to achieve my goals in life.

Likewise, my friends also have a special place in my heart, because without their unconditional support and constant motivation would not have been possible to complete this thesis successfully.

Lastly, I would like to express my gratitude to all the participants who answered my survey and all the researchers worldwide who took the first steps into such an exciting topic.

Thank you!

Abstract

In the past few years, it has been possible to watch a rise in technological developments in all areas, especially in Marketing, in terms of understanding better consumer's behaviour. Hence, Voice Assistants were created in order to enhance people's quality of life by simply doing tasks users want them to do. Additionally, self-driving cars were also an invention that could help people's daily lives since it allows excellent efficiency in smart cities and reduces stress and costs for companies.

This thesis decided to fulfil the gap and connect both technologies mentioned before since there was a lack of literature. Here, it is possible to understand which drivers affect the perceived usefulness and ease of use in adopting Voice Assistants and autonomous vehicles. Thus, it discusses consumers' intentions to purchase self-driving cars with Voice Assistants embedded and how willing people are to spread positive feedback to their peers about these technologies together.

Data collection and analyses were performed using quantitative analyses, with the help of an online survey developed based on previous literature of different researchers regarding the topics mentioned previously. Throughout this thesis, it is discussed the main conclusions withdrawn to help companies and scholars perform better in their future strategies and studies.

Keywords: Voice Assistants, Self-driving Cars, Consumer Behaviour

JEL: M31, M39.

Resumo

Nos últimos anos, tem sido possível observar um aumento da evolução tecnológica em todas as áreas, especialmente em Marketing, em termos de melhor compreensão do comportamento do consumidor. Assim, foram criados Assistentes por Voz a fim de melhorar a qualidade de vida das pessoas, simplesmente fazendo tarefas que os utilizadores querem que elas façam. Além disso, os carros autónomos foram também uma invenção que pode ajudar a vida diária das pessoas, uma vez que permite uma eficiência perfeita em cidades inteligentes e reduz o stress e os custos para as empresas.

Esta dissertação pretende preencher essa lacuna e juntar as duas tecnologias mencionadas anteriormente, uma vez que não existia literatura que o fizesse. Aqui, é possível compreender que fatores afetam a perceção da utilidade e da facilidade de utilização na adoção de Assistentes por Voz e de veículos autónomos. Assim, também é abordada a intenção dos consumidores em comprarem carros autónomos com Assistentes por Voz incorporados e o quão dispostos os consumidores estão a divulgar uma opinião positiva às pessoas mais próximas sobre estas tecnologias.

A recolha de dados e as análises foram realizadas utilizando análises quantitativas, através de um questionário online que foi desenvolvido com base na literatura existente de diferentes investigadores relativamente aos tópicos anteriormente mencionados. Ao longo desta dissertação, são discutidas as principais conclusões retiradas para ajudar empresas e investigadores a terem um melhor desempenho nas suas estratégias e estudos futuros.

Palavras-chave: Assistentes por Voz, Carros Autónomos, Comportamento do Consumidor

JEL: M31, M39.

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Glossary of Acronyms

Acronym	Definition
VA	Voice Assistant
AI	Artificial Intelligence
IoT	Internet of Things
apps	Applications
WOM	Word-of-mouth
TAM	Technology Acceptance Model

1. Introduction

Throughout the years, there have been many technological developments, some of which were successful hits, but others were not that useful in order to enhance people's quality of life. This master thesis intends to aggregate two pieces of technology that have the potential to empower and improve the quotidian of the users: VAs and self-driving cars.

Therefore, it is essential to understand the usefulness of using VAs since consumers frequently use them as tools for various daily tasks, most of which are straightforward information requests or domestic instructions (Dellaert et al, 2020). Moreover, self-driving cars can have a relevant role in society, because they can decrease the number of car accidents, improve traffic flow and reduce stress, create more transportations access for disabled people and reduce environmental pollution due to more efficient driving (Dixon, Hart, Clarke, O'Donnell & Hmielowski, 2018). Hence, these two improvements can bring many advantages to having smarter cities and more satisfied people.

These have been said, it is fair to state that the technologies still have space to improve their features, even though some brands already commercialise them. Concerning VAs, big brands such as Apple, Amazon or Google already have some successful products with interesting sales, like Siri, Alexa or Assistant, respectively. Thus, accordingly to a study (*Vixen Labs*, 2022), it is stated that the usage of this device had an increase from the year 2021 to 2022 and also the application in cars is one of the three main usages people give to it in Germany, the United Kingdom and the United States of America. Additionally, the study (*Vixen Labs*, 2022) states that the amount of people who use VAs on a daily basis has about doubled, since the year 2021, and consumers are likely to use this device to do tasks related to shopping that are most important to them, such as tracking orders, delivery statuses or searching for information about products. These help to justify the pertinence of finding more valuable insights into the Portuguese market and how this could impact the shopping experience, two of the key goals of this dissertation's practical part.

Furthermore, a report by McKinsey & Company (Heineke, Heuss, Kelkar & Kellner, 2021) estimates that by the year 2024 or 2025, self-driving cars and fully automated vehicles are expected to be used more in people's daily lives, and trucks are forecast to be by the end of the decade around the years 2027 and 2031. This report (Heineke et al, 2021) also gives the main reasons for this, including the need for technological improvements, regulatory support and available capital. This difference in the stages of technological development between both technologies is also reflected in the literature review that will be presented in the next chapter of this thesis. In addition, self-driving cars with VAs embedded also have much space to grow, even though there are not many studies that approach these two pieces of technology together yet, but the pattern of purchase of these two gadgets separately is increasing a lot over the years, according to a study from Vixen Labs (2022).

Therefore, the primary purpose of this study is to understand the impact of a VA on the consumer, in the self-driving cars industry. It is not available enough information to help managers and researchers define strategies to help introduce this product in the market most accurately.

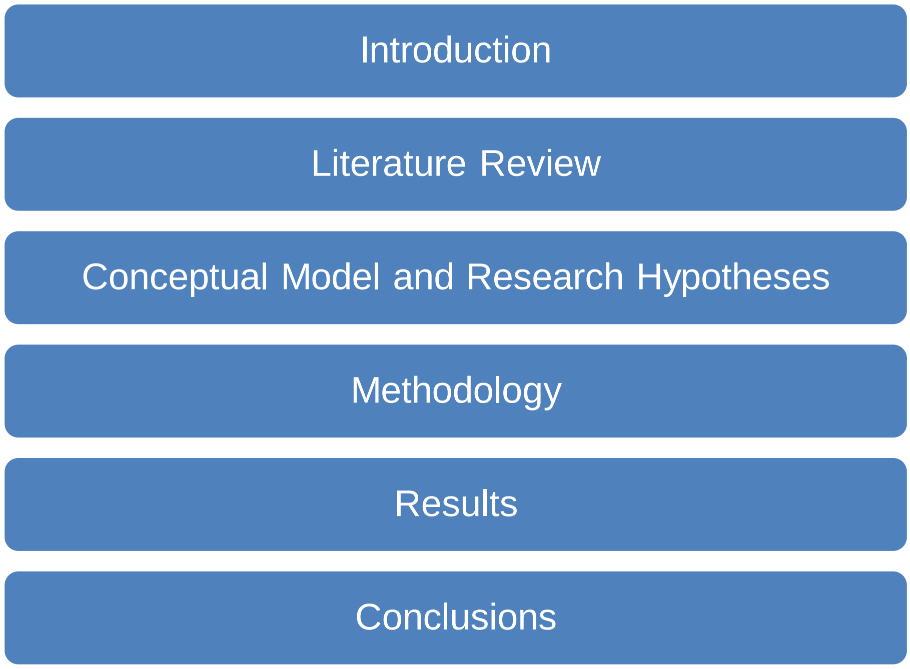
Therefore, to help to address the research objectives, this dissertation is divided into six main chapters: introduction, literature review, conceptual model and research hypotheses, methodology, results and conclusions. In the first one, it is presented the literature review based on the research already made by other investigators in previous years, it is the basis of this work and gives a general contextualisation of what is happening in this area. In the second one, the conceptual model is presented as the starting point of the empirical part, and then the author's suggested research hypotheses are proposed:

- Hypothesis 1a: Anthropomorphism positively influences Perceived Ease of Use.
- Hypothesis 1b: Anthropomorphism positively influences Perceived Usefulness.
- Hypothesis 2a: Relation Cohesion positively influences Perceived Ease of Use.
- Hypothesis 2b: Relation Cohesion positively influences Perceived Usefulness.
- Hypothesis 3a: Interaction Frequency positively influences Perceived Ease of Use.
- Hypothesis 3b: Interaction Frequency positively influences Perceived Usefulness.
- Hypothesis 4a: Brand Trust positively influences Perceived Ease of Use.
- Hypothesis 4b: Brand Trust positively influences Perceived Usefulness.
- Hypothesis 5a: Perceived Ease of Use positively influences Intention to Use Self-driving Cars.
- Hypothesis 5b: Perceived Ease of Use positively influences WOM Intentions.
- Hypothesis 6a: Perceived Usefulness positively influences Intention to Use Self-driving Cars.
- Hypothesis 6b: Perceived Usefulness positively influences WOM Intentions.

Moving forward, the methodology highlights how the research approach was conducted and structured, how data was collected and describes the study's sample. Finally, the results present a quantitative analysis of the information gathered within the research in order to understand what the data means, and in the conclusions are presented the main theoretical and managerial contributions this thesis gives to the community. Also, the limitations and future research are mentioned in this last chapter.

This dissertation has the structure presented in Figure 1.

Figure 1 Structure of the dissertation



Source: own elaboration

2. Literature Review

2.1. Voice Assistants

Before understanding the impact of VA on the consumer, it is relevant to understand the major concepts implied in this subject. Firstly, it is crucial to study AI, which is the basis of this technology. It refers to the capacity of machines to reproduce intelligent human behaviours, more precisely, the cognitive functions that people associate with the human brain, which includes problem-solving and the ability to learn, which requires big data and high processing power by the machines (Syam & Sharma, 2018). Also, it incorporates three crucial elements: data collection and storage, which gathers information from the most various sources; statistical and computational techniques that will leverage the knowledge to predict behaviours and interests of the consumer; and output systems which will communicate with consumers (Puntoni, Reczek, Giesler & Botti, 2021). Hence, AI is still a bit ambiguous in consumers' minds, because they still perceive it as a negative thing, which means it is an obstacle to adoption (Davenport, Guha, Grewal & Bressgott, 2020).

Therefore, a VA is a type of voice-enabled AI tool (Poushneh, 2021). This technology is a software agent with the ability to interpret a human voice and give back the most relevant information to the user so that a task can be performed, mainly used via smartphone or computer (Hoy, 2018). Moreover, a VA can keep a conversation with a user in natural language and answer in both text and speech form (Zahariev, Shunkevich, Nikiforov & Azarov, 2020). In order to correctly function, it has to have several components, which include voice recognition, voice language apprehension, dialogue manager, natural language generation, text-to-speech converter and knowledge base (Subhash, Srivatsa, Siddesh, Ullas & Santhosh, 2020).

Furthermore, VAs have several applications in the daily life of a human being, such as sending and reading text messages and emails, making phone calls, answering user's informational questions, setting alarms and calendar reminders, making wishlists and easy math calculations, controlling media playback, managing IoT devices and expanding its capabilities by interfacing with other applications through voice command (Hoy, 2018). Currently, researchers are exploring how to integrate VAs into in-car systems (Ning, Xia, Ullah, Kong & Hu, 2017), with some brands already doing it successfully, as is going to be approached later in this thesis. Nevertheless, this technology has been already tested in vehicles, with the example of a voice alert system embedded in car manufacturers Chrysler, Dodge and Nissan, in the 1980s, with many limitations in terms of alerts and warnings and lacking smart technologies, interaction, poor voice recognition and incorrect pronunciation (Large, Clark, Quandt, Burnett & Skrypchuk, 2017).

Despite all the previously described advantages, VAs also bring some risks to the users, such as leaks of personal information and unauthorised access to smart devices, via hiding voice commands, downloading malicious apps or even using an FM antenna (Alepis & Patsakis, 2017). These risks are some of the reasons why people tend not to use this kind of technology and must be developed to fix them so that people feel more secure using VA devices.

At the moment this thesis was written, two major forms of VA were available in the market: mobile apps and smart speakers. The first includes Apple's Siri, Amazon's Alexa, Google Assistant and Microsoft Cortana, and the other includes Amazon's Echo, Google's Home and Apple's Home (Poushneh, 2021). Thus, the Covid-19 pandemic has accelerated the purchase of home-based voice-controlled devices and it is predicted that by the year 2022, 135,6 million people will be using VA devices in the United States of America (Petrock, 2020). Thus, the VA market size worldwide is projected to value around €6,22 billion by 2025 (*Market Research Future*, 2020).

2.2. Voice Assistants and Consumer's Behaviour

In order to study the impact of VA in consumers' life is relevant to learn how they engage with voice. With that aim, a study was conducted by Microsoft and it was found that 72% of voice searches are done through a digital assistant (for example, Siri) and around a third are made with a smart home speaker, also it is essential to notice that voice skills or actions through a smart home speaker account for more than a half of the population of the study (Olson & Kemery, 2019). This study shows that most people use VA to avoid doing some physical actions and do searches on the Internet. Some of these tasks include looking up relevant information, having spontaneous dialogues with the VA, playing songs and checking the weather (Pradhan, Lazar & Findlater, 2020).

Furthermore, a study (Vailshery, 2021) with the aim to analyse the purchase habits of consumers stated that almost the same amount of people who have already attempted to make a purchase either with a digital assistant or a smart home speaker are satisfied (check appendix A) or are not interested in it at all. However, the same study (Vailshery, 2021) showed that a significant number of people are willing to try this technology, and only a few do not enjoy the experience. These have been said, it is possible to state that this technology will most likely be helpful if it was more accessible to the consumer because a majority is satisfied or wants to try it.

One of the reasons why people rely on VAs is to avoid responsibility for decisions. This technology has the ability to prioritise alternatives so that users have to consider fewer options, even though this might mean losing power in the decision-making process, users feel that they share the responsibility of choice with another person (the VA), which leads to the feeling described above (Dellaert et al, 2020). On the other hand, the consumer finds it helpful to avoid

VAs in some situations. Additionally, people tend not to use VAs when decision autonomy is linked to a sense of self-determination and self-esteem (Dellaert et al, 2020).

Moreover, when dealing with VA, it is essential to consider the human dimension. Kim et al (2019) found out that if the appearance and behaviours of VA robots are more humanised, it is more likely humans will interact with them, however, some boundaries should be established because if the devices are too friendly, people will get negative feelings and discomfort, leading to rejection. Hence, consumers rely more upon humans for subjective tasks and the objective ones could be done with the help of AI technologies (Castelo, Bos & Lehmann, 2019), even though people are likely to anthropomorphise technology, even if there are no human characteristics, as voice (Moriuchi, 2019). Moreover, it is relevant to understand that humans tend to attribute human characteristics to voices (for example, if a robotic voice is male or female) despite the fact that humans also can vary their voice and judgments depending on their personality traits (Scherer, 1978; Apple, Streeter & Krauss, 1979). Thus, consumers with more intellectual abilities are more likely to use VA more efficiently (Dellaert et al, 2020).

Moving forward, Hernández-Ortega, Aldas-Manzano and Ferreira (2021) found out the frequency of interactions between humans and VA is the key to building a positive affective relationship between both, leading to another conclusion which states that users can feel the same amount of satisfaction and interest towards a VA, as they feel towards another person and, consequently, the same feelings toward the VA's brand. This represents that a person cares about a VA as if it was another human, from the point there is a relationship established. This relationship can also be supported by the Theory of Relational Cohesion (Lawler, Thye and Yoon, 2000), which states that when a person experiences an emotion, their brain goes through a cognitive process that partly attributes the emotion to relationships or groups that make up the framework for exchange, i.e., groups can also be a significant part and have intrinsic value due to the positive emotions generated from the trade, leading to relational commitment. Thus, the effect of uncertainty cannot be forgotten as well (Lawler et al, 2000). It is important to state as well that people are willing to provide a VA, in a driving situation, an equal social position and engage in conversations with it as if they were speaking to a real person (Large et al, 2017), which will make this technology evolve in order to become more social and friendly.

In addition, Pagani, Racat and Hofacker (2019) discovered that customers feel an increase in personal engagement with touch-only devices rather than others where voice is included, and hybrid interactions with voice and touch decrease the power of the relationship between engagement and brand trust, and by brand trust (Chaudhuri and Holbrook, 2001), it means the willingness of the typical consumer to trust a brand's ability to fulfil its purpose. The low development of VA technologies might explain this compared to others, such as touch, if it is considered the time they are already available to the consumers in the market.

The user's past experience with a VA, related to the number of times it was used in previous times, also affects the relationship between the user and the device itself (Loureiro, Japutra, Molinillo & Bilro, 2021). This experience also impacts long-term behaviour, emotional bonds and relationship quality (Loureiro et al, 2021; Schmitt, Brakus & Zarantonello, 2015). Additionally, past experiences can also induce internal consumer responses, such as sensations, feelings, cognitions, and behavioural responses (Schmitt et al, 2015). Even though VAs bring a lot of advantages, they still have some barriers that must be overcome, such as hearing loss, noisy surroundings and privacy concerns (Pradhan et al, 2020), which are going to be discussed further in this thesis.

In spite of what is previously written, as an AI technology, consumers tend to perceive VAs as a negative thing that will not understand what they want, which interferes with the adoption process. In order to boost its positioning, Davenport et al (2020) suggest this technology as an artificial learning organism or as a mixture of AI and anthropological skills. Thus, another essential factor is that consumers may also feel a loss of autonomy and independence when using this kind of tool, even though it varies according to utilitarian or hedonic products (Davenport et al, 2020).

2.3. Self-driving Cars

A self-driving car can be defined as a motor vehicle with the capacity to automatically drive without any direct human guidance with the help of software and sensors (Dixon et al, 2018). The need for this technology came in order to reduce the harmful impacts of driving routines on drivers' health and improve traffic efficiency so that it can be more fluid and less stressful (Körber, Baseler & Bengler, 2018). In addition, autonomous cars can be classified into different levels of automation, according to the degree of independence of a vehicle.

Therefore, according to SAE International Levels of Driving Automation, driving automation technologies can be categorised into six levels (check appendix B). Generally, the first three Levels (Levels 0 to 2) state the driver is able to start driving at any time and the person behind the wheel is fully monitoring the road, and the other three Levels (Levels 3 to 5) assume the vehicle's AI capacities are enough to drive the car and monitor the road (Teoh, 2019). More precisely, Level 0 does not have almost any automation capabilities, only small electronic stability, Level 1 has lateral or longitudinal automation capabilities (such as lane-keeping and speed controls, respectively), Level 2 has, simultaneously, both characteristics of the previous Level; Level 3 has the add-on of only needing human intervention when the driving automation system asks to, Level 4 refers to automation that will only ask the driver to take control of the car in control-access roads, and Level 5 is the fully autonomous one (Teoh, 2019). At the time this thesis was written, Tesla and Volkswagen, with VW traffic jam assist, which is a minimal-risk technology that makes the car stop if the user does not react to a warning, (Metz et al, 2021) were the only manufacturers to produce the highest Level achieved in the SAE International Levels of Driving Automation, which is Level 2. Thus, the brand consumers prefer and trust the most for self-driving cars technology is Tesla and they would consider this brand twice as often as an unknown one (Eggers & Eggers, 2021).

There are also other scales to define the levels of self-driving, such as the one proposed by the Federal Highway Research Institute (BASt) or the other proposed by the National Highway Traffic Safety Administration (NHTSA), which are similar, and only differ in the level of focus on the distribution of tasks between driver and vehicles and the number of levels, i.e., five levels instead of six (Hopkins & Schwanen, 2021).

Another essential concept regarding partial automation technology is Transfers of Control (Gershon, Seaman, Mehler, Reimer & Coughlin, 2021), the partnership between both parts: driver and technology, which happens in partial automation (like Level 2 of SAE Levels). Hence, in order to have a safe trip (Gershon et al, 2021), all the Transfers of Control must be done perfectly and in harmony, adapting them to the needs, desires and availability of the parts involved. The failure of self-driving technology or driver's distraction can be some of the reasons causing these Transfers not to work correctly, resulting in accidents. Additionally, Vogelpohl, Kühn, Hummel, Gehlert and Vollrath (2018) suggest three main reasons why Transfers of Control take more unwanted time: the degree to which automation is being monitored by the driver, the characteristics of non-driving associated tasks and the difficulty of the scenario to which the driver must respond.

Michon (1985) stated there were taxonomic and functional models, the first involved no interaction among parts and the other included relationships between all parts. Transfers of Control can be inside functional models of driving behaviour which can be divided into three levels: strategic, manoeuvre and control (Gershon et al, 2021). The strategic level is related to the overall travel planning, choosing the best routes and the most efficient time constraints, which is associated with proactive behaviours that take time to decide; the manoeuvre reflects the skills to drive a vehicle, typically it is a reactive behaviour and it takes seconds to decide; lastly, the control explains the instinctive reactions to obstacles taking less than a second to respond, which asks for immediate inputs, generally, they are automatic action patterns (Ranney, 1994; Gershon et al, 2021). Interactions between drivers and automation technologies take place at all levels of functional models of driving behaviour, such as, on a strategic level as proactively turning off automation, considering factors like locations, time or comfort; on a manoeuvre level as deactivating automation on reaction to environmental nonplanned variables; and on control level linked with quick and instinctive responses to an environmental stimulus (Gershon et al, 2021).

Lastly, Gkartzonikas & Gkritza (2019) highlighted some of the benefits of adopting self-driving cars, such as safety, increased mobility efficiency, cost reductions, faster and more accessible parking, well-being resulting from less stress and more productivity. On the other hand, there are concerns and barriers customers experience that make them avoid self-driving cars, such as the failures of equipment or the autonomous system, legal issues related to whom to blame in case of any technology accidents, cybersecurity worries, leaks of personal trip information and environmental concerns (Karnouskos, 2020; Gkartzonikas & Gkritza, 2019).

2.4. Self-driving Cars and Consumer's Behaviour

In order to understand the impact of self-driving cars on the consumer, it is essential to study how the general audience perceives it and which features can make a difference in customers' technology choices.

Recent studies investigated that humans are sensitive to different tones of voice in speech, regarding VA, when simultaneously performing driving and non-driving tasks (Wong, Brumby, Babu & Kobayashi, 2019). In general, people are more likely to choose a more assertive tone of voice for everyday navigation, because they perceive it as more trustful (Wong et al, 2019) and it is also studied that the voice should describe the reason for the action, instead of describing it, leading to safest performance from the drivers (Koo et al, 2014). In addition, Teoh (2019) referred the name of the self-driving technology also affected the perception of how autonomous a vehicle is, with names like "Autopilot" and "ProPilot" being linked with higher levels of autonomy perception to the consumer.

Moreover, drivers also tend to lose focus on the driving task, with Level 2 of SAE International Levels of Driving Automation or just by using the adaptive cruise control technology (basically, it partially controls the longitudinal control of the car), because they feel it is not necessary to do any driving chores and start engaging with nondriving behaviours, such as texting, watching videos or even sleeping, leading to a non-safe driving (Teoh, 2019; Lin, Ma & Zang, 2018). Furthermore, users with more experience in self-driving technologies are two times more likely to engage in secondary activities while performing autopilot features in the car (Dunn, Dingus, Soccolich & Horrey, 2021). Also, Dunn et al (2021) suggest that driving automation skills can lead more quickly to drowsiness due to the lack of actions throughout the driving procedure, which can occur more easily in users with no self-driving experience. On the other hand, drivers with traffic accidents historic are more likely not to trust this kind of technology (Metz et al, 2021), as expected.

Thus, it is important that the design of the self-driving technology is user-friendly, in order to use it safely and, this way, prevent many troubles, such as difficulty leading with the technology itself, causing issues to the driver when using it, inappropriate levels of trust in the technology and overload of the cognitive levels, resulting in lack of usability (Ulahannan et al, 2020). Also, it is essential to consider that users take about two weeks to adapt to how and when to use this kind of technology (Lin et al, 2018).

Nevertheless, (Gershon et al, 2021) drivers tend to use higher degrees of automation whenever they are available, except for situations where they want to perform different functions outside automation capabilities, such as passing another vehicle or simply demonstrating driver's choices in terms of function execution. In addition, drivers tend to deactivate autopilot technology when they face dense traffic circumstances (Lin et al, 2018). Thus, strategic Transfers of Control are the ones that occur the most and drivers tend to disengage from automatic to manual driving by their own choice to anticipate a previously thought situation (Gershon et al, 2021). This way, some behaviours associated with non-driving related tasks, even if they are voluntary or enforced by the situation, time budget or urgency can be avoided in order to enhance the duration and quality of Transfers of Control and users can feel more comfortable integrating VA in their vehicles (Gershon et al, 2021; Louw et al, 2019). Thus, the complexity of Transfers of Control can be explained by the number of factors present throughout the shift to manual driving, the difficulty with which meaning may be given to the factors and the predictability of the future state of these factors (Vogelpohl et al, 2018). This has been said, it is possible to assume that VA can help reduce accidents because it can replace human actions just by ordering it by voice, with AI aid when needed, increasing safety inside a vehicle.

Finally, there are five steps of adaptation to systems for enhanced driver assistance: a first encounter, the first day that takes one to six hours; learning, when the driver understands how the technology works which takes three to four weeks; trust, it corresponds to when the driver is overconfident, usually occurs between the first and the sixth months; adjustments, i.e. the response to past self-driving experiences, that takes six to twelve months; and readjustments, which is similar to the previous one, but it is an on-going situation in the medium and long term, generally around one to two years (Metz et al, 2021). Thus, the amount of time drivers use to react to a challenge while driving is also important, with Vogelpohl et al (2018) stating that longer Transfers of Control mean a better reaction, because it indicates people took the required time to restore situational awareness before starting a manoeuvre.

It is essential to consider, as well, that demographic factors can have an influence on the probability of people using self-driving car technology. Hohenberger, Spörrle & Welpe (2016) suggest younger people are more willing to use and pay for this kind of technology than older people and (Dixon et al, 2018) youth tend to perceive fewer driving risks. This can be explained due to a lack of technology training and experience when those people were in the youngest stage of their lives, since technical support is vital in that stage of adoption, and, at the current point of life, the elderly tend to avoid technology that needs much effort in learning and using (Lee & Coughlin, 2014; Mitzner et al, 2010). Thus, technical support, which is more important in a higher age range, is crucial for purchase, installation, learning, operation and maintenance (Lee & Coughlin, 2014). Gender also influences the choice to go for autonomous vehicles, because men are more disposed to use technology than women (Payre, Cestac & Delhomme, 2014) and females are more likely to associate self-driving cars with negative emotions and higher levels of concern (Dixon et al, 2018).

WOM also plays an important role in consumers' behaviour toward self-driving cars with VAs embedded. WOM can be defined as informal contacts between private parties to evaluate goods and services rather than official complaints to companies or staff (Anderson, 1998). Thus, factors such as information quality, communication and WOM, created by consumers, have a serious impact on technology trustworthiness and their purchase intentions, keeping in mind that WOM is associated with customer ratings and reviews, user recommendations and referrals (Kim & Park, 2013). Moreover, online WOM is more successful than traditional WOM, because they are faster, more convenient, wider and more diverse and enable easier interactions, either face-to-face or non-face-to-face (Kim & Park, 2013). Further, the perception of quality and value is directly connected to WOM behaviour, i.e., a higher perceived quality results in greater customer WOM activity and vice versa (Liu & Lee, 2016; Guo, Susilo, Antoniou & Pernestål, 2022). Additionally, technology specialists receive more favourable reviews and are more likely to spread good WOM (Reinders, Frambach, & Kleijnen, 2015). When it comes to the moment of recommendation, WOM also plays a significant role in the transportation mode, being studied that safety, operations and efficiency improvements are key factors to shape user behaviours, more precisely, travel demands and users' needs (Guo et al, 2022).

Further, Eggers & Eggers (2021) found out that consumers are more attracted by self-driving cars in a rental situation than in a purchase scenario, and they would rather have a completely autonomous vehicle than one that is just partially autonomous. Additionally, a rental system is always preferred for a sharing economy, where consumers only pay for the temporarily rent time they use a car, which matches this technology (Krueger, Rashidi, & Rose, 2016). Hence, technology brands are the most preferred for purchasing or renting self-driving cars, with Google being the most desired; new brands are the least likeable for purchasing autonomous vehicles, with Tesla being the number one; and new brands and automakers brands are equally preferred for this technology, with Chevrolet being the top player in this last brand category, even though, besides the brand category, Tesla is the most preferred brand from all (Eggers & Eggers, 2021).

Lastly, Körber et al (2018) suggest that future research should find a way to improve the communication between the driver and autonomous driving, to reduce distractions and improve the amusement of driving. Even though the self-driving car market is relatively new, consumers are open to the idea of autonomous driving (Eggers & Eggers, 2021). This has been said, this master thesis suggests studying the implementation of VA technology in the transportation sector, on services such as Taxi or Uber (and similar), in order to improve the driver/passenger experience and to reduce accidents resulting from car crashes.

2.5. Technology and Consumers

This thesis's basis is consumers' willingness to use and accept technology, in general, in their daily life. In order to understand that it is important to study a theory that can explain this, the TAM. TAM is adapted from the Theory of Reasoned Action, which affirms that a person's behaviour is determined by the behavioural intention to do a certain behaviour and that is affected by the individual's attitude and the subjective norm related to that behaviour (Davis, Bagozzi & Warshaw, 1989). This has been said, the TAM tries to explain the degree of acceptance, by users, of information systems and a specific technology (Moriuchi, 2019). According to Davis et al (1989), the two major factors for computer acceptance behaviours are perceived usefulness, which can be defined as the possibility that a certain technology could enhance a user's performance in an organisational environment perspective, and perceived ease of use, which is related to the expectations of the user to use a user-friendly enough technology. The intention to use a particular technology also plays a significant role in the previous model (Brusch & Rappel, 2020). Thus, the behavioural intention to use a specific technology is also affected by the consumers' attitude to working with it and the perceived usefulness, previously described, which will result in the actual technology use (Davis et al, 1989). It is also essential to bold that the consumer's attitude plays a significant role in defining a belief and how a preference for a specific technology is made (Moriuchi, 2019). This helps explain the TAM's considerable role in adopting new technologies, specifically VAs and self-driving cars.

Another relevant factor that can help to understand how involved consumers are with technology is their privacy concerns regarding it. Privacy concerns are worries consumers have which make them fear adverse outcomes that will influence their willingness to divulge private data, even though these concerns vary with the most various factors, such as industry sectors, cultures and laws, and with personal characteristics and previous experiences, which explains why people have different judgements of fairness when it comes to companies private

data collection and its use (Pagani et al, 2019; Malhotra, Kim and Agarwal, 2004). Moreover, it is important to be aware that without the customer's knowledge or consent, companies frequently sell their clients' personal information they have collected and stored to third parties, such as Marketing, Human Resources or Government agencies, to be copied, used and analysed (Pagani et al, 2019; Brusch & Rappel, 2020). Also, institutional trust will have a favourable relationship with support for autonomous vehicles (Dixon et al, 2018).
Another critical factor is that the localisation also affects the attitude toward VA (Moriuchi, 2019) and, much likely, toward self-driving cars, as it will be studied further in the practical part of this dissertation.

In addition, the user's technology expertise can help explain the consumers' level of involvement with technology. This refers to the knowledge component, which can be interpreted as knowledge of a particular subject that can be acquired via an outcome of experience, study or training (Loureiro et al, 2021; Reinders et al, 2015). Thus, the decision effectiveness process is also affected by technology expertise, since in the first stage the number of accessible information enhances this process, from a certain point it starts to decrease, leading to the opposite effect on the effectiveness (Reinders et al, 2015). Additionally, more knowledge not always leads to better decision-making, because relying excessively on deliberation and reflection impairs the quality of the decision (Nordgren & Dijksterhuis, 2009). This has been said, it is likely technology experts may use a new product (either a VA or a self-driving car) incorrectly (Reinders et al, 2015), which might lead to a decrease in the adoption stage, however, it could be an opportunity to convert new customers to engage with these technologies, as long as the motivation to learn is present. On the other hand, Pradhan et al (2020) sustain that two factors positively impact the usage of technology: prior technology use experience and the understanding of the Internet, nevertheless, some barriers make people not use technology, such as usability or the absence of user-friendly interfaces. Furthermore, early adopters have more realistic expectations of utility and are less likely to become disappointed with technology when using it, since adoption time offsets the negative consequences of past experiences (Reinders et al, 2015).

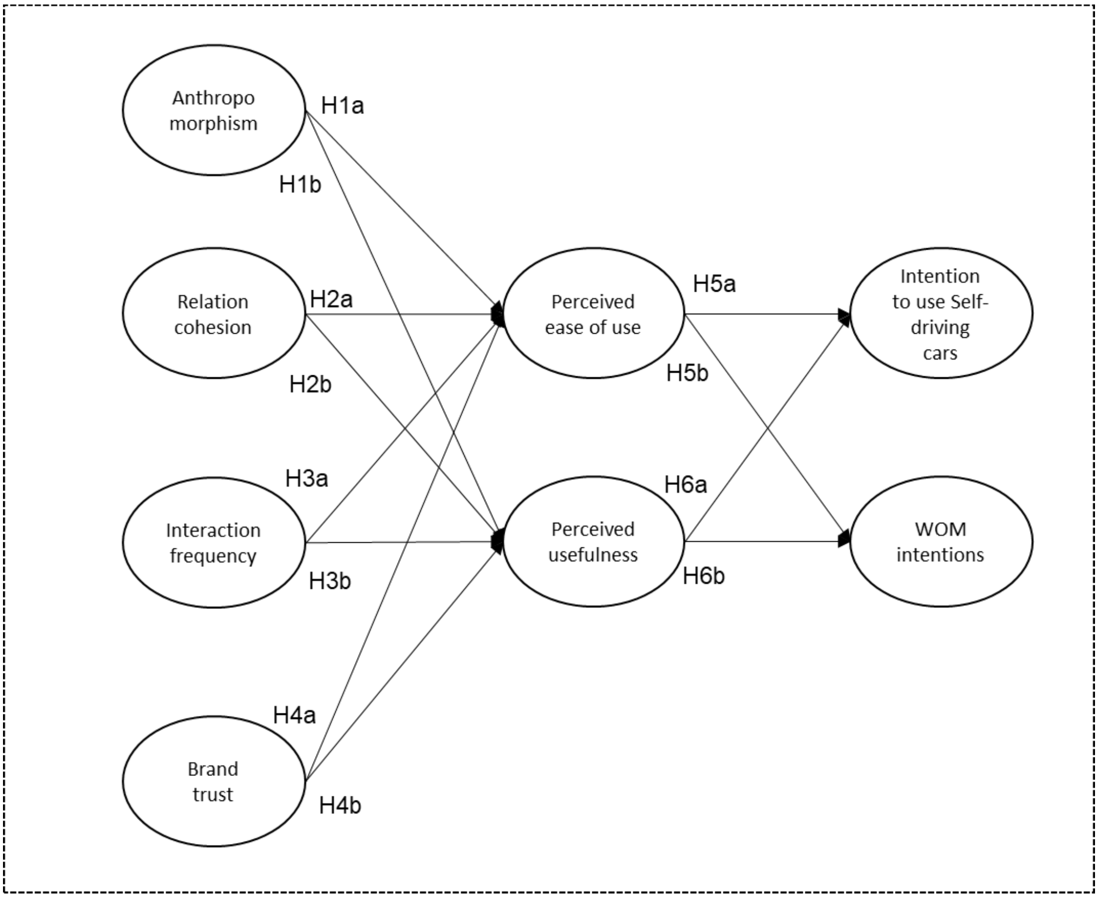
Regarding VAs, technology expertise could weaken the relationship between the user's attachment to the device and the perceived value for customers (Loureiro et al, 2021). Despite that, it only means users do not develop a deep relationship with the VA, but they can still use it when they find it useful.

3. Conceptual Model and Research Hypotheses

Researchers and scholars have been studying the relationship between VAs and consumers in the past few years. However, there was a lack of knowledge integrating self-driving cars into this equation. With this in mind, the conceptual model in Figure 2 suggests a possibility of associations between different constructs, based on the existing literature, that the author of this thesis would like to offer to the scientific community.

As of now, several different brands already integrate VAs into their products, which might explain why consumers find it easier to relate to this technology and might be more available to build a relationship. On the opposite, autonomous cars are still not too developed in the Portuguese context, leading to the necessity to evaluate the intention to use the technology.

Figure 2 Conceptual Model



Source: own elaboration

Furthermore, these distinct hypotheses are offered so we can understand more easily the impact of these technologies on the consumer:

H1a: Anthropomorphism positively influences Perceived Ease of Use.

H1b: Anthropomorphism positively influences Perceived Usefulness.

H2a: Relation Cohesion positively influences Perceived Ease of Use.

H2b: Relation Cohesion positively influences Perceived Usefulness.

H3a: Interaction Frequency positively influences Perceived Ease of Use.

H3b: Interaction Frequency positively influences Perceived Usefulness.

H4a: Brand Trust positively influences Perceived Ease of Use.

H4b: Brand Trust positively influences Perceived Usefulness.

H5a: Perceived Ease of Use positively influences Intention to Use Self-driving Cars.

H5b: Perceived Ease of Use positively influences WOM Intentions.

H6a: Perceived Usefulness positively influences Intention to Use Self-driving Cars.

H6b: Perceived Usefulness positively influences WOM Intentions.

4. Methodology

4.1. Research Approach

The main goal of this chapter is to explain how the literature review approached earlier in this master thesis will be tested. The research hypotheses will be formed according to the research developed throughout this thesis, keeping in mind the primary purpose of the investigation. This quantitative research aims to make conclusions from the sample and generalise them to the general population to find out how VAs and self-driving cars can be assembled and implemented in app-based transportation to improve consumers' daily life.

There were two types of sources in order to do this investigation: primary and secondary. The first one concerns the quantitative research done by the author and the other concerns the previous information already studied by other investigators, which in this case is related to academic journals of marketing science, consumer and business researches, and reports, books and relevant websites.

The quantitative research method chosen was an online survey, with the help of Qualtrics Survey Software, in order to statistically test the assumptions made. Thus, this survey was designed to try to withdraw conclusions from the developed conceptual model and check if these technologies can be implemented in the chosen area.

In order to conduct this investigation, the ten Principles incorporated by the Market Research Society (Baker & Hart, 2016) were followed to respect the respondents' privacy and opinions.

4.2. Data Collection and Sample

This data was collected via an online survey in order to expand knowledge regarding both VAs and self-driving cars.

The online survey previously mentioned is a questionnaire mainly with a pre-determined Likert scale (see Appendix C) and conducted through a non-random sample, according to convenience and snowball effects, so that a significant number of answers is more easily attainable and the sample to study gives results that are good enough to withdrawal realistic conclusions.

The survey was designed both in Portuguese and English in order to accomplish a higher number of respondents and not exclude nationalities. It was intended that the participants could express their opinion regarding the structure of the questionnaire, so that is why a pre-test was done with 11 people. Regarding their demographic characteristics, these people were chosen to represent the final sample best.

After applying the feedback proposed by the pre-test sample and in order to obtain a large sample to be relevant enough to the general population, the survey previously described was distributed via the Internet (with the help of the Qualtrics tool) and shared through social media platforms (such as LinkedIn, Facebook, Instagram and WhatsApp) and e-mail to the contacts of the author of this proposal.

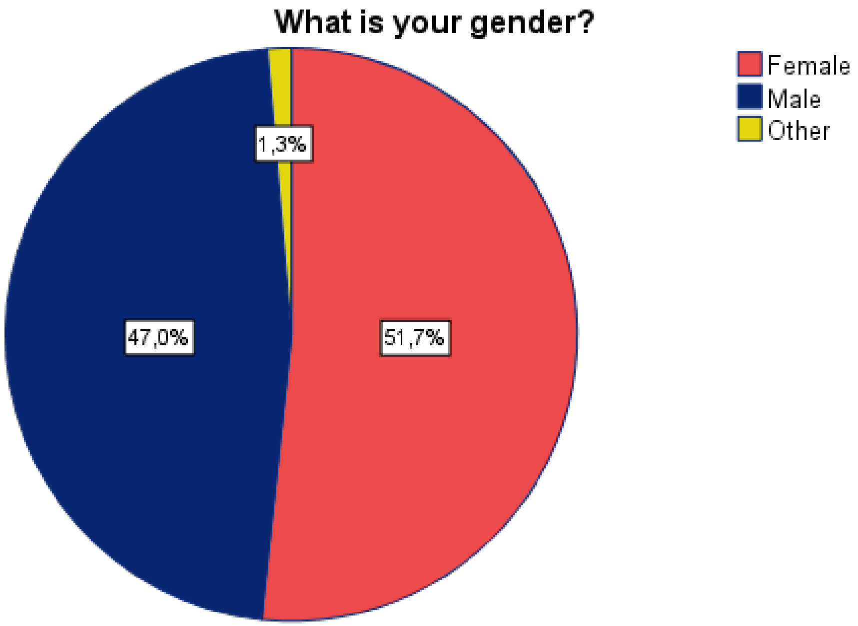
Moreover, the survey briefly described what was expected from the respondents with some general information, followed by a small explanation of what a VA is. Afterwards, the survey tries to understand each respondent's perception regarding VAs and self-driving cars and how willing they are to integrate them into their daily life. The last section of the survey is intended to obtain demographic information about the people who are part of the sample who help in this research, such as gender, age group, level of education and country of residence. All questions were mandatory to answer in order to withdraw better conclusions. This survey was available to fill in from the 22nd of June 2022 until the 30th of July 2022 and would take around 7 minutes to answer.

4.3. Sample Design

After all data was collected and the sample was large enough (higher than 30 respondents) in order to have relevant conclusions, it was conducted an extended analysis with the help of IBM SPSS software so that it was possible to analyse the results and the information could be correctly addressed and studied. It was made simple descriptive statistics, exploratory analysis and multiple linear regressions.

The sample that illustrates the people who have participated has 302 people. From this number, 51,7% represent females, which accounts for 156 people and 47% represent males, accounting for 142 people. Additionally, a residual of 1,3%, representing 4 people, do not feel comfortable disclosing their gender (Figure 3). These have been said, it is possible to conclude that this gender distribution is well balanced.

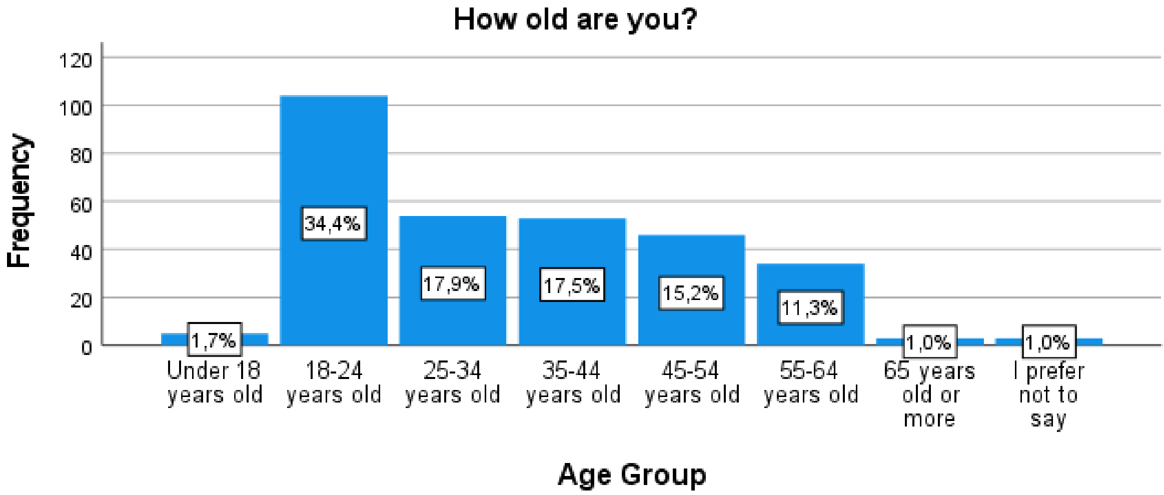
Figure 3 Distribution of Gender



Source: IBM SPSS Data

In order to get a better overview of this sample, it was created several age groups (Figure 4): under 18 years old, 18 to 24 years old, 25 to 34 years old, 35 to 44 years old, 45 to 54 years old, 55 to 64 years old and above 65 years old. Another group was created for people who do not want to reveal their age group. It can be stated that most people are between 18 and 24 years old (34,4%) and the second age group more represented is 25 to 34 (17,9%) followed by the range between 35 to 44 years old (17,5%). It is also relevant to mention that people aged 45 to 54 years old characterise 15,2% of the sample and people from 55 to 64 years old represent 11,3%. In sum, a large majority of the people from this survey (96,3%) are between 18 and 64 years old. The other age groups account only for a small part of the sample.

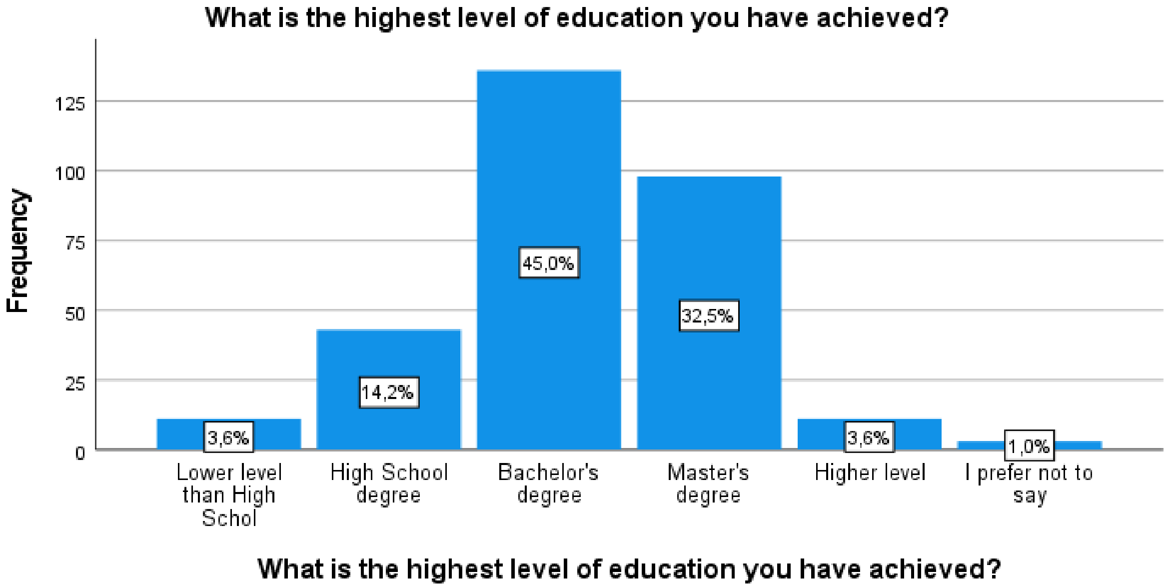
Figure 4 Distribution of Age Groups



Source: IBM SPSS Data

Moving forward, the level of education helps to characterise the sample as well. People were asked what the highest level of education they have achieved from the following possibilities: lower level than high school, high school degree, bachelor's degree, master's degree, higher level or if they do not preferer to say (Figure 5). Most participants had already completed a university degree, with 45% of the people achieving a bachelor's degree and 32,5% of the respondents obtaining a master's degree. Thus, 14,2% of people stated that the highest degree they have achieved was a high school one. In addition, the same number of respondents (11 people) obtain no degree or a higher level than a master. People with no interest in saying their degree only attain 1% of the sample. The non-random sample might contribute to the high levels of education of the sample and Facebook groups where people answer each other's searches.

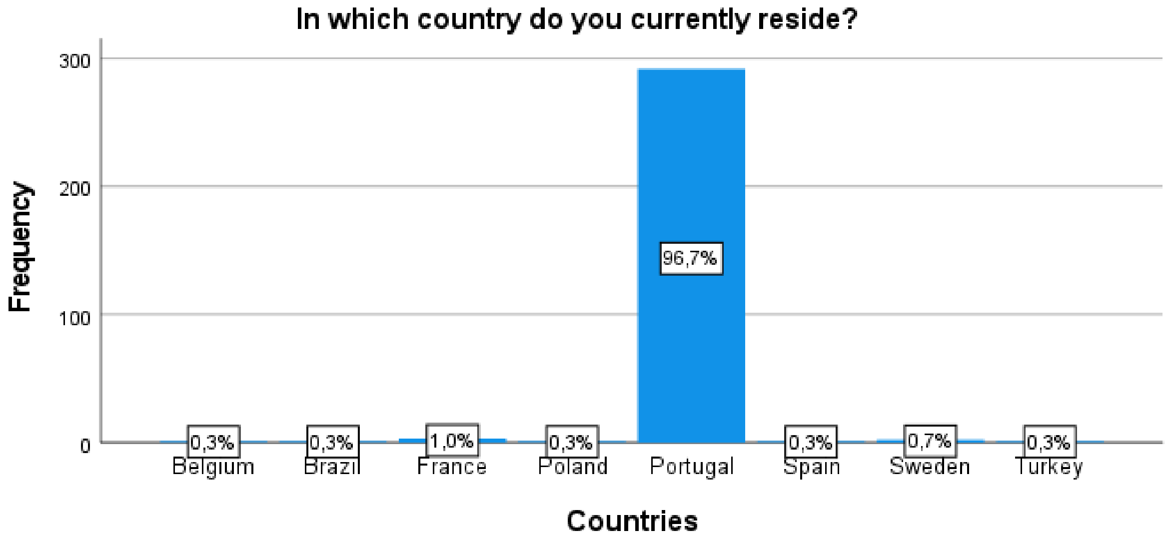
Figure 5 Distribution of Education Level



Source: IBM SPSS Data

Lastly, regarding the country of residence (Figure 6), almost everyone lived in Portugal (96,7%), except only a few people that lived in the rest of Europe, such as in Belgium (0.3%), France (1%), Poland (0,3%), Spain (0.3%), Sweden (0,7%) and Turkey (0.3%), and outside Europe, in Brazil (0.3%). Once again, the non-random sample and the Facebook groups help explain the small dispersal of residencies in the sample.

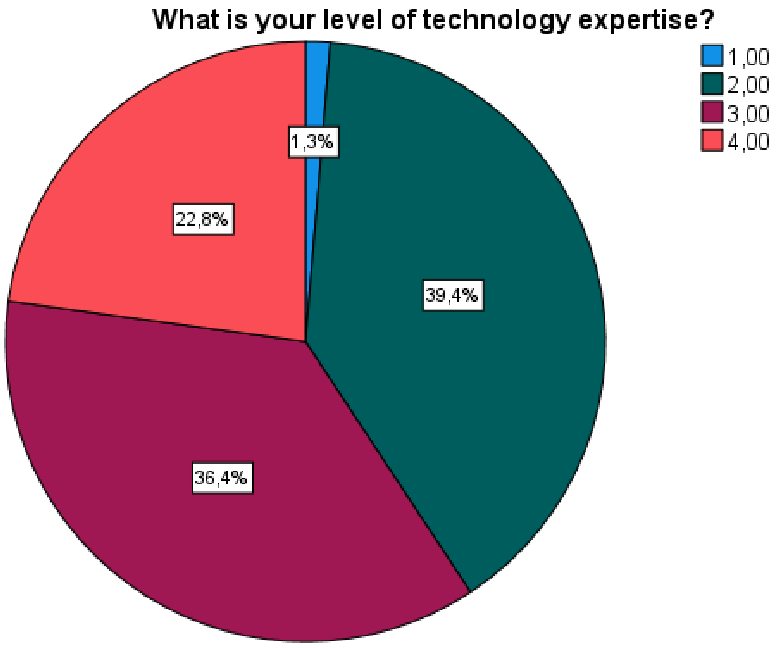
Figure 6 Distribution of Country of Residence



Source: IBM SPSS Data

After studying the demographic data about the survey's sample, it is relevant, as well, to check people's technology knowledge, the number of times they used VA in the past year and the degree of familiarity with self-driving cars in order to have deeper knowledge of the study's sample. The level of technology expertise is divided into four categories: not experienced (1), average user (2), experienced (3) and very experienced (4). With the help of Figure 7, it is possible to understand that most people are average users (39,4%) or experienced (36,4%). Also, a few people described themselves as very experienced (22,8%) and a small percentage (1,3%) are not experienced with technology. Overall, the mean of technology expertise is around 3 (approximately 2,8), which means this sample can be described as experienced technology users.

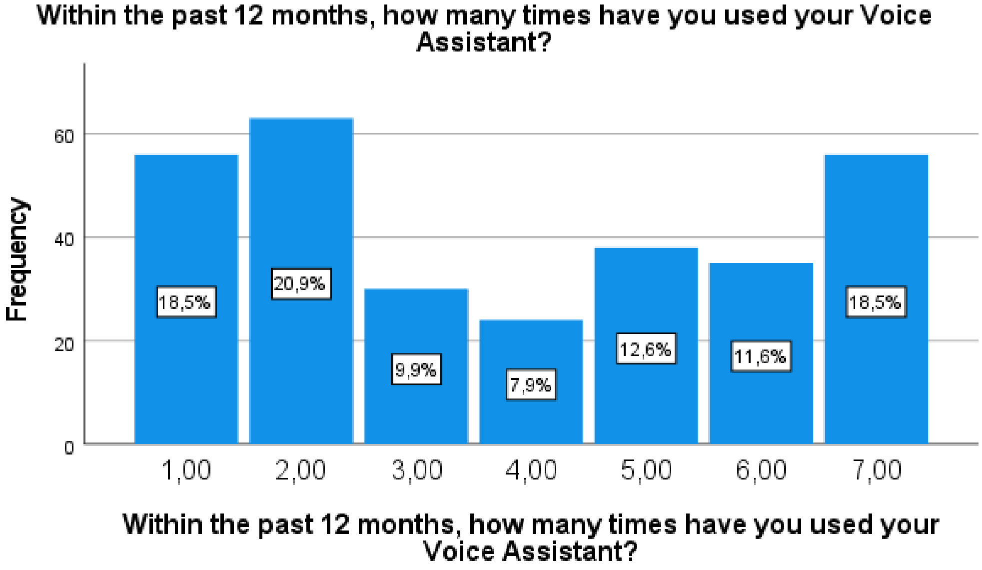
Figure 7 Distribution of the Level of Technology Expertise



Source: IBM SPSS Data

Regarding the number of times people used their VA in the past 12 months (Figure 8), respondents had to choose from a pre-determined Likert scale from 1 (never) to 7 (often) what was the number that described best their level of use. It is possible to conclude they do not use it that often (20,9%). However, the number of people who use it often and not at all are the same (18,5%), leading to conclude that people think a VA is very useful or they do not use it, do not know how to use or do not know they have it (this last possibility may happen to people who do not know they have Siri in their iPhone, for example). Also, 7,9% of the sample use VAs sometimes.

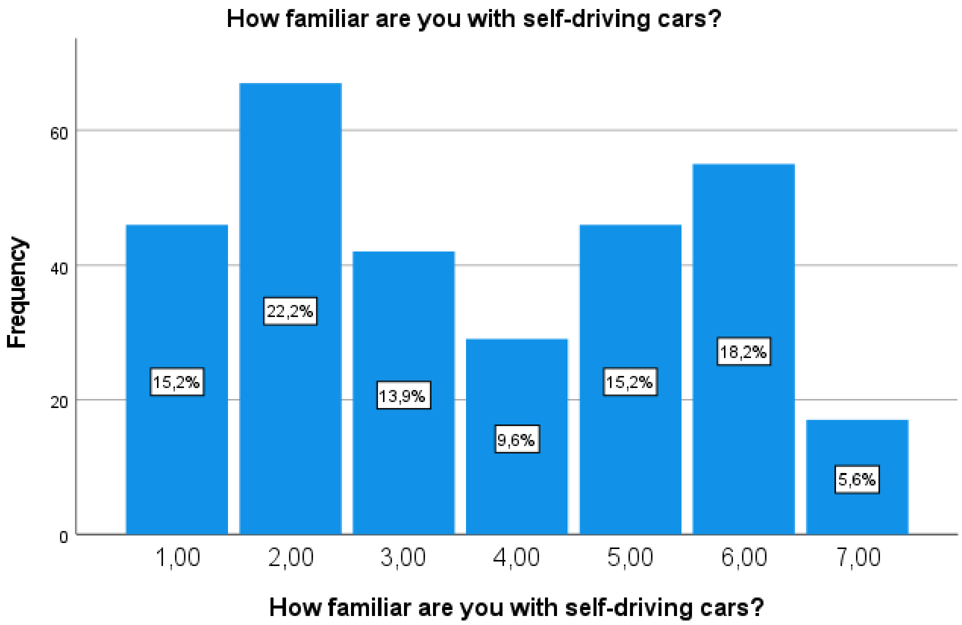
Figure 8 Distribution of VA Usage, in the Previous 12 Months



Source: IBM SPSS Data

Finally, people do not seem very familiar with self-driving cars at this point (Figure 9). Most people (22,2%) are unfamiliar with this technology. This might be explained because 96,7% of the sample lives in Portugal, as previously stated, and this technology is not very developed in this country. However, 39% of the sample are between levels 5 and 7, meaning they have a few or more familiarity with self-driving cars. Overall, 51,3% of people are not very familiar with the technology and 9,6% are only moderately familiar.

Figure 9 Distribution of the Familiarity with Self-driving Cars



Source: IBM SPSS Data

5. Results

5.1. Descriptive Statistics

5.1.1. Anthropomorphism

The first construct to analyse was Anthropomorphism, from Kim et al. (2019) studies. Here, it was used 10 questions on a 7-point Likert scale (5 warmth-related traits and 5 competence-related traits). In Table 1, it is displayed their mean and standard deviation values.

After a careful analysis, it was concluded that the 5 items related to competence-related traits have higher mean values, with the item “efficient” being the one with the highest mean value (6,74), followed by “competent” with a mean value of 6,65. On the other hand, the 5 warmth-related traits are the ones least relevant to people, with the item “warm” being the less relevant, followed by “sociable”. This suggests that respondents value a VA more if it has efficiency and competency skills rather than warmth and sociability skills.

The item “sociable” has the highest standard deviation value (1,647), which means it is the least reliable item from Anthropomorphism. On the contrary, “efficient” also has the lowest standard deviation value (0,691).

Lastly, the construct Anthropomorphism is made by the mean of all items’ means and the result is 5,7318 with a standard deviation of 0,79537. Since Anthropomorphism is above the average of a 7-point Likert scale, it can be stated that it has a positive influence.

Table 1 Descriptive Statistics of Anthropomorphism

	Minimum	Maximum	Mean	Std. Deviation
Sociable	1	7	4,76	1,647
Friendly	1	7	5,10	1,525
Kind	1	7	5,02	1,579
Likeable	1	7	5,41	1,305
Warm	1	7	4,52	1,584
Competent	1	7	6,65	0,808
Intelligent	1	7	6,50	0,862
Skilful	1	7	6,16	0,940
Efficient	1	7	6,74	0,691
Capable	1	7	6,45	0,775
Anthropomorphism	**1,00**	**7,00**	**5,7318**	**0,79537**

Source: own elaboration (based on IBM SPSS output)

5.1.2. Relational Cohesion

Moving forward to the following construct was Relational Cohesion, with the help of the research of Hernández-Ortega et al. (2021), through 6 questions in a 7-point Likert scale format. The values of the mean and the standard deviation are shown in Table 2.

The items of this construct have mean and standard deviation values very close to each other. The item “cooperative” is the one with the highest mean value (4,80), followed by “convergent” (4,52) and “integrative” (4,49), which means these three attributes describe the best a relationship between a person and a VA. The item “close” is the one with the lowest mean value (4,09) and the highest standard deviation value (1,852) meaning “close” is not an attribute that best describes the relationship previously mentioned. Moreover, the item “integrative” has the smallest standard deviation value (1,603), which means it might be the most reliable item of the six.

Computing the variable for the construct of Relational Cohesion results in a mean of 4,3918, still above the average of a 7-point Likert scale, resulting in a medium positive influence and a standard deviation value of 1,50301.

Table 2 Descriptive Statistics of Relational Cohesion

	Minimum	Maximum	Mean	Std. Deviation
Close	1	7	4,09	1,852
Cooperative	1	7	4,80	1,645
Integrative	1	7	4,49	1,603
Solid	1	7	4,23	1,707
Cohesive	1	7	4,23	1,691
Convergent	1	7	4,52	1,729
Relational Cohesion	**1**	**7**	**4,3918**	**1,50301**

Source: own elaboration (based on IBM SPSS output)

5.1.3. Interaction Frequency

Next, the construct Interaction Frequency was analysed, based on the studies of Hernández-Ortega et al. (2021), which had 3 questions on a 7-point Likert scale, with the results of the mean and the standard deviation present in Table 3.

It is possible to conclude that the item “my VA always tries to resolve my doubts” is the behaviour that best describes consumers regarding their interaction with a VA and it is also the most reliable item, because it has the highest mean value (4,79) and the lowest standard deviation value (1,868).

On the other hand, the item “I usually interact with my VA several times a day” reflects that people still do not use the VA that many times a day when compared to the other two behaviours, once it has the lowest mean value (3,66).

Overall, the construct Interaction Frequency has a mean value of 4,1887 (almost neutral, but still a slightly positive influence) and a standard deviation value of 1,90666.

Table 3 Descriptive Statistics of Interaction Frequency

	Minimum	Maximum	Mean	Std. Deviation
I usually interact with my VA several times a day	1	7	3,66	2,277
I often ask my VA questions	1	7	4,12	2,143
My VA always tries to resolve my doubts	1	7	4,79	1,868
Interaction Frequency	**1**	**7**	**4,1887**	**1,90666**

Source: own elaboration (based on IBM SPSS output)

5.1.4. Brand Trust

Brand Trust aims to measure the level of trust people have in VAs. It is built on 4 questions designed on 7-point Likert scales, based on and adapted from Pagani et al. (2019). The results of the mean and the standard deviation are shown in Table 4.

From analysing the table, it is possible to conclude that both the mean and standard deviation values of each item are very close to each other. Hence, the item "my VA is reliable" is the one with the highest mean (5,25) and the lowest standard deviation (1,381) values. On the other side, the item "I trust on my VA" is the one with the lowest mean value (5,05) and the highest standard deviation value (1,600).

This has been said, it is possible to conclude that consumers rely on VA, even though the levels of trust still have to be increased.

In general, the construct Brand Trust has a mean value (5,1730) above the average of a 7-point Likert scale, indicating that it has a positive influence and a standard deviation value of 1,31661.

Table 4 Descriptive Statistics of Brand Trust

	Minimum	Maximum	Mean	Std. Deviation
I trust on my VA	1	7	5,05	1,600
My VA is reliable	1	7	5,25	1,381
My VA is honest with me	1	7	5,20	1,390
My VA is dependable	1	7	5,20	1,427
Brand Trust	**1**	**7**	**5,1730**	**1,31661**

Source: own elaboration (based on IBM SPSS output)

5.1.5. Perceived Ease of Use

The survey also intends to study the construct Perceived Ease of Use, which belongs to the study by Moriuchi (2019). The output of the means and standard deviations were generated.

In Table 5, it was determined that the item "I find the VA to be easy to use" was the one with the highest mean value (5,30) and, at the same time, the biggest standard deviation value (1,467). This means people found VA easy to use, but it is not a piece of very reliable information.

Furthermore, the item "I find it easy to get the VA to answer my questions" is the one people agree the less, since it has the lowest mean value (5,00), followed right after the other one "My interaction with the VA is clear and understandable", with a mean value of 5,06. Regarding the standard deviation, the item with the lowest value is "I find it easy to get the VA to answer my questions", with 1,414, being the most reliable.

In sum, the Perceived Ease of Use has a decent mean value (5,1203), meaning people tend to agree it has a positive influence, with a standard deviation value of 1,27585.

Table 5 Descriptive Statistics of Perceived Ease of Use

	Minimum	Maximum	Mean	Std. Deviation
My interaction with the VA is clear and understandable	1	7	5,06	1,420
I find the VA to be easy to use	1	7	5,30	1,467
I find it easy to get the VA to answer my questions	1	7	5,00	1,414
Perceived Ease of Use	**1**	**7**	**5,1203**	**1,27585**

Source: own elaboration (based on IBM SPSS output)

5.1.6. Perceived Usefulness

The construct Perceived Usefulness was also studied, with the help of the research, as well, of Moriuchi (2019). Below, in Table 6, are the mean and standard deviation values of the items that build this construct.

Undoubtedly, the item "Using a VA is better than using real customer agents" is the one with the lowest mean (2,85), which means people still think a VA cannot replace a real person. Also, the standard deviation values are all close to each other, but the previous item has a value of 1,699, being the highest. In addition, it is relevant to mention that the item "Using a VA enhances my repurchases" also has a low mean value of 3,79, meaning people do not make multiple purchases just because of their VA experience in the previous acquisition.

On the other hand, the item "Using a VA increases my time-effectiveness when I am gathering information/shopping" has the biggest mean value (4,38), followed by the item "Using a VA improves my shopping experience" with a mean value of 4,32.

All in all, the Perceived Usefulness is relatively neutral since its mean value is 4,0153 and the standard deviation value is 1,37147.

Table 6 Descriptive Statistics of Perceived Usefulness

	Minimum	Maximum	Mean	Std. Deviation
Using a VA improves my shopping experiences	1	7	4,32	1,636
Using a VA increases my time-effectiveness when I am gathering information/shopping	1	7	4,38	1,576
Using a VA would enable me to accomplish my shopping decision/information gathering	1	7	4,15	1,617
Using a VA solves my shopping decisions/information gathering easier	1	7	4,19	1,691
Using a VA enhances my repurchases	1	7	3,79	1,605
Using a VA is better than using real customer agents	1	7	2,85	1,699
VA saves me the time when I am looking for shopping decisions/information gathering	1	7	4,18	1,591
Overall, I find a VA to be useful when I need shopping decisions/information gathering	1	7	4,26	1,646
Perceived Usefulness	**1**	**7**	**4,0153**	**1,37147**

Source: own elaboration (based on IBM SPSS output)

5.1.7. Word-of-mouth Intentions

Another relevant construct to analyse is Word-of-mouth intentions, used and adapted from Kim and Park (2013) research. In Table 7, it is illustrated the results of the mean and standard deviation.

The item “I would tell others positive things about self-driving cars with a VA” is the one with the highest mean value (4,99), which allows concluding people see this technology in a positive way and are willing to spread the word. On the other side, the item “I am likely to encourage others to consider self-driving cars with a VA” shows this is the behaviour that is less likely to happen, because it has the lowest mean value of 4,55. Regarding the standard deviation, the item least reliable is “I am likely to recommend self-driving cars with a VA to my friends or acquaintances” as it is the highest value (1,652).

Overall, the construct Word-of-mouth Intentions positively influences the model, because the mean value (4,7376) is above the 7-point Likert scale neutral point. Hence, the standard deviation value is 1,48960.

Table 7 Descriptive Statistics of Word-of-mouth Intentions

	Minimum	Maximum	Mean	Std. Deviation
I would tell others positive things about self-driving cars with a VA	1	7	4,99	1,573
I would provide others with information on self-driving cars with a VA	1	7	4,79	1,580
I am likely to recommend self-driving cars with a VA to my friends or acquaintances	1	7	4,62	1,652
I am likely to encourage others to consider self-driving cars with a VA	1	7	4,55	1,641
Word-of-mouth Intentions	**1**	**7**	**4,7376**	**1,48960**

Source: own elaboration (based on IBM SPSS output)

5.1.8. Intention to Use Self-driving Cars

Finally, the construct Intention to Use Self-driving Cars is based on and adapted from Brusch and Rappel (2020). The results of the mean and standard deviation values are displayed in Table 8.

There is an item (“Given the chance, I intend to use a self-driving car”) that highlights from the others, because its mean value is, by far, the highest: 5,16. On the other hand, people do not transform their willingness to use in the actual purchase, since the item “I have strong intentions to buy a self-driving car” is the one with the lowest mean value of only 3,03, meaning they slightly disagree with it. The item “I’m considering using a self-driving car” has a standard deviation value of 1,841, which is the biggest and the least reliable.

By computing the means of these four items, the construct Intention to Use Self-driving Cars is neutral (4,1904) and does not significantly influence the model. Thus, the standard deviation value is 1,46178.

Table 8 Descriptive Statistics of Intention to Use Self-driving Cars

	Minimum	Maximum	Mean	Std. Deviation
Given the chance, I intend to use a self-driving car	1	7	5,16	1,711
I will recommend a self-driving car to others	1	7	4,58	1,595
I'm considering using a self-driving car	1	7	3,99	1,841
I have strong intentions to buy a self-driving car	1	7	3,03	1,811
Intention to Use Self-driving Cars	**1**	**7**	**4,1904**	**1,46178**

Source: own elaboration (based on IBM SPSS output)

5.2. Exploratory Analyses

In this section, it is going to be performed some exploratory analyses, such as reliability and validity analysis. Then, the outputs and the results are analysed in order to withdraw relevant conclusions.

5.2.1. Reliability and validity analyses

In order to assess the quality and consistency of the sample, it was conducted reliability and validity analyses. Through Cronbach's Alphas, computed for all items and constructs, it was possible to understand which constructs were appropriate enough to fit the model and to describe the sample best.

The Cronbach's Alpha coefficient can be any value between 0 and 1, with values closer to 1 representing reliable and consistent situations and close to 0 the opposite. Hence, this value should be higher than 0,7 so that it can be acceptable, even though it is preferable to be higher than 0,8. The excellency point is when the value is equal to or above 0,9.

In this case, as Table 9 shows, all the constructs are above 0,7, which means they are good enough to be reliable and the sample is consistent. If it is taken a closer look, it can be stated that WOM Intentions is the construct with the highest value (0,943), followed by Relational Cohesion (0,942) and Perceived Usefulness (0,940). On the other hand, the construct Anthropomorphism has the lowest Cronbach's Alpha value of 0,846, but as mentioned, it is good enough.

These eight constructs as an all were also subjected to the Cronbach's Alpha reliability test, which obtained a result of 0,874, demonstrating once more a substantial reliability value.

Table 9 Cronbach's Alphas

Construct	Cronbach's Alphas
Anthropomorphism	0,846
Relational Cohesion	0,942
Interaction Frequency	0,892
Brand Trust	0,928
Perceived Ease of Use	0,868
Perceived Usefulness	0,940
WOM Intentions	0,943
Intention to Use Self-driving Cars	0,860
All eight constructs	**0,874**

Source: own elaboration (based on IBM SPSS output)

5.3. Multiple Linear Regression

In order to study the associations between the constructs presented in the conceptual model, shown earlier in this thesis, simple and multiple regressions were conducted. Then, to proceed with the multiple regression analysis, it was necessary to test the assumptions so that conclusions could be withdrawn to the general population. For all intervals, the confidence level is 95%.

5.3.1. Assumptions of the Multiple Regression

As said before, the following assumptions must be fulfilled in order to proceed: the linearity of the model, the randomness of the sample, linear independence (absence of multicollinearity), exogeneity of the independent variables, constancy of the variances of the residuals across predicted values (homoskedasticity) and normally distributed error component.

The Linearity of the Model

The theoretical model was built on the premise that independent and dependent variables are linearly related. Following are the multiple regression models for the established conceptual model:

$$\text{Intention to use self-driving cars} = \beta_0 + \beta_1 \text{ x Anthropomorphism} + \beta_2 \text{ x Relation cohesion} + \beta_3 \text{ x Interaction frequency} + \beta_4 \text{ x Brand trust} + \beta_5 \text{ x Perceived ease of use} + \beta_6 \text{ x Perceived usefulness} + \varepsilon$$

$$\text{WOM intentions} = \beta_0 + \beta_1 \text{ x Anthropomorphism} + \beta_2 \text{ x Relation cohesion} + \beta_3 \text{ x Interaction frequency} + \beta_4 \text{ x Brand trust} + \beta_5 \text{ x Perceived ease of use} + \beta_6 \text{ x Perceived usefulness} + \varepsilon$$

These have been said, it is possible to state that the model assumes linearity and, consequently, the assumption holds.

The Randomness of the Sample

Since the author of this thesis wants to generalise the results of this sample to the population, it is necessary that the sample was collected randomly. Hence, the sample was randomly selected and tried to characterise the population the most.

Linear Independence

If the variables under study have a robust linear correlation between them, it indicates that some issues can happen within the research, meaning this multicollinearity. With the aim to guarantee there is no multicollinearity among variables, it is necessary to study the Tolerance and VIF values through the collinearity statistics. In case any Tolerance value is below 0,2 or one of the VIF values is above 10, this would mean multicollinearity.

As Table 10 illustrates, all the Tolerance and VIF values are above 0,2 and under 10, respectively, which means this assumption holds, i.e., there is no correlation among the explanatory variables.

Table 10 Collinearity Statistics

	Tolerance	VIF
Anthropomorphism	0,985	1,015
Relational Cohesion	0,421	2,377
Interaction Frequency	0,341	2,933
Brand Trust	0,445	2,247
Perceived Ease of Use	0,569	1,756
Perceived Usefulness	0,569	1,756

Source: own elaboration (based on IBM SPSS output)

Exogeneity of the Independent Variables

Multiple regression is based on the idea that independent variables are unrelated to residual terms. According to Table 11, all constructs have a Pearson correlation value of 0 with the residuals, meaning the constructs are not correlated to residuals. This way, the assumption is verified and holds.

Table 11 Correlations between Independent Variables and Residual Terms

	Anthropo-morphism	Relational Cohesion	Interaction Frequency	Brand Trust	Perceived Ease of Use	Perceived Usefulness	Residual
Anthropo-morphism	1,000	0,101	0,044	0,083	0,068	0,086	0,000
Relational Cohesion	0,101	1,000	0,743	0,646	0,659	0,679	0,000
Interaction Frequency	0,044	0,743	1,000	0,727	0,728	0,625	0,000
Brand Trust	0,083	0,646	0,727	1,000	0,762	0,608	0,000
Perceived Ease of Use	0,068	0,659	0,728	0,762	1,000	0,656	0,000
Perceived Usefulness	0,086	0,679	0,625	0,608	0,656	1,000	0,000
Residual	0,000	0,000	0,000	0,000	0,000	0,000	1,000

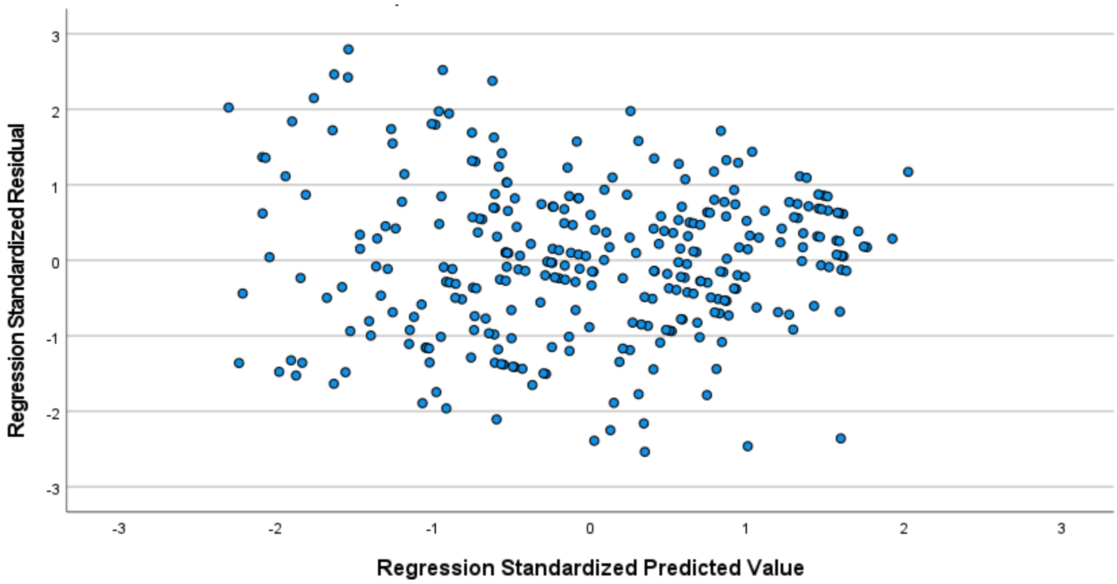
Source: own elaboration (based on IBM SPSS output)

The Constancy of the Variances of the Residuals Across Predicted Values

An essential requirement for regression models is the homoscedasticity of residuals, because it should be assumed that a model has to produce equally accurate predictions for all values. As a result, the residuals' variance must remain consistent over the predicted values, which can be visible with the help of the scatterplots in Figures 10 and 11, where the dots should be distributed uniformly over the horizontal axis in order to have equality of variance.

By analysing Figure 10, for WOM Intentions as the dependent variable, it is possible to state that the residuals seem to be horizontally evenly distributed.

Figure 10 Scatterplot of the Distribution of the Residuals (WOM Intentions as Dependent Variable



Source: IBM SPSS output

In addition, Figure 11 allows concluding that the residuals are also horizontally evenly distributed for Intention to Use Self-driving Cars as the dependent variable.

Figure 11 Scatterplot of the Distribution of the Residuals (Intention to Use Self-driving Cars as Dependent Variable)

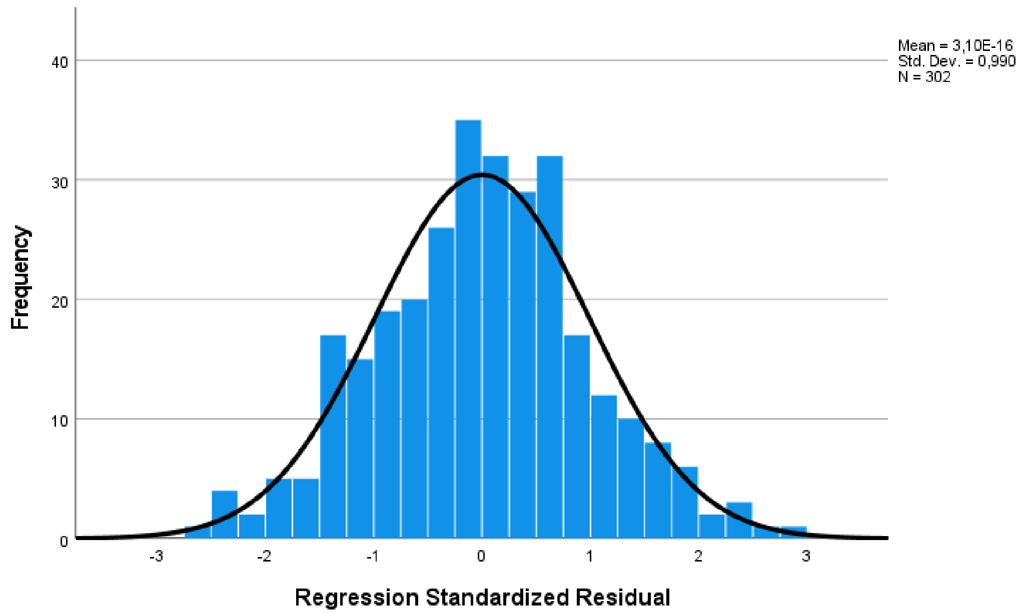
Source: IBM SPSS Data

This way, it is possible to conclude that this assumption holds in both situations, with the different dependent variables.

Normally Distributed Error Component

Figure 12 shows the standardised residuals' histogram with a superimposed normal distribution curve. This histogram helps to conclude about the normal distribution of the model, in which in this case, the residuals and the normal distribution curve match up properly. Additionally, the mean and standard deviation values (displayed in the top right corner of Figure 12) should be around 0 and 1, respectively, which can be confirmed in this case.

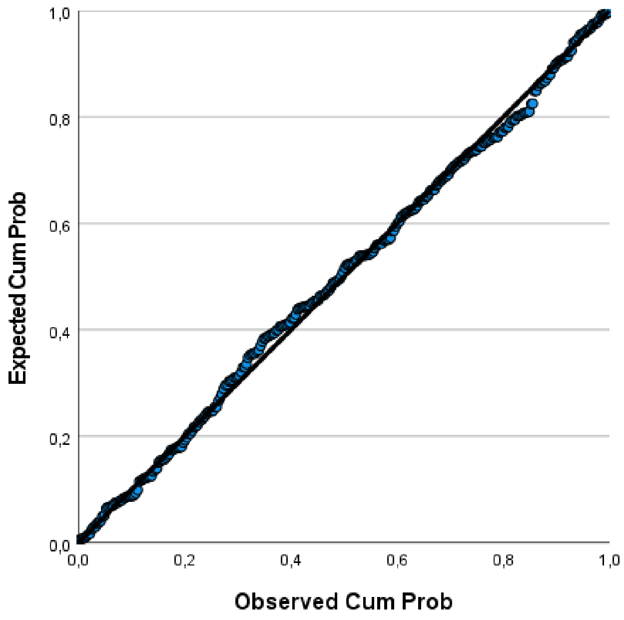
Figure 12 Histogram of the Distribution of the Residuals (WOM Intentions as Dependent Variable)



Source: IBM SPSS Data

Moving on to the P-Plot of Residuals, it represents the expected against the observed cumulative probability. If data is perfectly normally distributed, it would fall precisely on the diagonal line, and if not, it meant data would be less normally distributed. By observing Figure 13, it can be stated that the dots fall quite exactly on the diagonal line, hence it is appropriate to say the residuals are normally distributed.

Figure 13 Normal P-Plot of Residuals (WOM Intentions as Dependent)

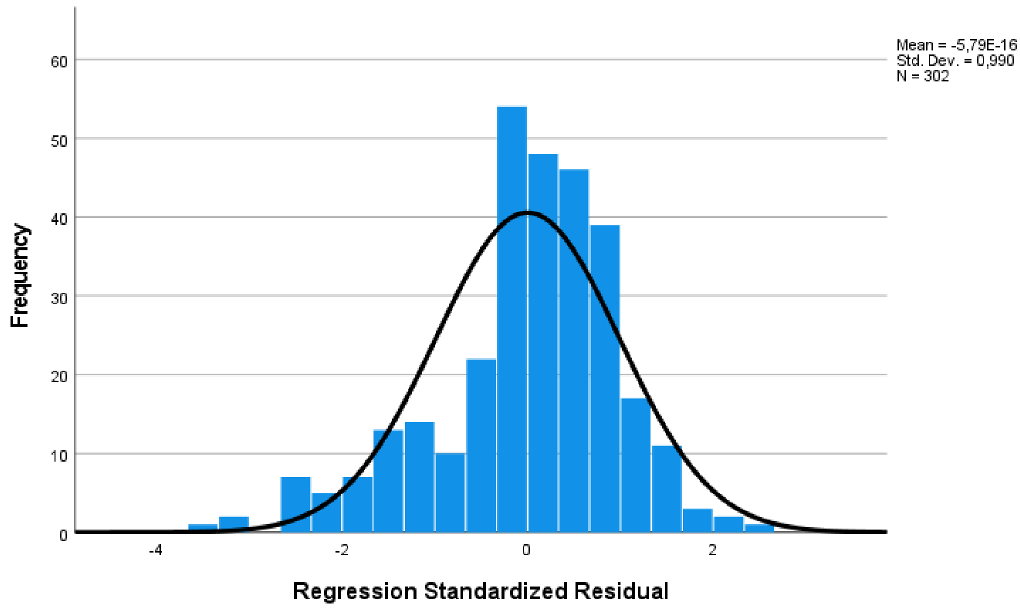


Source: IBM SPSS Data

Furthermore, having both conclusions in mind and having in mind WOM Intentions as Dependent Variable, the assumption holds. Although, the same process needs to be done considering Intention to Use Self-driving Cars as the dependent variable.

Now taking into consideration Intention to Use Self-driving Cars as dependent variable, the conclusions seem to be a bit different. By looking at Figure 14, the histogram suggests that the residuals and the normal distribution curve do not match up clearly.

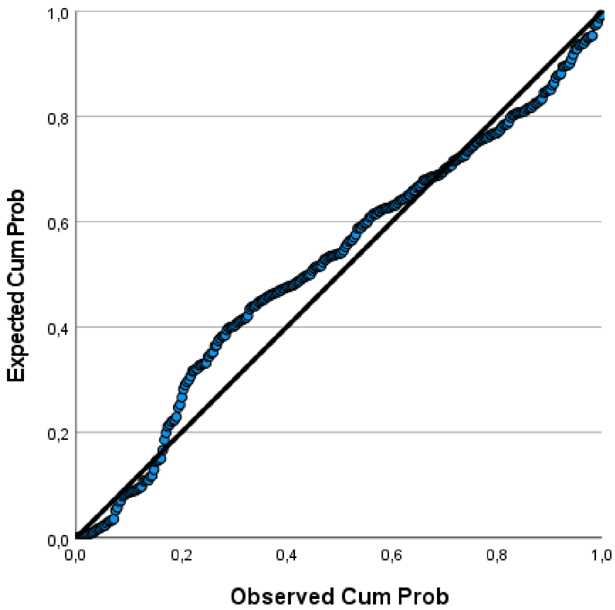
Figure 14 Histogram of the Distribution of the Residuals (Intention to Use Self-driving Cars as Dependent Variable)



Source: IBM SPSS Data

In addition, Figure 15 helps to support the conclusion withdrawn previously. The dots in this P-Plot of Residuals clearly do not fall on the diagonal line, which means it is not perfectly normally distributed. Consequently, the residuals are not normally distributed.

Figure 15 Normal P-Plot of Residuals (Intention to Use Self-driving Cars as Dependent Variable)



Source: IBM SPSS Data

In sum, it can be stated that this assumption does not hold in both dependent variables, which means the model cannot be generalised for the general population.

Correlation of the Residual Terms

The residuals must be independent in order to conduct a multiple regression analysis correctly, otherwise, autocorrelation will appear in the results. The Durbin-Watson statistic can be used to determine if the residuals are independent or not. This value must be around 2 to result in no correlated residuals, which in this case verifies, once the value is 1,942 (for WOM Intention as the dependent variable) and 1,970 (for Intention to Use Self-driving Cars as the dependent variable), as it is possible to see in Table 12.

This way, it is possible to state that this assumption holds.

Evaluation of the Model

The model's suitability can be established once all the pre-requisites of the multiple regression analysis have been examined, including how accurately our model can predict the numbers we observed. Table 12 shows a significant correlation between the predicted and observed values in terms of the Intention to Use Self-driving Cars as the dependent variable, because the multiple correlation coefficient is 0,621. However, when it comes to the WOM Intentions as the dependent variable, the coefficient value is slightly low (0,418). The adjusted R^2 for the model (considering WOM Intentions as the dependent variable) is 0,158 (R^2 = 0,175), which indicates a small fit. Although the Intention to Use Self-driving Cars as dependent variable has higher values (adjusted R^2 = 0,373; R^2 = 0,386), it is still a coefficient value slightly low, indicating a moderate fit.

Table 12 Model Summary of the Dependent Variables

	R	R^2	Adjusted R^2	Durbin-Watson
WOM Intentions	0,418	0,175	0,158	1,942
Intention to Use Self-driving Cars	0,621	0,386	0,373	1,970

Source: own elaboration (based on IBM SPSS output)

Tables 13 and 14 allow checking whether the predictors significantly predict the criterion. The predictors Anthropomorphism, Relational Cohesion, Interaction Frequency, Brand Trust, Perceived Ease of Use and Perceived Usefulness statistically significant predict WOM Intentions (Table 13), F (6,295) = 10,401, p < 0.001.

Table 13 Significance of the Model (WOM Intentions as Dependent Variable)

		df	F	Sig.
WOM Intentions	**Regression**	6	10,401	<,001
	Residual	295	-	-
	Total	301	-	-

Source: own elaboration (based on IBM SPSS output)

Also, the predictors Anthropomorphism, Relational Cohesion, Interaction Frequency, Brand Trust, Perceived Ease of Use and Perceived Usefulness statistically significant predict Intention to Use Self-driving Cars (Table 14), as well, F (6,295) = 30,879, p < 0.001.

Table 14 Significance of the Model (Intention to Use Self-driving Cars as Dependent Variable)

		df	F	Sig.
Intention to Use Self-driving Cars	**Regression**	6	30,879	<0,001
	Residual	295		
	Total	301		

Source: own elaboration (based on IBM SPSS output)

In sum, as not all the assumptions are completely fulfilled, the results of the multiple regression analysis can only characterise this sample. This way, it is not possible to generalise the conclusions to all the population and no inferences can be withdrawn using this model.

5.3.2. Multiple Regression: Perceived Ease of Use as a dependent variable; Anthropomorphism, Relation Cohesion, Interaction Frequency and Brand Trust, as independent variables

Considering the conceptual model previously presented, it is possible to identify the role of each variable. In order to understand if the constructs Anthropomorphism, Relation Cohesion, Interaction Frequency and Brand Trust, here as independent variables, positively impact the dependent variable Perceived Ease of Use (H1a, H2a, H3a, H4a) was calculated the adjusted regression equation, from the regression coefficients (Table 15):

$$PEU = 1,442 + 0,003 \times A + 0,132 \times RC + 0,186 \times IF + 0,444 \times BT + \varepsilon$$

In this model, Anthropomorphism, Relation Cohesion, Interaction Frequency and Brand Trust were the four predictors and the criterion was Perceived Ease of Use. These variables have regression coefficient values of 0,003 (SE = 0,055), 0,132 (SE = 0,045), 0,186 (SE = 0,039) and 0,444 (SE = 0,050), respectively. This means that for each value incremented in any of the four variables, Perceived Ease of Use increases the four values mentioned.

In terms of linear correlation into Perceived Ease of Use, it is visible that Relation Cohesion (sig. = 0,003), Interaction Frequency (sig. ≈ 0) and Brand Trust (sig. ≈ 0) are present because the sig. value is under 0,050. On the other hand, Anthropomorphism has a sig. value (0,954) lower than 0,050, resulting in the inverse behaviour, showing no linear correlation to the dependent variable.

The results show:

- H1a: Anthropomorphism negatively influences Perceived Ease of Use;
- H2a: Relation Cohesion positively influences Perceived Ease of Use;
- H3a: Interaction Frequency positively influences Perceived Ease of Use;
- H4a: Brand Trust positively influences Perceived Ease of Use.

Table 15 Coefficients of the Multiple Regression, Perceived Ease of Use as Dependent Variable

		Unstandardised Coefficients		Sig.	Collinearity Statistics	
		β	**Std. Error**		**Tolerance**	**VIF**
Dependent variable: **Perceived Ease of Use**	(Constant)	1,442	0,351	**0,000**		
	Anthropomorphism	0,003	0,055	**0,954**	0,985	1,015
	Relational Cohesion	0,132	0,045	**0,003**	0,421	2,377
	Interaction Frequency	0,186	0,039	**0,000**	0,341	2,933
	Brand Trust	0,444	0,050	**0,000**	0,445	2,247

Source: own elaboration (based on IBM SPSS output)

5.3.3. Multiple Regression: Perceived Usefulness as a dependent variable; Anthropomorphism, Relation Cohesion, Interaction Frequency and Brand Trust, as independent variables

Moving forward to study the relationship between the same independent variables as previously (Anthropomorphism, Relation Cohesion, Interaction Frequency and Brand Trust), however with a different dependent variable (Perceived Usefulness) now. By studying Table 16 is possible to withdraw the following adjusted regression equation, where Perceived Usefulness is the criterion:

$$PU = 0{,}482 + 0{,}031 \times A + 0{,}386 \times RC + 0{,}104 \times IF + 0{,}238 \times BT + \varepsilon$$

The four independent variables have, respectively, regression coefficient values of 0,031 (SE = 0,070), 0,386 (SE = 0,057), 0,104 (SE = 0,050) and 0,238 (SE = 0,063). The same incrementation taught is applicable here: for every increase in one of the independent variables, the dependent variable (Perceived Usefulness) increments the respective regression coefficient value.

The linear correlation is visible in the variables Relation Cohesion (sig. ≈ 0), Interaction Frequency (sig. = 0,037) and Brand Trust (sig. ≈ 0), once they have sig. values lower than 0,050. On the opposite, Anthropomorphism has the opposite behaviour (sig. = 0,662), meaning it is higher than 0,050, not being linear correlated.

The results show:

- H1b: Anthropomorphism negatively influences Perceived Usefulness;
- H2b: Relation Cohesion positively influences Perceived Usefulness;
- H3b: Interaction Frequency positively influences Perceived Usefulness;
- H4b: Brand Trust positively influences Perceived Usefulness.

Table 16 Coefficients of the Multiple Regression, Perceived Usefulness as Dependent Variable

		Unstandardised Coefficients		Sig.	Collinearity Statistics	
		β	Std. Error		Tolerance	VIF
Dependent variable: **Perceived Usefulness**	(Constant)	0,482	0,446	**0,281**		
	Anthropomorphism	0,031	0,070	**0,662**	0,985	1,015
	Relational Cohesion	0,386	0,057	**0,000**	0,421	2,377
	Interaction Frequency	0,104	0,050	**0,037**	0,341	2,933
	Brand Trust	0,238	0,063	**0,000**	0,445	2,247

Source: own elaboration (based on IBM SPSS output)

5.3.4. Multiple Regression: Intention to Use Self-driving Cars as a dependent variable; Perceived Ease of Use and Perceived Usefulness, as independent variables

The conceptual model also suggests that the Intention to Use Self-driving Cars is positively impacted by Perceived Ease of Use and Perceived Usefulness. By looking at Table 17 is possible to elaborate the adjusted regression equation:

$$IUSC = 1{,}369 + 0{,}368 \times PEU + 0{,}370 \times PU + \varepsilon$$

Furthermore, the predictor Perceived Ease of Use has a regression coefficient value of 0,368 (SE = 0,072) and Perceived Usefulness a value of 0,370 (SE = 0,067). This means that for every incrementation in the predictors, Intention to Use Self-driving Cars (criterion) increases the coefficients values, respectively.

In addition, Perceived Ease of Use (sig. ≈ 0) and Perceived Usefulness (sig. ≈ 0) show a positive linear correlation to Intention to Use Self-driving Cars, since both predictors have sig. values lower than 0,050, suiting the prediction well.

The results show:

- H5a: Perceived Ease of Use positively influences Intention to Use Self-driving Cars;
- H6a: Perceived Usefulness positively influences Intention to Use Self-driving Cars.

Table 17 Coefficients of the Multiple Regression, Intention to Use Self-driving Cars as Dependent Variable

		Unstandardised Coefficients		Sig.	Collinearity Statistics	
		β	Std. Error		Tolerance	VIF
Dependent variable: **Intention to Use Self-driving Cars**	(Constant)	1,369	0,287	**0,000**		
	Perceived Ease of Use	0,368	0,072	**0,000**	0,569	1,756
	Perceived Usefulness	0,370	0,067	**0,000**	0,569	1,756

Source: own elaboration (based on IBM SPSS output)

5.3.5. Multiple Regression: WOM Intentions as a dependent variable; Perceived Ease of Use and Perceived Usefulness, as independent variables

Lastly, the conceptual model highlights the relationship between WOM Intentions (dependent variable) and Perceived Ease of Use and Perceived Usefulness (independent variables). Table 18 allows to study the adjusted regression equation:

$$WOM = 2{,}255 + 0{,}095 \times PEU + 0{,}361 \times PU + \varepsilon$$

The variable Perceived Ease of Use has a regression coefficient value of 0,095 (SE = 0,081), indicating that any increase in this variable results in an incrementation of 0,095 in

WOM Intentions. Additionally, Perceived Usefulness has a lower regression coefficient of 0,361 (SE = 0,075), meaning every increase in Perceived Usefulness leads to a 0,361 rise in WOM Intentions.

Regarding the linear correlation to WOM Intentions, it is visible in Perceived Usefulness (sig. ≈ 0) since the sig. value is lower than 0,050. In contrast, Perceived Ease of Use has the inverse behaviour (sig = 0,241) since the sig. value is higher than 0,050.

The results show:

- H5b: Perceived Ease of Use negatively influences WOM Intentions;
- H6b: Perceived Usefulness positively influences WOM Intentions.

Table 18 Coefficients of the Multiple Regression, WOM Intentions as Dependent Variable

		Unstandardised Coefficients		Sig.	Collinearity Statistics	
		β	Std. Error		Tolerance	VIF
Dependent variable: **WOM Intentions**	(Constant)	2,255	0,322	**0,000**		
	Perceived Ease of Use	0,095	0,081	**0,241**	0,569	1,756
	Perceived Usefulness	0,361	0,075	**0,000**	0,569	1,756

Source: own elaboration (based on IBM SPSS output)

In sum, given the result of the multiple regression above, Table 19 summarises the main conclusions:

Table 19 Hypotheses Validation

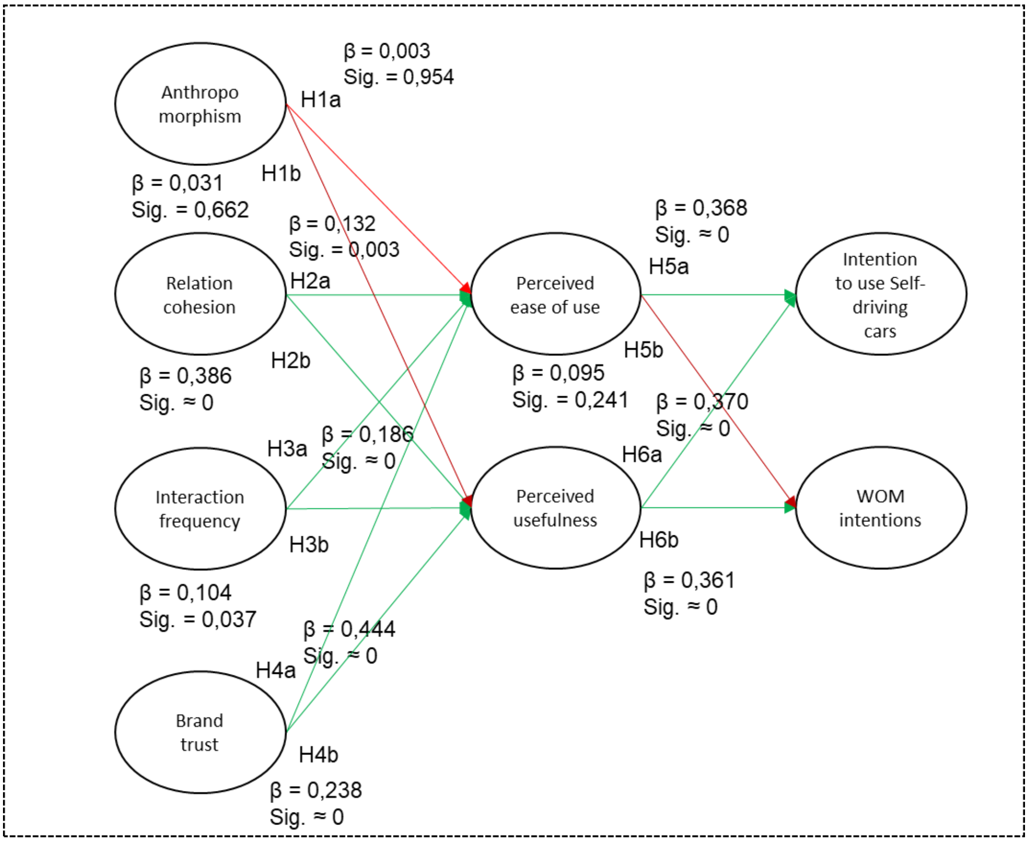
Hypotheses	Validation
H1a: Anthropomorphism positively influences Perceived Ease of Use.	No
H1b: Anthropomorphism positively influences Perceived Usefulness.	No
H2a: Relation Cohesion positively influences Perceived Ease of Use.	Yes
H2b: Relation Cohesion positively influences Perceived Usefulness.	Yes
H3a: Interaction Frequency positively influences Perceived Ease of Use.	Yes

H3b: Interaction Frequency positively influences Perceived Usefulness.	Yes
H4a: Brand Trust positively influences Perceived Ease of Use.	Yes
H4b: Brand Trust positively influences Perceived Usefulness.	Yes
H5a: Perceived Ease of Use positively influences Intention to Use Self-driving Cars.	Yes
H5b: Perceived Ease of Use positively influences WOM Intentions.	No
H6a: Perceived Usefulness positively influences Intention to Use Self-driving Cars.	Yes
H6b: Perceived Usefulness positively influences WOM Intentions.	Yes

Source: own elaboration

Lastly, it is possible to take a closer look at the conceptual model (Figure 16) and to understand the valid relationships and the ones that are not supported.

Figure 16 Results of the Conceptual Model



Source: own elaboration

6. Conclusions

Nowadays, many brands have already introduced VAs into the market and continue developing new skills for these AI devices. It is also being investigated how this technology can increase the quality of life by helping people with their daily tasks, allowing them to be more efficient, regardless of their demographic characteristics. In addition, some studies try to explain how the futuristic technology of self-driving cars, which already exists and is commercialised by car manufacturers, can help decrease car accidents and be a benefit to increase people's daily lives. However, there was a lack of research in combining these two sets of technology to find the best solutions possible to enhance the quality of the routine of every driver in the world. The main purpose of this thesis is to positively contribute to the increase of the quality of life by integrating VAs in self-driving cars to turn driving into a more efficient process.

In this section is going to be examined the research objectives of this dissertation along with the theoretical and managerial implications. Also, here are the present limitations that this study faced in obtaining the best results possible and what is the gap to future discoveries in the fields of VAs and self-driving cars.

6.1. Theoretical contributions

In order to understand the theoretical contributions is essential to remind the main objective of this thesis which was to find out the impact of VAs on the consumer, in the self-driving car industry.

This research supports every suggested hypothesis in the conceptual model, except the ones where the predictor was Anthropomorphism and Perceived Ease of Use, this last one when WOM Intentions was the dependent variable. This shows that the human characteristics that people associate with these technologies negatively influence the usefulness and ease of use they give to both VAs and self-driving cars technologies. These results support the theory suggested by Kim et al (2019), where they go even further and state that the warmth traits are more negative than the competence traits, which was also studied and evidenced in this thesis.

The relation cohesion between the user and technologies positively influences the ease of use and usefulness. The elements that enhance this relation the most are cooperation, convergency and integration, turning these technologies into a regular habit. Hernández-Ortega et al. (2021) reinforce this statement by saying that it can lead to successful interactions and positive emotions, which reflects in the engagement with the technologies and the referral to new users.

Moreover, the interaction frequency of these technologies also showed significant importance in the final model. Furthermore, it positively influences the consumers' usefulness and ease of use. This is consistent with the literature, because Hernández-Ortega et al. (2021) support this, as well, and suggest that frequent interactions can improve cohesive relationships between the user and the gadget.

The level of trust consumers deposit in a brand, in this case in these technologies, is also relevant. Therefore, VAs appeared to be something on which consumers rely on. Here, Pagani et al. (2019) suggested that a gadget with voice interaction decreases the level of acceptance by consumers, meaning that the literature does not support this conclusion. This might be explained because the consumers look for simple tasks and adding voice sometimes can be challenging to make the VA follow a request due to a lack of understanding.

Consumers' perceived ease of use gives the possibility to understand there was knowledge on how to use a VA, but people struggled to make it answer to specific questions, which is aligned with the idea presented in the previous paragraph and also is supported by the literature. Moreover, consumers' perceived usefulness seemed relevant since people understand the benefits in terms of efficiency regarding a VA, but they still prefer to use real agents instead of this technology to help them with their purchases.

As explained earlier in the literature, the TAM assumes that the perceived ease of use and the perceived usefulness determine an individual's behavioural intention to use a specific system (Davis et al, 1989). This is supported by the investigation of this thesis, which realised that the two variables both positively influence the model, except when the usefulness is applied to WOM intentions (which happens oppositely, as previously mentioned).

Regarding the WOM intentions, people do want to use and experiment a self-driving car with a VA, however when it comes the time actually to purchase one, they feel way more hesitant, which might be because of the lack of availability in Portugal and also because of the higher prices that these vehicles have. Nevertheless, it is relevant to refer the intention to buy a self-driving car with a VA refers to the willing consumers have to say good things about the technology because they find it appropriate, but they still do not feel comfortable encouraging their peers to buy one, much likely because of the reasons previously mentioned.

These have been said, consumers already feel VA is a technology that is important, but still needs some improvements to become more efficient. The self-driving cars also have similar feedback, this meaning they still do not attract consumers that much, even though their willingness to try them. In sum, consumers are willing to try self-driving cars with VAs embedded, but before purchasing one, they want the prices to be more attractive and technology more developed.

6.2. Managerial implications

Based on this thesis, the self-driving car industry is recommended to see the benefit of implementing VAs on their cars. Here, we study which factors influence consumers to adapt to these recent technologies and what can persuade them actually to purchase the final product. It is believed that the literature review and the analysis of the results of this investigation should be taken into account for a deeper comprehension of the subject.

Moreover, some companies are already doing a great job moving into the future regarding technology. It can be highlighted that Tesla is the one which is more advanced in terms of implementing these new AI technologies. Even though this company is facing some legal and ethical issues regarding VAs, there is an essential upgrade in the quality of life in consumers' lives. This also impacts more companies than the technology ones, since if all car brands adopt the two technologies described in this thesis, it can lead to smarter and more efficient cities, reducing traffic, costs and stress.

Furthermore, the development of cohesion in the relationship between users and devices, the growth in the number of times people interact with these technologies and the trust they deposit in it can highly enhance the perceived ease of use and usefulness. Thus, the intention to use self-driving cars will be positively affected by the effort users put into learning on how to use them and how valuable they are, on a daily basis. Also, the intention to spread positive feedback is directly affected by the value users feel the technology adds to increase their quality of life.

In addition, companies should develop the implementation of these technologies based on the idea that consumers give more value to them, when they do user requests more efficiently and do not value a lot of warmth-related traits. Additionally, they look for systems where they feel to be part of the process of getting them to point A to point B. Thus, aligned with efficiency, people want the VA to resolve their doubts quickly, so that they can consider it more reliable than the ones that currently exist, because at this point they still do not find it very trustful to resolve their issues, which can be pointed out because of the efficiency of the Portuguese idiom. Ease of use plays a crucial role when it comes to the adoption process, because consumers feel these are technologies that are easy to use, but still very inefficient, as it was previously described.

This research also shows that real agents are still a crucial part of the purchase process, because a large majority still need to have human contact with a real person in order to be convert into regular customers. However, the consumer decision journey process might not have in all stages a real person and can be replaced by technology, especially in the information-gathering period, where consumers feel VAs can add much value. This is also applicable in the process of considering self-driving cars, because people really have the desire to use a self-driving car, but they still do not complete the purchase. VAs can have a crucial role here to help gather enough information, especially in Portugal where this technology is not widespread yet. Thus, there is already a will to give positive feedback to others, but it still does not reflect in encouraging others into the actual purchase.

Finally, it is possible to state that VAs and self-driving cars can help boost efficiency on a company level and a social level. Companies can reduce costs and improve their employees' quality of life, and society can have smarter cities if these technologies are applicable on a broader scale.

6.3. Limitations

Despite the author of this thesis making every effort in order to present the best results possible and the most pertinent research, every study has its own constraints regarding the investigation approach, methodology, duration and costs.

The first limitation is related to the methodology used. On the one hand, quantitative research is easier to analyse because the results are based on numerical information. On the other hand, it does not offer more details than the ones stated by the numbers, which means there are no additional justifications to help to explain the results and the behaviours obtained through the analysis.

Another relevant topic to address is related to the sample characteristics. In this study, the sample has a large majority of people who live in Portugal, creating a lack of knowledge regarding other countries of the world and limiting the possibility of withdrawing any conclusions that apply to people from different geographic locations, as well. Thus, the age groups of the study are also quite similar to the author's age group, which happened in order to obtain more easily answers to the survey. However, it limited a little the heterogeneity in terms of feedback from people of different ages.

Since this thesis was written during the COVID-19 period, it was difficult to find literature that could support if the consumer's behaviour suffered any constraints regarding VAs and self-driving cars. The only possible information to withdraw was that it accelerates the purchase of VA devices to have at home, like Amazon's Alexa, but nothing regarding the application of it in autonomous vehicles.

6.4. Future research

Considering what was written in the previous section, there is space for some developments and new investigations into this topic.

One can be interesting to study alternative methodologies to obtain more context regarding consumers' choices regarding VAs and self-driving cars. For example, it might be interesting to do a focus group to understand the skills consumers look up on a VA or what they expect from a self-driving car in terms of skills. This focus group should be done with a sample that illustrates the best markets where consumers use this kind of technology more regularly, such as the United States of America or China.

Furthermore, it can be interesting to implement this investigation in the public transportation sector, on buses, taxis or even private transportation, such as Uber, Cabify or Bolt. This way, the costs for the companies would decrease since a driver will no longer be needed and the customer experience would be enhanced. At the same time, it would bring some ethical issues because some jobs would be lost. However, that is the main reason there is space for developing this master's thesis.

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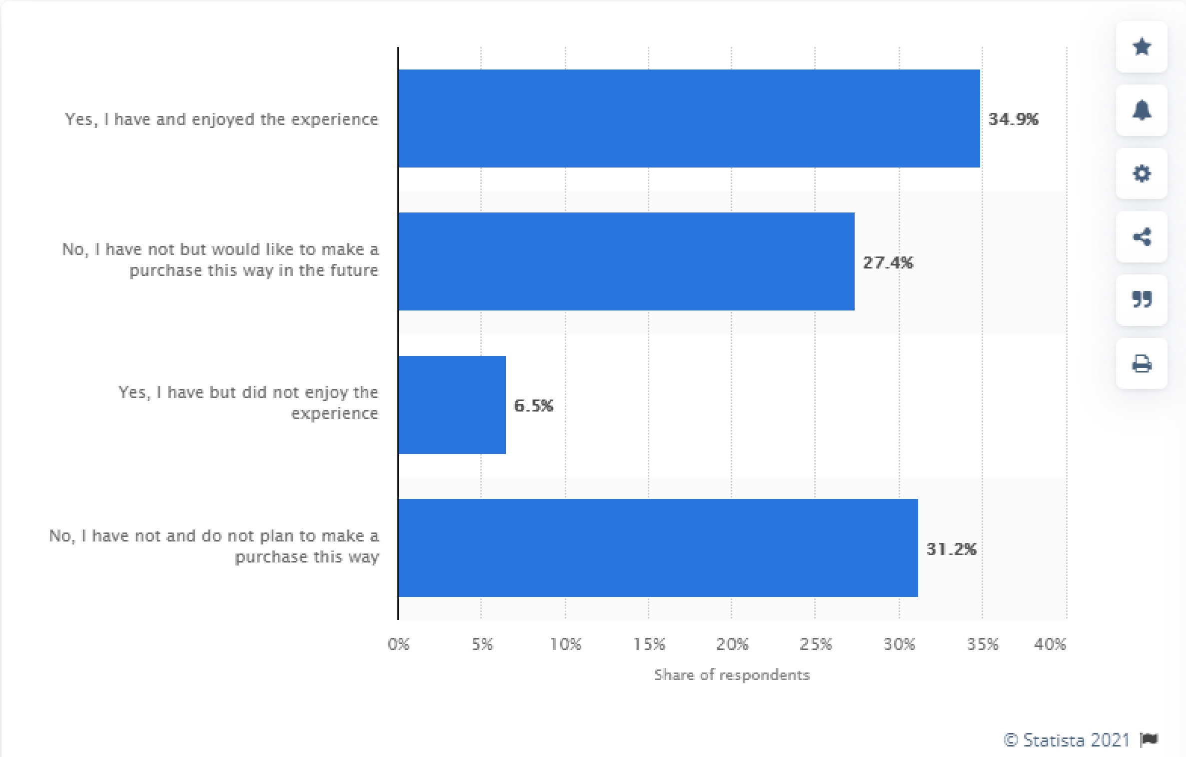
Appendices

<u>Appendix A</u>: Have you ever attempted to make a purchase using either a digital assistant or your smart home speaker?



Appendix B: SAE International Levels of Driving Automation:

SAE J3016™ LEVELS OF DRIVING AUTOMATION™

Learn more here: sae.org/standards/content/j3016_202104

	SAE LEVEL 0™	SAE LEVEL 1™	SAE LEVEL 2™	SAE LEVEL 3™	SAE LEVEL 4™	SAE LEVEL 5™
What does the human in the driver's seat have to do?	**You are driving** whenever these driver support features are engaged – even if your feet are off the pedals and you are not steering			**You are not driving** when these automated driving features are engaged – even if you are seated in "the driver's seat"		
	You must constantly supervise these support features; you must steer, brake or accelerate as needed to maintain safety			When the feature requests, you must drive	These automated driving features will not require you to take over driving	
	These are driver support features			**These are automated driving features**		
What do these features do?	These features are limited to providing warnings and momentary assistance	These features provide steering **OR** brake/ acceleration support to the driver	These features provide steering **AND** brake/ acceleration support to the driver	These features can drive the vehicle under limited conditions and will not operate unless all required conditions are met		This feature can drive the vehicle under all conditions
Example Features	• automatic emergency braking • blind spot warning • lane departure warning	• lane centering **OR** • adaptive cruise control	• lane centering **AND** • adaptive cruise control at the same time	• traffic jam chauffeur	• local driverless taxi • pedals/ steering wheel may or may not be installed	• same as level 4, but feature can drive everywhere in all conditions

Appendix C: Online survey

In your opinion, how relevant are these characteristics in a Voice Assistant?

	Not at all relevant	Irrelevant	Slightly irrelevant	Neither relevant nor irrelevant	Slightly relevant	Relevant	Extremely relevant
Sociable	○	○	○	○	○	○	○
Friendly	○	○	○	○	○	○	○
Kind	○	○	○	○	○	○	○
Likeable	○	○	○	○	○	○	○
Warm	○	○	○	○	○	○	○
Competent	○	○	○	○	○	○	○
Intelligent	○	○	○	○	○	○	○
Skilful	○	○	○	○	○	○	○
Efficient	○	○	○	○	○	○	○
Capable	○	○	○	○	○	○	○

My relationship with my Voice Assistant is...

	Strongly disagree	Disagree	Slightly disagree	Neither agree nor disagree	Slightly agree	Agree	Strongly agree
...close	○	○	○	○	○	○	○
...cooperative	○	○	○	○	○	○	○
...integrative	○	○	○	○	○	○	○
...solid	○	○	○	○	○	○	○
...cohesive	○	○	○	○	○	○	○
...convergent	○	○	○	○	○	○	○

What is your level of agreement with these sentences?

	Strongly disagree	Disagree	Slightly disagree	Neither agree nor disagree	Slightly agree	Agree	Strongly agree
I usually interact with my Voice Assistant several times a day	○	○	○	○	○	○	○
I often ask my Voice Assistant questions	○	○	○	○	○	○	○
My Voice Assistant always tries to resolve my doubts	○	○	○	○	○	○	○

What is your level of agreement with these sentences?

	Strongly disagree	Disagree	Slightly disagree	Neither agree nor disagree	Slightly agree	Agree	Strongly agree
I trust on my Voice Assistant	○	○	○	○	○	○	○
My Voice Assistant is reliable	○	○	○	○	○	○	○
My Voice Assistant is honest with me	○	○	○	○	○	○	○
My Voice Assistant is dependable	○	○	○	○	○	○	○

What is your level of agreement with these sentences?

	Strongly disagree	Disagree	Slightly disagree	Neither agree nor disagree	Slightly agree	Agree	Strongly agree
I'm often concerned that the application could store my information for the next couple of years.	○	○	○	○	○	○	○
I feel anxious that the applications might know too much about me	○	○	○	○	○	○	○
I'm often concerned that the application could share the information I provide with other parties (MKT, HR or government agencies)	○	○	○	○	○	○	○
I'm often concerned other parties could actually collect my publicly available information with the application	○	○	○	○	○	○	○
I'm often concerned that my current public information may be stored by some other parties	○	○	○	○	○	○	○
I'm often concerned that other parties could share information they have collected about me	○	○	○	○	○	○	○
It often worries me that other parties could use the information they have collected about me from the application for commercial purposes	○	○	○	○	○	○	○

How familiar are you with self-driving cars?

Not familiar at all			Moderately familiar			Extremely familiar
1	2	3	4	5	6	7

What is your degree of agreement with these sentences?

	Strongly disagree	Disagree	Slightly disagree	Neither agree nor disagree	Slightly agree	Agree	Strongly agree
My interaction with the Voice Assistant is clear and understandable	○	○	○	○	○	○	○
I find the Voice Assistant to be easy to use	○	○	○	○	○	○	○
I find it easy to get the Voice Assistant to answer my questions	○	○	○	○	○	○	○

What is your level of agreement with these sentences?

	Strongly disagree	Disagree	Slightly disagree	Neither agree nor disagree	Slightly agree	Agree	Strongly agree
Using a Voice Assistant improves my shopping experiences	○	○	○	○	○	○	○
Using a Voice Assistant increases my time-effectiveness when I am gathering information/shopping	○	○	○	○	○	○	○
Using a Voice Assistant would enable me to accomplish my shopping decision/information gathering	○	○	○	○	○	○	○
Using a Voice Assistant solves my shopping decisions/information gathering easier	○	○	○	○	○	○	○
Using a Voice Assistant enhances my repurchases	○	○	○	○	○	○	○
Using a Voice Assistant is better than using real customer agents	○	○	○	○	○	○	○
Voice Assistants saves me the time when I am looking for shopping decisions/information gathering	○	○	○	○	○	○	○
Overall, I find a Voice Assistant to be useful when I need shopping decisions/information gathering	○	○	○	○	○	○	○

What is your attitude toward self-driving cars?

Useful	○	○	Not useful
Realistic	○	○	Not realistic
Informative	○	○	Not informative
Specific	○	○	Unspecific
Logical	○	○	Illogical

What is your level of agreement with these sentences?

	Strongly disagree	Disagree	Slightly disagree	Neither agree nor disagree	Slightly agree	Agree	Strongly agree
Given the chance, I intend to use a self-driving car	○	○	○	○	○	○	○
I will recommend a self-driving car to others	○	○	○	○	○	○	○
I'm considering using a self-driving car	○	○	○	○	○	○	○
I have strong intentions to buy a self-driving car	○	○	○	○	○	○	○

What is your level of agreement with these sentences?

	Strongly disagree	Disagree	Slightly disagree	Neither agree nor disagree	Slightly agree	Agree	Strongly agree
I would tell others positive things about self-driving cars with a Voice Assistant	○	○	○	○	○	○	○
I would provide others with information on self-driving cars with a Voice Assistant	○	○	○	○	○	○	○
I am likely to recommend self-driving cars with a Voice Assistant to my friends or acquaintances	○	○	○	○	○	○	○
I am likely to encourage others to consider self-driving cars with a Voice Assistant	○	○	○	○	○	○	○

Within the past 12 months, how many times have you used your Voice Assistant?

Never						Often
1	2	3	4	5	6	7

What is your level of technology expertise?

Not experienced	Average user	Experienced	Very experienced
1	2	3	4

What is your gender?

- ○ Male
- ○ Female
- ○ Other

How old are you?

- ○ Under 18 years old
- ○ 18-24 years old
- ○ 25-34 years old
- ○ 35-44 years old
- ○ 45-54 years old
- ○ 55-64 years old
- ○ 65 years old or more
- ○ I prefer not to say

What is the highest level of education you have achieved?

- Lower level than High Schol
- High School degree
- Bachelor's degree
- Master's degree
- Higher level
- I prefer not to say

In which country do you currently reside?