# VOICE ASSISTANT - AS A NEW SHOPPING MALL:
# KEY FACTORS OF VOICE SHOPPING ACCEPTANCE

**Doctoral Thesis**


**Presented by:**

*Sarah-Mira Ruder*

**Supervised by:**

*Dr. Joaquín Aldás Manzano*



Programa de Doctorado en Marketing

**Departamento de Comercialización e Investigación de Mercados**

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**TABLE OF CONTENTS**

## INDEX OF TABLES

# INDEX OF FIGURES

# CHAPTER 1: INTRODUCTION

# 1. INTRODUCTION

Voice shopping is one of the most important trends in online commerce due to the enhanced use of voice assistants (VAs) by people in their daily routines (Bawack et al., 2021b). This transformation offers new chances for marketers to sell their products and drives the engagement of the consumer with the voice assistant (Moriuchi, 2019). The omnipresence and the high flexibility encourage this progress; nevertheless, the adoption rates of voice shopping are still significantly lower than the adoption rates of VAs (Rzepka et al., 2020).

The four big tech players - Amazon, Apple, Google, and Microsoft - are offering the most prevalent VAs, which are either included in smartphones or in the form of a home speaker (Hoy, 2018). Notably, the VA use frequency of smartphones on a daily basis is almost double as high at 39.8% of smart speaker owners as the daily use of non-smart speaker owners at 19.1% (Kinsella, 2019). According to Mari et al. (2020, p. 407) “the act of placing orders online using VAs goes under the names of ‘voice commerce,’ ‘voice shopping,’ or ‘v-commerce’” and incorporates not only the transaction but the entire process from the product search, reviews, shopping lists, order tracking, as well as customer service. It has the potential to affect consumers and businesses over the whole commerce procedure, from the interaction between buyer and seller to the purchase itself, and especially the use of solely voice revolutionizes the way of interaction and creates new and more advanced possibilities for shopping (McLean & Osei-Frimpong, 2019). In Germany, there is a clear decline in traditional shops, which are progressively substituted by increasing e-commerce, with amazon.de being the biggest player in 2022, with fashion being the largest market at 25.0%, followed by hobby and leisure at 24.6%, electronics at 21.3%, furniture and homeware at 9.8%, care products at 8.2%, grocery at 6.0%, and DIY at 5.2% (Uzunoglu, 2023). Therefore, VAs are important to facilitate e-commerce for consumers. However, voice shopping also introduces challenges, such as the narrowed product offer, as there is no visual support, and the risk of firms losing against brands held and advertised by retailers, such as Amazon (Mari, 2019). Nonetheless, VAs are able to act as personal assistants by providing recommendations based on the data received and taking on a central role in interpersonal interactions with consumers (Hernández-Ortega et al., 2021). There is a rising need for VAs due to the ability to use verbal commands and, herewith, enable customers to accomplish various tasks while voice shopping; therefore, convenience and saving time are the principal reasons for consumers (Zaharia & Würfel, 2021).

Artificial intelligence (AI) plays a key role in this movement and enables the commercial sector to enjoy increasing demand and popularity worldwide (Tuzovic & Paluch, 2018). Along with AI, the technological enhancements in machine learning and natural language processing (NLP) empower the continuous improvement of the interactions between VAs and customers and permit context-based conversations (Moussawi et al., 2021). One major booster for the rapidly increasing adoption rates of VAs is the digitalization, along with the consumers' changed patterns and routines, as due to the pandemic people study and work from home more often, thus, they use VAs even more than predicted (Petrock, 2020). Remarkably, in Germany in 2021 17.9 million smart speaker are installed out of a 69 million adult population in total, thus presenting a significantly high growth rate of 34%, while in the United States, as a result of the pandemic, supply bottlenecks and buying restraints have slowed down the impact of the growth, but smart speaker consumer adoption still recorded its highest number ever in 2021 with a penetration of 90.7 million adults having access to a smart speaker (Kinsella, 2021a).

There is a need for research on the key factors influencing voice shopping acceptance due to the increasing importance of voice shopping. Companies must know which factors they should consider in order to be successful. This investigation is essential in showing how the acceptance of voice assistants influences the actual use of voice shopping.

Furthermore, voice shopping unleashes a meaningful potential for transforming and leveraging marketing (Tuzovic & Paluch, 2018). Due to its continuous growth, it calls attention not only to businesses but also to researchers worldwide to understand the aspects that shape customers' perceptions toward voice assistants. However, there are only a few studies that investigate this topic in-depth and address the actual use of voice shopping.

The purpose of this study is to assess the determinants affecting innovation adoption considering AI. The research concentrates on discovering the main factors that lead consumers to adopt voice shopping. Additionally, it tries to understand the consumers' responses regarding the acceptance of VAs and the actual use of voice shopping. The study analyzes what drives the adoption and enhances the use. Furthermore, it is vital for companies and brands to bear these drivers in mind to enhance the selling potential. Therefore, it is necessary to determine the factors that raise the adoption. Establishing such principles can help companies improve their product offers significantly. Moreover, the result has a positive effect on the daily lives of the users, as a higher willingness to accept leads to more voice shopping, which consequently improves the user experience. In light of its theoretical and practical implications, this paper presents an added value over the few empirical studies using the service robot acceptance model (sRAM) created by J. Wirtz et al. (2018). Gained knowledge of the applied model provides critical insights to researchers and supportive guidance to managers.

According to Zaharia and Würfel (2021) technology acceptance is primarily committed to the voice assistants themselves and the voice shopping studies are still in an early stage, resulting in most of the scientific research concentrating on the use of the technology acceptance model (TAM) or the unified theory of acceptance and use of technology (UTAUT) or UTAUT2. However, reflecting the special traits of voice technology, such as hands-free application, a voice-based user interface, and control by voice, these models are not accurate enough to explicate the technology adoption (McLean & Osei-Frimpong, 2019). Additionally, the latest results of adoption models are limited in generalizability and the selection of attributes is less holistic; hence, from an academic viewpoint, this study enriches the literature, as voice assistants are a novel topic in the AI field, commanding further investigation (Fernandes & Oliveira, 2021).

In order to address the research gaps, this study applies and extends the sRAM (J. Wirtz et al., 2018) to explain the consumers' drivers for VA acceptance as well as for the actual use of voice shopping. Therefore, this study suggests that aside from the well-studied functional elements, including perceived usefulness, perceived ease of use, and subjective social norms, which are part of the TAM, further elements need to be considered. These are the social-emotional elements involving perceived humanness, perceived social interactivity, perceived social presence and, as an extension of the original sRAM dimensions, also the hedonic motivation. Additionally, the relational elements, including trust and rapport, are examined to understand the influence of these determinants on the VA adoption and the model is extended by the antecedents control, risk, and personalization to comprehend their impact on the relational elements. Some authors applied the sRAM in the context of service encounters with VAs (Fernandes & Oliveira, 2021), in the hotel sector with service robots (Fuentes-Moraleda et al., 2020), in retail banking with frontline service robots (Amelia et al., 2021), in daily life with the VA Siri (Al-Makhmari et al., 2023), and in public environments with autonomous delivery robots (Abrams et al., 2021) to demonstrate the effect of these elements on customer acceptance.

The overall aim of this doctoral thesis is to accomplish research into the technology adoption of VAs, which is attained by realizing the objective of establishing and analyzing the determinants for the acceptance of voice shopping in Germany. Considering the characteristics of VAs and users, based on the sRAM with functional, social-emotional, and relational elements.

For the purpose of this paper, Germany is selected as the country of investigation, exclusively focusing on the voice assistant Alexa from Amazon, as so far this is the only smart voice assistant with the option of voice shopping in Germany. There is an immense potential for growth, as 85% of Germans possess or use at the minimum one device that includes a voice assistant, however, at the end of 2018, only 26% of individuals were using a voice assistant in Germany (Tas et al., 2019). In 2020, the number of users only slightly increased to 31% (ARD/ZDF-Onlinestudie, 2020). Herewith, the transition from owning a VA to the actual use of voice shopping bears a lot of possibilities. By comparing the development of voice shopping with that of web adoption, one can conclude that VAs might become the new shopping mall; however, besides awareness and perceived benefits, more provided shopping experiences are necessary (Kinsella, 2021b). Therefore, it is fundamental to comprehend the adoption of this technology in a German context. Based on these reasons, this survey was undertaken.

The contributions of this study are fourfold. First, by analyzing the motivators to adopt VAs, findings regarding the functional elements present the prominent role of perceived usefulness and that perceived ease of use has a direct impact only if the user has already applied voice shopping. Though, if the perceived usefulness of the VA is shown, perceived ease of use and subjective social norms demonstrate their indirect influence on the customer acceptance.

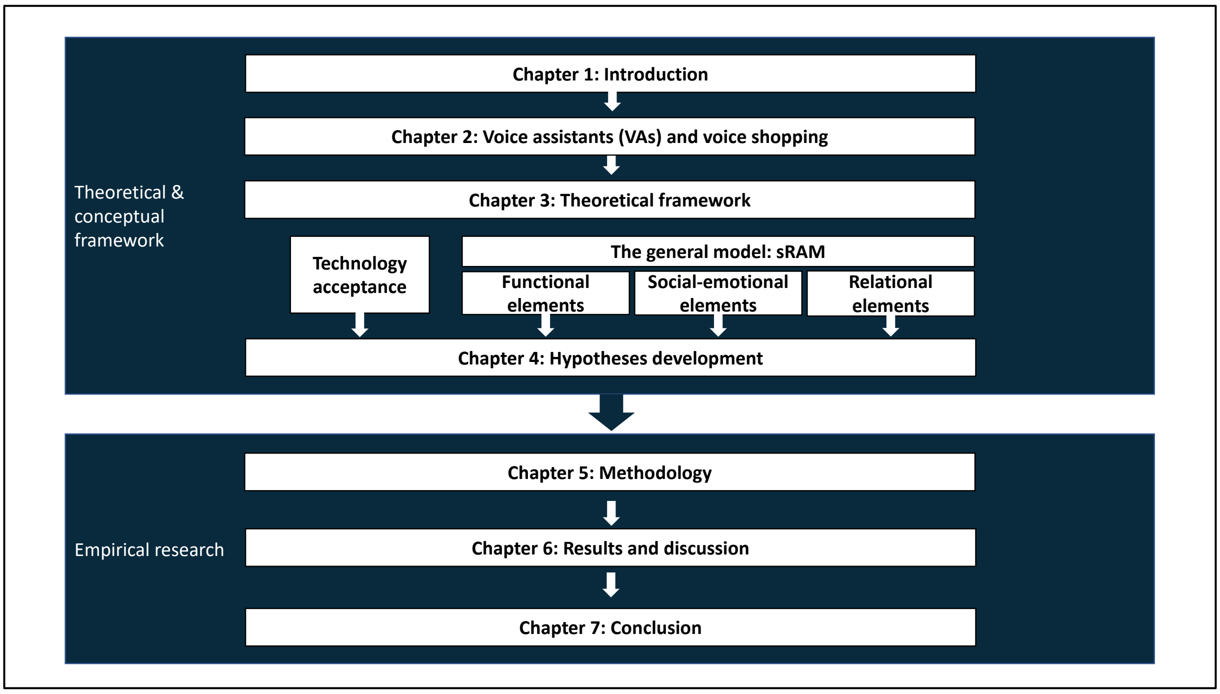
Second, this paper extends the original social-emotional elements of the sRAM by hedonic motivation and shows that, contrary to the expectations of the conceptual framework of the sRAM, only hedonic motivation has a significant effect on the acceptance of users, especially of non-voice shopping users, and afterwards the actual use of voice shopping. So, this study defines the social-emotional elements and their need for the adoption of VAs based solely on hedonic motivation. Therefore, by incorporating hedonic motivation, the study explains that for users who have not yet experienced voice shopping and its advantages, entertainment factors are of high importance.

Third, this paper is one of the first to consider and examine the impact of the antecedents of the relational elements trust and rapport in the sRAM. Thereby, emphasizing control, risk, and personalization instead of only concentrating on trust and rapport. Thus, this research extends the knowledge of previous studies on the sRAM. Additionally, it shows that solely trust is of relevance, while rapport has no impact.

Fourth, this study not only examines the customer acceptance of VAs but also reveals results regarding the actual use of voice shopping in Germany. Herewith, it delivers a pioneering work that validates the sRAM in the voice shopping context, reacting to prior calls regarding the need for empirical research on the actual use of VAs (Fernandes & Oliveira, 2021).

Referring to the layout, this doctoral thesis is based on two phases. The first phase exists of a theoretical and conceptual framework, being of documentary nature, and comprises the literature review of voice assistants, voice shopping, technology acceptance, the general model of sRAM, functional elements, social-emotional elements, and relational elements. The second phase covers the empirical nature and seeks to contrast the hypotheses of the theoretical model. Figure 1.1 shows the structure of the doctoral thesis.

FIGURE 1.1: **Structure of the doctoral thesis**



The initial chapter gives a general overview of the doctoral thesis by establishing the context of voice shopping, defining the term, and explaining the main reasons. This chapter provides the motivation for undertaking this research and the importance of voice shopping in Germany. Chapter 2 gathers the academic literature review of voice assistants (VAs) and voice shopping in an international context and shows the differences between Germany and other countries in an international setting. It examines the meaning of utilizing VAs for voice shopping, explains the terms and functioning, and reveals the reasons for voice assistants and voice shopping in detail. Furthermore, it investigates the development of VAs, the effects on consumers, and the implications for businesses and marketing. The subsection voice shopping additionally provides an overview of the conversational commerce system and tackles the low and high involvement purchases.

Subsequently, Chapter 3 demonstrates the academic review of technology acceptance, including the different models investigating technology acceptance. The most well-known technology models are reviewed, including the theory of reasoned action (TRA), the theory of planned behavior (TPB), and the technology acceptance model (TAM) including its extensions. It covers further well-established theories, including the social cognitive theory (SCT), the innovation diffusion theory (IDT), the unified theory of acceptance and use of technology (UTAUT), and the extended unified theory of acceptance and use of technology (UTAUT2). However, this research focuses on the sRAM, and therefore, an overview of the general model sRAM is given, highlighting the definitions of the constructs as well as its functional elements, social-emotional elements, and relational elements, respectively, the antecedents. Additionally, further determinants deriving from existing literature are considered within the section on social-emotional elements and relational elements and examined in the context of technology acceptance, voice assistant, and voice shopping. Moreover, gender effects as well as other factors influencing the acceptance and the actual use, are examined.

Chapter 4 rounds up the theoretical and conceptual framework by proposing the hypotheses development. Hence, this chapter deals with the objective, and based on the explained elements, the hypotheses of this research are elaborated. The hypotheses are structured according to the three elements proposing the relations between the constructs of acceptance and actual use. Beginning with the functional elements and the influence of perceived usefulness, perceived ease of use, and subjective social norms on the customer acceptance of VAs, followed by the effect of the social-emotional elements perceived humanness, perceived social interactivity, perceived social presence, and hedonic motivation on the acceptance of VAs, and the third cluster, the relational elements along with the impact of trust, control, risk, personalization, and rapport on the acceptance. Furthermore, the last two sections discuss the influence of the customer acceptance of VAs on the actual use of voice shopping and summarize the developed research model.

After the theoretical and conceptual framework, the empirical research follows. Chapter 5 outlines the methodology. The purpose of this chapter is to explain and justify the approach and structure of the doctoral thesis. It exposes the research design and describes the sample selection, the data collection process, the questionnaire design, and the measurement scales included in the study. Furthermore, it shows a descriptive analysis of the data and demonstrates the reliability and validity of the measurement model in order to estimate the model.

The subsequent chapter presents the results of the primary research based on the analysis carried out and the discussion. The aim of this chapter is to discuss the primary data in depth. It provides the estimation of the model, the contrast of the hypotheses, and the discussion of the accepted or rejected hypotheses in the framework of voice shopping. The findings are debated in relation to the research objectives and literature review. The research is conducted through an online survey, specifically with users living in Germany who have experienced the VA Alexa.

The final chapter concludes the results of the primary and secondary research in relation to the research objective and hypotheses. The theoretical and practical implications, limitations of the research, and future lines of study are provided.

To sum it up, the purpose of this study is to create and test a holistic model that clarifies the acceptance of VAs and the actual use of voice shopping in Germany by providing information concerning the factors impelling innovation adoption of artificial intelligence-based voice assistants. Based on various academic approaches, this study derives from the sRAM. Thus, proposing a model based on functional, social-emotional, and relational elements allows understanding the importance of the customer acceptance of voice assistants and how they influence the actual use of voice shopping. In order to achieve this goal, empirical data of 499 users of Amazons' Alexa, specifically those living in Germany, is collected, afterwards analyzed, and through structural equation modeling, most of the hypotheses are confirmed, namely the functional, partly the social-emotional, as well as the relational elements.

# CHAPTER 2: VOICE ASSISTANTS (VAs) AND VOICE SHOPPING

# 2. VOICE ASSISTANTS (VAs) AND VOICE SHOPPING

This chapter presents the meaning of using VAs for voice shopping in today's world. It defines the terms VA and voice shopping, shows the development, and reveals the reasons. The implications for consumers and businesses are explained and at the end of each subchapter, the significance of VAs and voice shopping in marketing is examined.

## 2.1. Voice assistants (VAs)

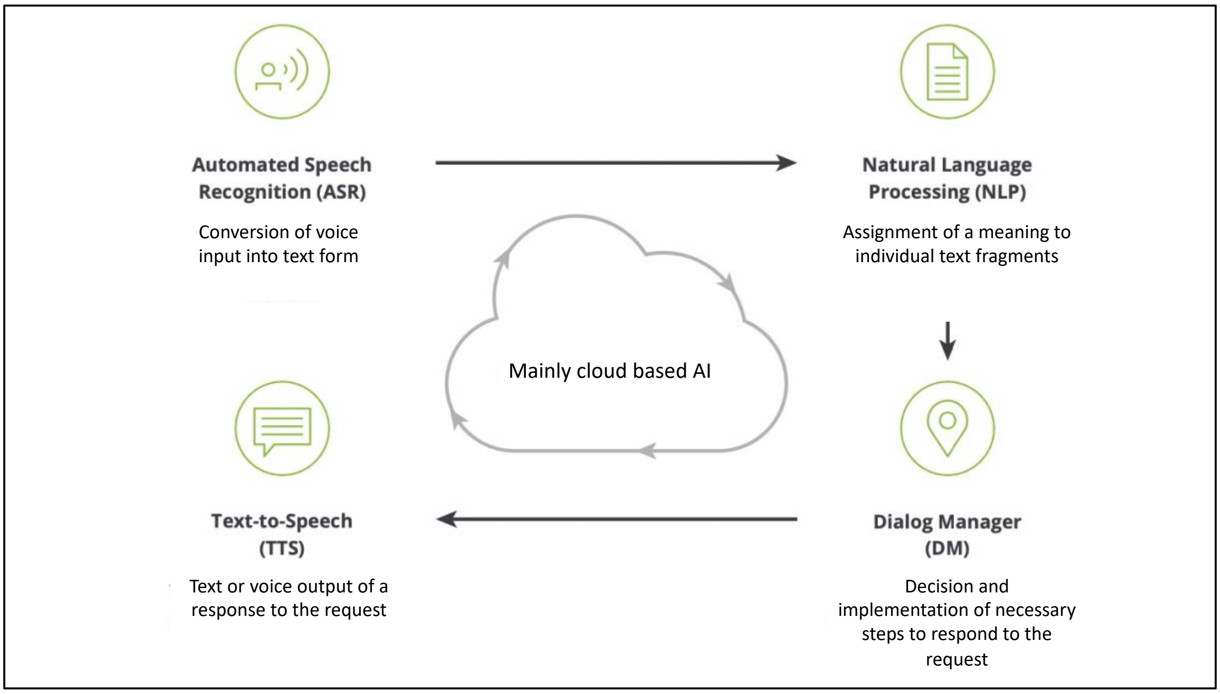
The ubiquitous digitization, the nationwide provision of the internet and the growth of smartphones alter the interactions and behavior amongst people and with businesses (Eeuwen, 2017). Additionally, the voice interface including voice search is showing a continuous increase not only for smartphones, but also for automotive interfaces and Internet of Things (IoT) devices (Tuzovic & Paluch, 2018). Therefore, VAs are becoming more important for researchers and companies (Guzman, 2019). The progress of natural language processing and generally accessible technology lead to a notable growing use of voice assistants (Hoy, 2018). Moreover, there exists a rising need for users to integrate VAs into their daily routine, which offers the possibility for businesses to take into account the incorporation of technology in their approach (Moriuchi, 2019).

Hoy (2018) explains VAs as the fulfillment of the science fiction dream of having a conversation with a machine. VAs can be defined as "an integrated microphone and speaker device that connects to voice-activated assistant software" (K. Lee et al., 2019, p. 564). Besides this technical definition VAs can be described as "conversational agents that perform tasks with or for an individual, whether of functional or social nature and own the ability to self-improve their understanding of the interlocutor and context" (Mari, 2019, para. 2). Furthermore, there exists a wide range of different terms for voice assistants, such as service robots (J. Wirtz et al., 2018), digital voice assistants (Fernandes & Oliveira, 2021), voice-controlled smart assistants

(Schweitzer et al., 2019), intelligent personal assistants (Han & H. Yang, 2018), and personal intelligent agents (Moussawi et al., 2021). These VAs can appear as built-in software agents for computers and smartphones or as in-home devices such as Bluetooth speakers (Mari et al., 2020). The oldest VA is Siri from Apple, which started in 2010 as a separate app and one year later being integrated into iOS. Cortana from Microsoft followed in 2013, and a year later Alexa from Amazon with its home speaker called Echo. In 2016 Google's Assistant was launched in the app and with its speaker, called Google Home, and in 2018 Apple introduced the Apple HomePod (Hoy, 2018).

Due to AI, machine learning as well as natural language processing, VAs are able to receive voice commands and respond to the user by executing them (Pal et al., 2020). The four core technologies to assure an ingenious interplay of software and hardware are the software components automated speech recognition (ASR), natural language processing (NLP), dialog manager (DM), and text-to-speech (TTS) (Monitor Deloitte, 2018). Benefiting from these technologies VAs are getting more advanced and are now capable of interacting in intricate conversations and performing a high variety of tasks (McLean & Osei-Frimpong, 2019). Hoy (2018) explains that after receiving the keyword, the VA records the command of the user and transmits it to a specific server to process the data, which afterwards sends the adequate information back to the VA in order to react to the user. These smart assistants support the users' lives in many ways by delivering solicited information and recommendations (Gupta et al., 2018). Among these versatile tasks are sending and reading messages, providing weather forecasts and personalized news, telling jokes, creating lists, reminders, and alarms, recommending and playing music, controlling IoT devices, and purchasing products online (Chattaraman et al., 2019; Smith, 2020; H. Yang & H. Lee, 2019). In sum, these functions should improve productivity in organizing and handling the professional and private lives of consumers (Sarikaya, 2017). Figure 2.1 shows the mainly cloud based software components.

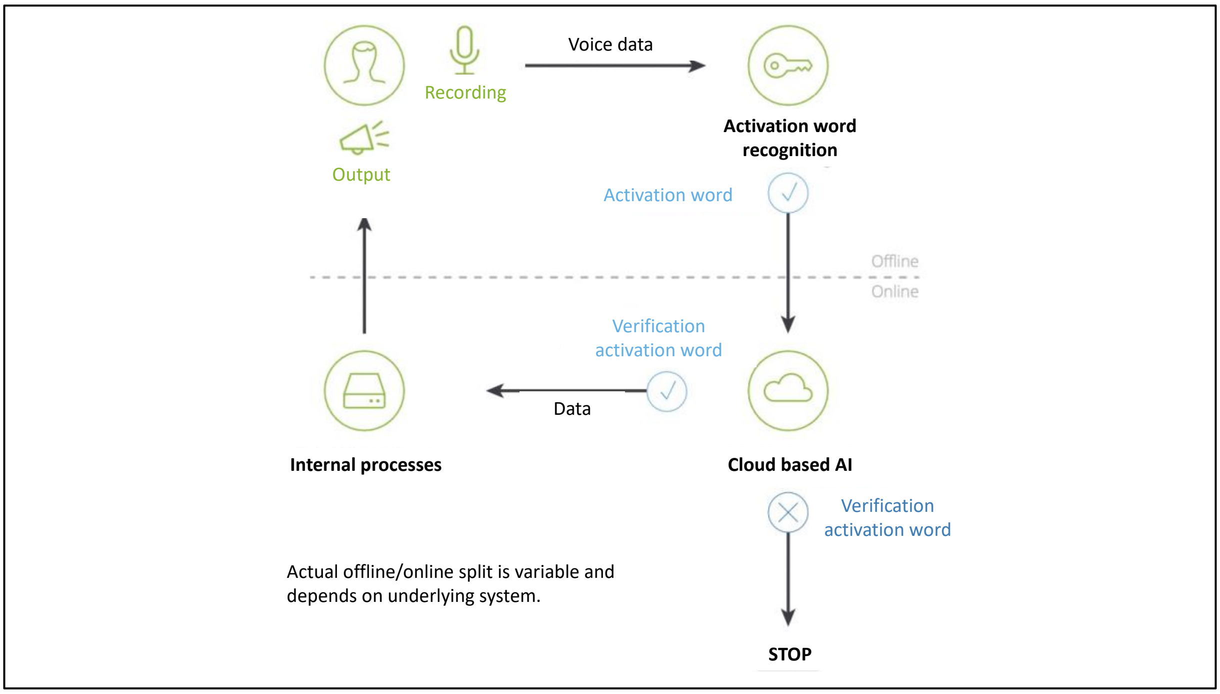
FIGURE 2.1: **Overview of mainly cloud based software components**




Source: Monitor Deloitte (2018)

For the smooth interaction of software and hardware in VAs, the interface in between, connecting both components, is also of great importance, and in voice shopping this interface is usually located in the cloud to retrieve current prices or availability, as cloud based systems are connected to the internet, they have the advantage of immediate availability of innovations and updates, and even large amounts of data can be processed quickly in this way (Monitor Deloitte, 2018). Figure 2.2 shows the hardware software interface.

FIGURE 2.2: **Hardware software interface**




Source: Monitor Deloitte (2018)

### *2.1.1. Development of VAs*

The constantly increasing number of VAs worldwide is estimated to reach approximately an equivalent of the world's population, which signifies there might be more than eight billion VAs in 2024 (Laricchia, 2022). Countries like China, India, and Indonesia are leading by looking specifically at internet users, who have used a VA at least once (Tas et al., 2019). Followed by the United States, where VAs are considered as mainstream, counting 31.7% in 2018 and 34.9% in 2019 of the total population using a VA at least once a month, and the millennials presenting the biggest user group (Petrock, 2020). Whereas in Europe, Germany is behind other European countries, such as Italy, Spain, and France, and below the European average of internet users, who have used a VA at least once, counting 26% at the end of 2018 (Tas et al., 2019). Additionally, the number of VA users only marginally increased to 31% in 2020 (ARD/ZDF-Onlinestudie, 2020). Regardless of the end device, the adoption rate of individual voice assistants differs significantly. Referring to the online survey of Tas et al.

(2019) the service Cortana, which in principle has the highest installed base of around 59% among the respondents, is actually only used by 7%. Even though the adoption of VAs in Germany seems to be rather slow, it is quite similar to the adoption process of other information and communication technologies, such as smartphones (Tas et al., 2019). According to Rogers (1962), there exist five different types of technology adopters: the innovators, the early adopters, the early majority, the late majority, and the laggards. Presently, the VAs are in the third phase, the early majority phase, referring to the innovation adoption curve by Rogers (Tas et al., 2019). This phase takes more time than the innovators and the early adopters due to the deliberate approach, but it is a critical tie in the entire process of innovation adoption (Rogers, 1962).

#### *2.1.2. Implications for consumers*

Referring to Klaus and Zaichkowsky (2020) the main driver of VAs is convenience through saving time and effort, considering AI as an enabler pushing convenience to the next level. Moreover, customers benefit from the flexibility and personalization; the communication via voice is more natural than writing; the voice interface facilitates the interaction by consuming less time and offering smooth handling, and the conversation can be faster as people are able to talk more words per minute than they are able to type (Tuzovic & Paluch, 2018). Besides the general availability, the continuously provided updates and advances of VAs are an advantage (Strayer et al., 2017). Additionally, the practical functions of VAs, such as looking up recipes or tracking orders, facilitate the daily lives of the users (McLean & Osei-Frimpong, 2019). Especially, the voice user interface offers the benefit of multitasking without reading or typing; thus, not only presents a high degree of convenience but also overcomes barriers (Hoy, 2018). For users with disabilities, such as mobility impairments, VAs are helpful to turn on the lights or lock doors, while for blind people, VAs can be useful for giving information on the weather or the time (Pradhan et al., 2018). For older people, VAs can be beneficial due to planning algorithms that adapt to the person's situation, and for people with dementia, the VA can reply to the same question infinite times, thus giving support, especially by not becoming impatient (Wolters et al., 2016). Additionally, Rzepka et al. (2020) bring enjoyment to the fore as a major benefit for consumers when utilizing their VA. Nonetheless, one of the most significant advantages of VAs is that they grant access to data and information (Moriuchi, 2019).

However, the access to personal data and information causes a high level of reluctance regarding the use of VAs, remarkably in Germany, considering the high availability of VAs being pre-installed in smart devices (Tas et al., 2019). Possibly, there is a link between these data protection and privacy concerns and speech comprehensibility, as the quantity of personal data and information has to rise in order to achieve better intelligibility (Klein et al., 2020). Mistakes in speech recognition decrease the perceived users' technological advancement and cause a negative customer experience (Rzepka et al., 2020). Different languages and dialects can be challenging, as they might have an impact on the consumers' voice experience and can even pose a barrier to utilize VAs for both parties, the users and the providers (Rozumowski et al., 2020). Even though automated speech recognition is continuously improving, especially for female speakers with dialect the accuracy rate is still low (Tatman, 2017). Accents have even a lower accuracy rate between 50%-80% (Danielescu, 2020). Therefore, to enhance the experience for other dialects, accents, languages, and markets, data and content need to be reutilized or created (Sarikaya, 2017).

### *2.1.3. Implications for businesses*

Businesses like Amazon, Facebook, Google, or Microsoft are penetrating markets worldwide by frequently attempting different approaches to increase user engagement via voice technologies (Moriuchi, 2019). From a company point of view, VAs offer an opportunity to get in touch with the customer, as they are able to attain a profound understanding of the users' preferences as well as buying intentions due to the ubiquity and flexibility, wherever and whenever there is a need for information (Smith, 2020). VAs are a game changer for the users and the firms, because the accomplishment of tasks changes as well as the process of buying goods and the interaction between the customer and the company (McLean & Osei-Frimpong, 2019). Nevertheless, the interaction style of a VA differs from other devices completely and bears challenges as the communication occurs step by step, whereas on a device with a screen, a multitude of information is shown at the same time (Mari et al., 2019). According to Fernandes and Oliveira (2021) the service sector has gone through tremendous changes and progress with the continuously expanding adoption of automated technologies involving chatbots, service robots, and AI-based digital VAs. The adoption of these automated technologies in the service frontline opens the path and may substitute the conventional way of interactions between the frontline employee and the customer (Marinova et al., 2017). There is a clearly visible shift from a human-driven service frontline to a technology-driven one (J. Wirtz et al., 2018). Via VAs, clients have the chance to get in contact with companies and to search for information, for example, Starbucks is offering a conversational ordering system and other firms are developing their own conversational interface, such as Domino's Pizza (Fernandes & Oliveira, 2021). Firms can take advantage of incorporating novel conversational technologies, such as VAs, into their business activities and thus foster and strengthen the relation between the customer and the company and creating a high loyalty (Moriuchi, 2019). Additionally, due to the health crisis and pandemic, VAs emerged as supportive technologies in the healthcare domain by delivering personalized emergency content and communication with information seeking end-users (Sezgin et al., 2020). Therefore, the increasing proportion of adoption of VAs, independent of the device, offers a new communication channel for various industries (Rzepka et al., 2020). However, in order to take full advantage of VAs, businesses have to focus on the benefits and provide better services than the existing consumer interfaces (Rzepka et al., 2020).

### *2.1.4. Importance in marketing*

Furthermore, VAs are offering a new, modern way to advance the marketing of products and services (Tuzovic & Paluch, 2018). In general, the marketers can be divided into two groups: on the one hand, the firms producing the devices and the customer interfaces, like Amazon or Google, and on the other hand, the goods and services companies using these consumer interfaces to get in touch with their clients (Pagani et al., 2019). Nevertheless, advertising on VAs means for both parties changing the way of thinking, similar to radio advertising, messages can be sent by real persons or by the VA itself (Smith, 2020). H. Lee and Cho (2020) differentiate between four types of adverts: the contextual adverts, non-contextual adverts, voice search recommendations, and voice search listing adverts. The contextual adverts relate to product ads based on the current use or service being offered to the consumer by the VA (Yeun Chun et al., 2014). Whereas the non-contextual adverts imply ads for products or services that are not connected to the current use of the VA (H. Lee & Cho, 2020). Another type of advert are the voice search recommendations, which appear while a user is searching for a certain thing and the VA recommends a particular brand, good, or service (H. Lee & Cho, 2020). Additionally, voice search listing adverts appear for the customer as if they were organic search results (Narayanan & Kalyanam, 2015). However, the efficacy of contextual adverts of VAs is higher than the efficacy of non-contextual adverts (D. Kim et al., 2018).

One opportunity and part of VA based marketing strategies is Alexa skills, which can be explained as a particular sort of program within an application (Lopatovska et al., 2018). The categories of Alexa skills are very diverse, including travel and transportation, food and drink, games, movies and TV, kids, music and audio, productivity, and smart home. For example, the national railway company of Germany developed the Deutsche Bahn skill, which facilitates the search for individual travel information, whereas the IKEA Home smart 1 offers the user the ability to regulate the lights, blinds, outlets, and air purifiers by voice.

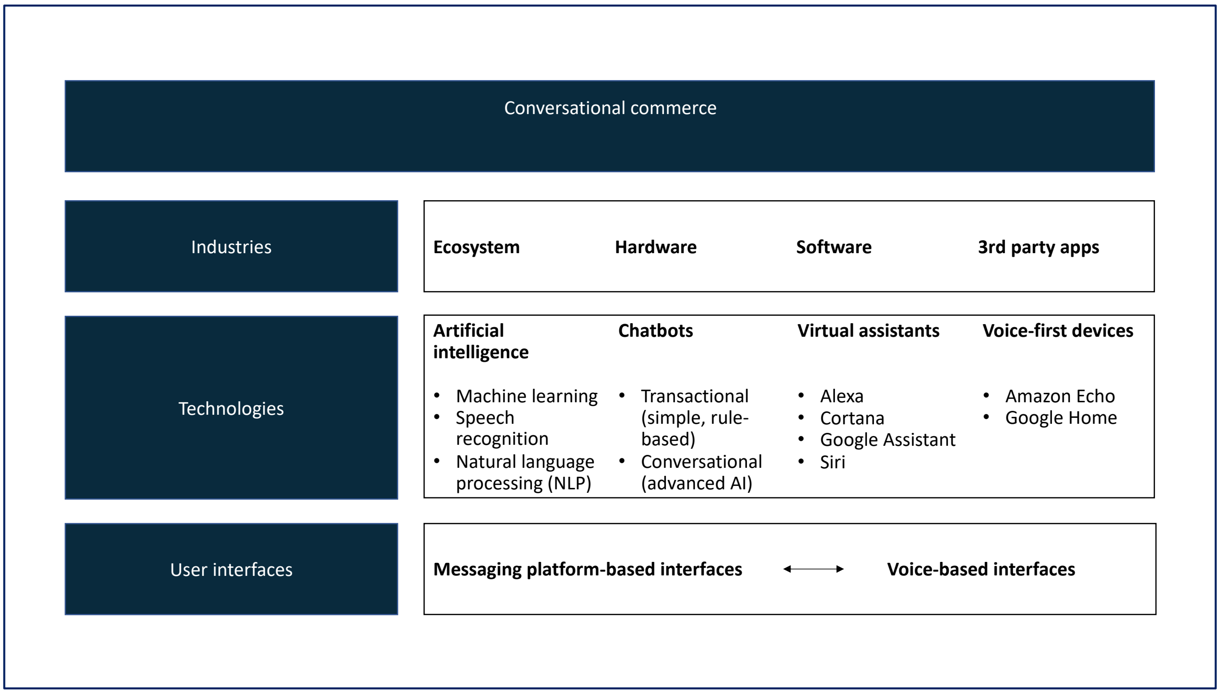
## 2.2. Voice shopping

Voice shopping is referring to Bawack et al. (2021b) gaining progressively popularity amongst users due to the omnipresence of VAs in their daily activities. Since the beginning of online shopping, developments in technology have altered the classical online shopping (Rzepka et al., 2020). Meanwhile, online shopping has steadily become a standard, and the technological advances comprising VAs support the progress (Moriuchi, 2019). Nevertheless, the intermediation of a VA affects the basic logic of online shopping (P. Hu et al., 2022). Purchasing a product without the physical availability was the first barrier to bridge in the area of online shopping, whereas in voice shopping, the user is additionally limited by the absence of visual content (Mari et al., 2020). Particularly, businesses, marketers, and researchers are challenged by voice interaction solely without visible content (Rhee & Choi, 2020).

According to Keeney (1999, p. 533) online shopping, also known as internet commerce, can be generally defined as “the sale and purchase of products over the internet”. Berkowitz (2016) refers to conversational commerce, mint in 2015 by the former Uber developer Chris Messina, as “transactions (including inquiry, purchase, or customer service) that are increasingly started and completed through chat interfaces, such as messaging apps and voice assistants”. Whereas five years later, Bawack et al. (2021b, p. 1) describe the term voice shopping as “the use of artificial intelligence (AI)-based voice assistants like Amazon’s Alexa and Google’s Google Assistant to shop online”. The term is not only limited to the act of buying a product or service; it can be any phase or customer touch point of the process, such as the voice search, the customer service, or the rebuy (Mari et al., 2020). The VA Alexa from Amazon is the first possibility of voice shopping in Germany, and in order to purchase a product, the Amazon Prime membership as well as the one-click order function are prerequisites.

Tuzovic and Paluch (2018) summarize the technological drivers of voice shopping in innovations in AI involving machine learning, speech recognition, and natural language processing, increasing power of chatbots, increasing the popularity of VAs, as well as voice-first devices such as Amazon Echo. In addition to a new way of interacting, these driving technologies offer a customized shopping experience through continuous learning, as well as convenience as users can just talk, and time savings as shopping can be done from anywhere, while cooking, driving, or doing another task (Klaus & Zaichkowsky, 2022). AI can be defined as "the theory and development of computer systems able to perform tasks that normally require human intelligence" (Schatzky et al., 2014, p. 2). As such, machine learning is a technology being part of AI that enables computers to learn like human beings, however, quicker and without explicit programming (Conick, 2017). Further cognitive technologies are speech recognition, which concentrates on precisely and robotically transcribing human language, and natural language processing, which means the capability of a computer to process and create natural and grammatically correct text (Schatzky et al., 2014). Referring to Forrester's State of Chatbots report, the chatbot as a technological driver has the ability to advance business, information sharing, customer service, and marketing (Cameron, 2017). Besides VAs, the fourth technology of conversational commerce, according to Schatzky et al. (2014) covers the voice-first devices such as Google Home and the market leader Amazon Echo. Thereby, Schatzky et al. (2014) differentiate between two conversational user interfaces, the messaging platform-based interfaces and the voice-driven interfaces, as given by VAs. Figure 2.3 shows the elements of the conversational commerce ecosystem.

FIGURE 2.3: **Conversational commerce ecosystem**




Source: Tuzovic and Paluch (2018)

### *2.2.1. Development of voice shopping*

Referring to Tas et al. (2019) 51% of Alexa users in Germany are theoretically capable of voice shopping; however, only 21% order products via Alexa. Even though the number of people in Germany who have used a VA once are low, yet Germany belongs to the leading European countries regarding voice shopping, with 11% of users shopping at least weekly via voice, therefore, being above France with 9%, and above the European average of 8% and slightly behind China with 14% (PricewaterhouseCoopers, 2019). Taking a glance at the development of mobile shopping, Germany is still in its beginnings, benchmarked against 55% in China, but the weekly mobile shoppers increased from 14% in 2015 to 23% in 2018, which is above the European average (PricewaterhouseCoopers, 2019). Compared to general online shopping behaviors, the main categories customers purchase by voice are corresponding and comprise everyday household items as the leading category for voice shopping, followed by entertainment, music, movies, and apparel (Voice Shopping Consumer Adoption Report, 2018).

Apparel presents in the German online shopping market the most frequently bought product category and shows steady growth (Statistisches Bundesamt, 2023). Additionally, as a consequence of the pandemic, more persons study and work from home, which enhances the use of VAs even more than expected and alters audio listening habits among all age groups (Petrock, 2020).

### *2.2.2. Low and high involvement*

Referring to Tuzovic and Paluch (2018) voice shopping rather addresses the purchase process than the information search or even purchase services, where any consultancy is needed. Therefore, Alexa is rather used for the so-called low involvement buys, such as ordering toilet paper or batteries, thus, household items, that can be easily automated (Mari, 2019). Moreover, Rhee and Choi (2020) link the involvement of the consumer with the period and frequency of using a product as well as with the price, as consumers behave in a less thorough manner if the product is cheap. Low involvement buys are rather driven by need and when a decision is not of importance, for example, one is in the bathroom and notices they are running out of toilet paper; therefore, these can be related to convenience as well (Klaus & Zaichkowsky, 2022). The preference for low-cost products is reflected in voice shoppers' behaviors, with over 85% of purchases for products that are $100 or less, and the most popular average voice shopping order amount is $20-$50 (Voicebot, 2018). High involvement products can be, for example, smartphones; thus, products that consumers care about, that are often quite expensive and are intended for long-term use (Rhee & Choi, 2020). Additionally, as known from online shopping or also from a salesperson, voice shopping lacks the possibility for cross-selling, and after a buy, Alexa does not suggest supplementary products (Tuzovic & Paluch, 2018). Besides the challenges of not being able to see or compare the products, a further reason, why high involvement products are not suitable for voice shopping is the missing empathy, as a VA does not comprehend whether a product is urgent or important (Tuzovic & Paluch, 2018).

Nonetheless, after a positive experience of voice shopping with a low involvement product the step toward buying a high involvement product comes closer (Klaus & Zaichkowsky, 2022).

### *2.2.3. Implications for consumers*

For the consumer, the principal advantage of voice shopping is convenience, as it involves little time and effort to spend, especially on regular purchases, by outsourcing the decision to the VA, and additionally, voice shopping is the most frictionless customer experience (Klaus & Zaichkowsky, 2020). Simms (2019) points out that users face barriers during online shopping because they have to take out the device, unlock it, look for the app or website, start it, wait for it to load, and just then the shopping experience can begin. Therefore, in comparison to online shopping, the main benefit is utilizing a hands-free tool and being able to do different things while voice shopping (Tuzovic & Paluch, 2018). Furthermore, the users appreciate the new way of interacting with the device and the firms offering the products and services (Tuzovic & Paluch, 2018). Rzepka et al. (2020) mention as another benefit of voice commerce: enjoyment, deriving from the overall enjoyment a customer perceives while utilizing a VA.

On the other side, consumers' main concern with VAs is the digital disclosure of private data (Bawack et al., 2021a). Customers are not aware of where the information about them is stored, what happens to their data, and who can enter it (Tuzovic & Paluch, 2018). Albeit Rzepka et al. (2020) state that these privacy concerns regarding voice shopping do not exceed the common doubts about online shopping or VAs. Moreover, the explorative voice search can be very challenging for the customer due to the short-term memory and the short attention span (Mari, 2019). The first proposed search result is convenient for the customer; however, each further alternative search result causes more inconvenience for the consumer (Rzepka et al., 2020). Furthermore, browsing through a search list is faster than listening to the results read by the VA, and the users' brand awareness and voice application knowledge are necessary to gain access to third-party offers (Simms, 2019). Another disadvantage is the imperfect verbal skills of the technology, including the quality of the artificial sounding voice and the rather one-sided interactions (Tuzovic & Paluch, 2018).

### *2.2.4. Implications for businesses*

With regard to businesses, VAs open a novel platform to communicate with customers and to sell products and services (Tuzovic & Paluch, 2018). However, the negative effect of voice shopping for brands and companies is the narrowed product offering for the consumer, as the product recommendations arise from the VA's knowledge of the user (Pariser, 2011). The main challenges of voice shopping for companies imply the threat of the emerging power of retailers' products and services, the so-called private labels, the appearance in voice searches, and the probable higher costs of advertising expenditures (Mari, 2019). Private labels are brands usually held and advertised by retailers, such as Amazon, which can be categorized as brands offering lower prices than national businesses but at a standard quality (Gielens et al., 2021). The risk for companies losing business to private labels is high as, for instance, Amazon can recommend its private label products first, and additionally, the customers have the possibility to subscribe to a certain product and fully automate the buying process, thus building a barrier for the consumer to buy a different good, especially in the low involvement sector (Mari, 2019). The voice search consists of three key challenges for businesses. First, in the event of using Alexa when the customer does not indicate a certain brand, in 55% of the first suggestions Alexa mentions an Amazon's Choice product, and in 17% of the cases where Amazon has a private-label product, Alexa proposes it (Cheris et al., 2017). Second, considering there is no visual support for the customer, the VA usually provides two search results instead of offering a complete search result list, which calls for changes regarding product descriptions and SEO strategies (Tuzovic & Paluch, 2018). The third challenge for companies implies the category of recurrent buys, as the voice search results adjust to the consumer's buying history, which consequently might decrease the diversity in the search results (Mari, 2019). Thus, if a customer buys Dove body soap, the same brand will appear in the next search for body soap. Advertising spending might rise due to the limited possibilities of placing sponsored voice messages, whereas in the browser search several ads can be shown, the few voice ad options might cause a higher competition in between the brands and, therefore, higher costs (Mari et al., 2020).

#### *2.2.5. Importance in marketing*

Referring to Mari et al. (2020), VAs embody a disruptive potential for marketing, but seeing them as a promising marketing, sales, and distribution channel, as well as a growing influencer of customers' choices and additionally as a mediator between the brand and the customers, transforming the relation and consequently having an extraordinary effect on the brands. Even though voice shopping is still in the early adopters phase, it plays an important role in marketing, and some companies have included voice shopping in their marketing strategies (Tuzovic & Paluch, 2018). Even though, on average, most of the voice shopping use cases can be categorized as indifferent, meaning the customers' satisfaction neither grows nor shrinks when enhancing them, there are some appealing use cases companies can realize, such as "request delivery status", "receive availability info" or "find products" (Baier et al., 2018, p. 11). Due to the mentioned risks of the growth of private labels as well as the difficulties of appearing in voice searches, brands are forced to spend more on their branding than before and to set up a voice strategy (Simms, 2019). Moreover, brands frequently need a third party in order to present their products; thus, for marketers the companies Amazon, Apple, and Google represent a menace and a chance at the same time (Pagani, 2019). According to Klaus and Zaichkowsky (2022) businesses must distinguish between a low product involvement strategy and a high product involvement strategy due to the disruption in brand management. Prior research on the effectiveness of advertisements in voice shopping shows that interaction between the user and the VA enhances the success of advertisements (D. Kim et al., 2018). Particularly, advertisements for low involvement products are more effective when they involve interaction (D. Kim et al., 2018). By applying an adequate marketing strategy, the digital and the physical sales of goods can be boosted (Simms, 2019).

In order to improve the understanding of the drivers and barriers for VA acceptance and for the actual use of voice shopping, in the following chapter, the theoretical framework is elaborated, disclosing the academic review of different models related to technology acceptance as well as linking to different definitions of the variables.

# CHAPTER 3: THEORETICAL FRAMEWORK

# 3. THEORETICAL FRAMEWORK

In the third chapter, the technology acceptance will be discussed. It takes a glance at the history of adoption theories and models and examines the most influential ones in detail. The theoretical framework helps readers to understand the different technology acceptance approaches. Among the most well-known adoption theories and models are the theory of reasoned action, the theory of planned behavior, the technology acceptance model, the unified theory of acceptance and use of technology (UTAUT), the extended unified theory of acceptance and use of technology (UTAUT2), and the most recently developed model, the service robot acceptance model (sRAM).

## 3.1. Technology acceptance

Various studies in the area of information systems describe user behavior concerning the adoption and use of technologies based on models that allow for the verification of technology acceptance with the help of a set of dimensions analyzing the intention to utilize a certain system.

Interest in consumer behavior research has already emerged in the early stages of the evolution of marketing. According to Bigné-Alcañiz (2010) the first contributions on consumer behavior appeared in the 1950s, Myers and Reynolds include the term “consumer behavior” for the first time in a title in 1967, and the Association for Consumer Research (ACR) founded in 1969, was the trigger for the publication of the Journal of Consumer Research in 1974. But the impactful work by Engel, Kollat, and Blackwell, which appeared in 1968, dominates the market (Mittelstaedt, 1990). The adoption of technologies, such as the internet, mobile, and digital related technologies, brings a substantial change in the consumer behavior and a further promising line of consumer studies (Bigné-Alcañiz, 2010).

With technology moving into the daily lives of consumers, the need to understand why the technology is accepted or not increases. Therefore, the initial research derives from the area of psychology, striving to clarify the behavior (Granić & Marangunić, 2019). From this previous research, the theory of reasoned action (TRA) is developed by Martin Fishbein and Icek Ajzen (1975) and focuses on the prediction and understanding of people's social behavior. After revising the TRA, the theory is expanded by the theory of planned behavior (TPB), which ads, as a further predictor of intentions and behavior, the person's behavioral control over other factors (Ajzen, 1985). As an alternative to the TRA and TPB, the theory of interpersonal behavior (TIB) is adopted by Triandis, identifying emotions, social factors, and habits as core factors for building intention. Fred Davis adjusts the TRA by creating the technology acceptance model and according to Davis (1989) the two most important determinants for a user in order to accept or reject innovation technology are perceived usefulness and perceived ease of use. The TAM is extended by two separate studies. The TAM2 adds the social influence processes (subjective norm, voluntariness, and image) and cognitive instrumental processes (job relevance, output quality, result demonstrability, and perceived ease of use), which notably affect user acceptance (Venkatesh & Davis, 2000). A second study, the TAM3 identifies constructs influencing perceived ease of use, divided into anchor (computer self-efficacy, perceptions of external control, computer anxiety, and computer playfulness) and adjustment (perceived enjoyment and objective usability) (Venkatesh & Bala, 2008). From the TAM derives before the TAM2 also the Igbaria's model (IM), which adds explanation on extrinsic (perceived usefulness) and intrinsic (fun) motivators having an impact on the adoption or rejection of the new technology (Taherdoost, 2018).

In the 1980s, the social cognitive theory (SCT) arises by Albert Bandura and derives from the social learning theory (SLT) by Miller and Dollard, which can be traced back to the early 1940s (Momani & Jamous, 2017). The SCT is used to evaluate the use of technology based on the core constructs of performance outcome expectations, personal outcome expectations, self-efficacy, affect, and anxiety (Venkatesh et al., 2003).

Rogers' innovation diffusion theory (IDT) is a theory designed to help predict how people make decisions to adopt a new innovation by identifying their adoption patterns and understanding its structure (Rogers, 1962).

The unified theory of acceptance and use of technology (UTAUT) combines all models and theories into one (Venkatesh et al., 2003). This theory is later extended by Venkatesh et al. (2012) by three constructs: hedonic motivation, price value, and habit, the so called extended unified theory of acceptance and use of technology (UTAUT2).

According to V. Kumar (2017) there are three forces driving academic research in marketing: concepts, theories, and previous findings; these three forces not only enhance the knowledge base, but they also incent new investigations.

Technology acceptance models and theories are used in a broad range of fields to comprehend and forecast users' behavior among them blood donation, customers' purchase behaviors, diets, breast cancer checks, education elections, family planning, income, mode of transportation preference, use of birth control pills, use of computers, and women's career guidance (Taherdoost, 2018). Based on previous studies, Table 3.1 shows a summary of the most important theories and models, including their applications.

TABLE 3.1: **Adoption theories and models**

| Theory/Model | Year | Researcher | Applications |
|---|---|---|---|
| Theory of reasoned action (TRA) | 1975 | Fishbein Ajzen | General model, not designed for a specific behavior or technology (Momani & Jamous, 2017) |
| Theory of planned behavior (TPB) | 1991 | Ajzen | Various fields including advertising, public relations, and healthcare |
| Theory of interpersonal behavior (TIB) | 1977 | Triandis | Internet use |
| Technical acceptance model (TAM) | 1989 | Davis | Information technology and communication technology |
| Igbaria's model (IM) | 1996 | Igbaria | Information technology and communication technology (also microcomputer usage) |
| Extension of technology acceptance model | 2000 TAM2<br>2008 TAM3 | Venkatesh & Davis<br>Venkatesh & Bala | Information technology and communication technology |
| Social cognitive theory (SCT) | 1986 | Bandura | Mass communication (media contents studies and media effects studies)<br>Public health (physical activity, AIDS, breastfeeding) |
| Innovation diffusion theory (IDT) | 1995 | Rogers | Information technology and communication technology |
| Unified theory of acceptance and use of technology (UTAUT) | 2003 | Venkatesh et al. | Information technology and communication technology |
| Unified theory of acceptance and use of technology 2 (UTAUT2) | 2012 | Venkatesh et al. | Information technology and communication technology |

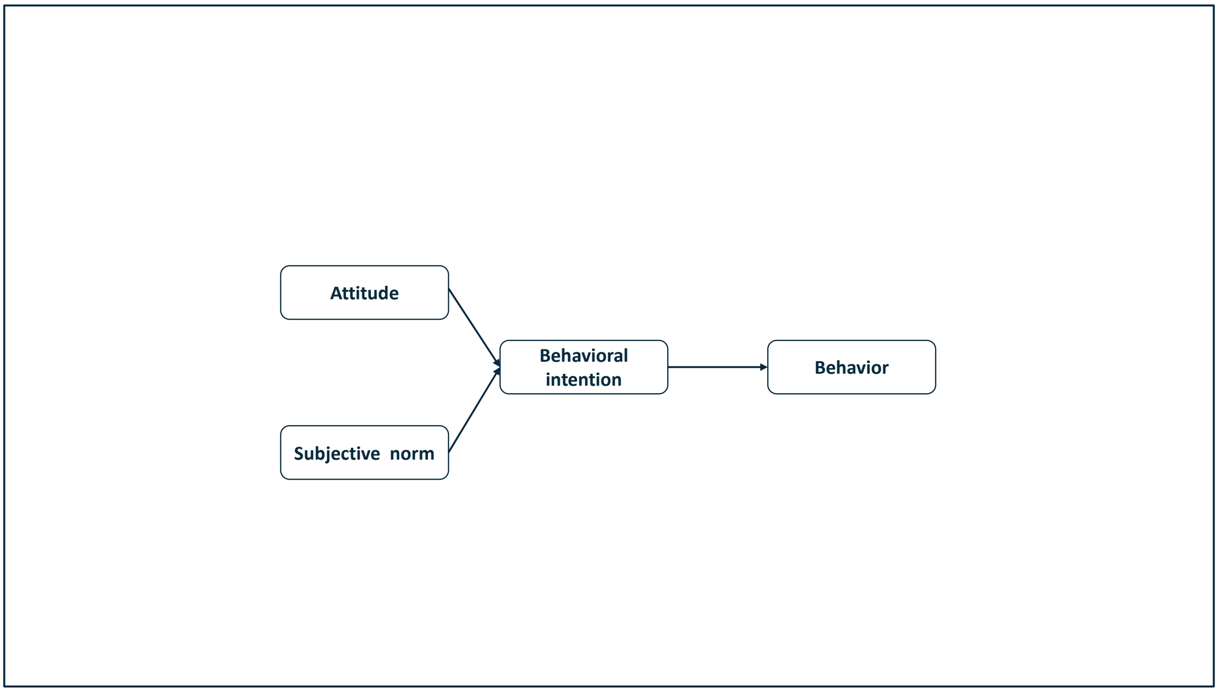
These technology acceptance theories and models have a similar structure; however, the explanation for the behavior and usage differs. It is possible to summarize the evolution stages for all mentioned technology acceptance theories and models having their roots in human behavioral studies, which can be divided into psychological and sociological studies starting in the 1940s until 2000 (Momani & Jamous, 2017). Within their study, Momani and Jamous (2017) identify the most important theories and models in the fields of technology acceptance and innovation adoption. Marketing as a discipline has been in existence for more than a century; its definition and content are in continuous evolution and expansion in a permanent desire to adapt to the changing environment (Bigné-Alcañiz, 2010). The evolution of technology acceptance is also constantly adapting and expanding.

### *3.1.1. The theory of reasoned action (TRA)*

In the field of social psychology, the theory of reasoned action (TRA) is known as the first and most referenced theory to foresee and examine the motivating effects on people's social behavior (Madden et al., 1992). This theory proposes that the choices of people for a specific behavior depend on their intention to be involved in it (Rzepka et al., 2020). Developed by Fishbein and Ajzen (1975) it is based on the determinants of consciously intentional behavior, aiming to explain the link between attitude and behavior where the behavioral intention has a direct influence on the behavior, and both the attitude and the subjective norm are direct antecedents to the behavioral intention. There exists a distinction between behavioral beliefs, which affect one's attitude toward the performance of the behavior, and normative beliefs, which affect one's subjective norm toward the behavior (Fishbein & Ajzen, 1975). Consisting of the four constructs of attitude, subjective norm, behavioral intention, and behavior, the determinant attitude can be defined as the extent to which someone has a positive or negative consideration of the respective behavior (Ajzen & Fishbein, 1980). While the subjective norm can be defined as a social element, implying the perceived social stress to fulfill the behavior, the intentional behavior presents the motivational element, including the eagerness and willingness to fulfill the behavior (Ajzen, 1985). Usually, the higher the intention, the more probable the realization (Ajzen, 1991).

Nevertheless, it has to bear in mind the TRA is a general model that is not designed for a specific behavior or technology (Momani & Jamous, 2017). The key limitation of the TRA is the inability to handle behaviors over which a person has or feels he has little control (Marangunić & Granić, 2014). Though the study by Rzepka et al. (2020) is based on the TRA, examining the benefits and costs influencing the attitude toward voice shopping. Figure 3.1 shows the four constructs of the theory of reasoned action (TRA).

FIGURE 3.1: **Theory of reasoned action (TRA)**




Source: Fishbein and Ajzen (1975)

### *3.1.2. The theory of planned behavior (TPB)*

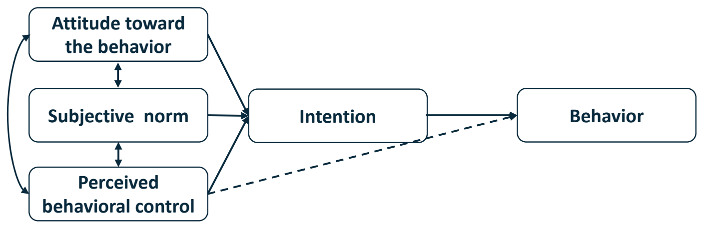
The theory of planned behavior (TPB) is an extension of the TRA (Ajzen & Fishbein, 1980; Fishbein & Ajzen 1975), filling the gap in handling behavior over which a person does not have control (Ajzen, 1991). As former studies of the TRA show a lack in predicting the intention and the behavior over which a person has incomplete volitional control, Ajzen adds the third variable, called perceived behavioral control (Godin & Kok, 1996).

In the TPB, the intention continues to play an important role and is expected to grasp the motivating elements affecting a behavior, indicating the keenness of the person as well as considering the intended endeavor to realize the behavior (Ajzen, 1991). The three constructs - attitude toward the behavior, subjective norm, and perceived behavioral control - influence the intention (Ajzen, 1991). The latest added factor perceived behavioral control, has a direct as well as an indirect influence on behavior via intention, signifying that the higher a person perceives to be in control, the higher the intention and performance to behave (Madden et al., 1992). The variable attitude toward the behavior might be high, as might be the variable subjective norm; however, with a low perceived behavioral control the intention to perform might be low, too (Madden et al., 1992).

The TPB is used in various fields, including health to clarify health-related behavior (Godin & Kok, 1996), internet purchasing to assess the relationships between internet purchasing and beliefs about the privacy and trust of the internet (George, 2004) and young people's use of social networking websites (Pelling & White, 2009).

Marangunić and Granić (2014) mention as a main limitation of TPB that it just functions when there is to a certain extent no volitional control; additionally, unintentional reasons are not reflected, and the theory assumes people are rational and make systematic decisions grounded on the existing information. Figure 3.2 shows the construct of the theory of planned behavior (TPB).

FIGURE 3.2: **Theory of planned behavior (TPB)**




Source: Ajzen (1991)

Based on the TRA, Triandis (1977) develops the theory of interpersonal behavior (TIB) in order to explain the influence of the emotions, social factors, and habits toward the user intention. According to Taherdoost (2018) in comparison to the TRA and the TPB, the principal drawback is the complexity of the model. Nonetheless, Moody and Siponen (2013) apply the TIB to investigate the non-work-related private use of the internet while being at work and successfully examine the influence of the variables affect, habit, role, and self-concept on internet use.

### *3.1.3. The technology acceptance model (TAM)*

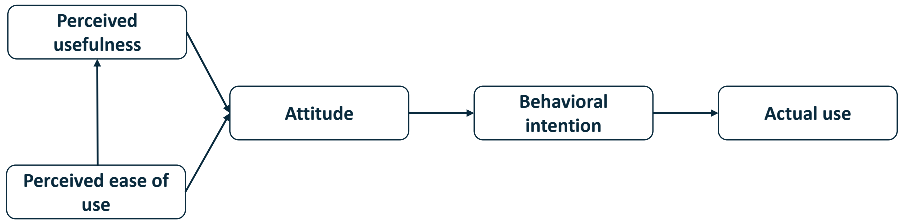
Studies in the field of information systems provide a variety of theoretical frameworks that can be used; however, the technology acceptance model (TAM) is possibly the utmost prominent model (Marangunić & Granić, 2014).  Deriving from previous behavior research, namely the theory of reasoned action (TRA) created by Fishbein and Ajzen (1975), which concentrates on the prediction and comprehension of people's social behavior. Referring to Momani and Jamous (2017) TRA is a fundamental theory; nevertheless, it is not created for a certain behavior or technology. Davis (1989) adjusts the TRA by creating the technology acceptance model. A less general model, designed in the area of information technology, complements TRA's attitude toward behavior with two technology acceptance determinants: perceived usefulness and perceived ease of use, but without the subjective norm (Momani & Jamous, 2017). The first important variable, perceived usefulness, presents the extent to which a person believes an application will support them in completing their task better, whereas the variable perceived ease of use means the extent to which people believe that utilizing a certain application will be easy and without effort (Davis, 1989). The attitude toward using a technology determines the behavioral intention (Davis, 1989; Davis et al., 1989). Therefore, if someone has a positive attitude toward voice assistants, this will have a positive influence on the person's intention to use the voice assistant. In the TAM, the actual use of a particular system is taken into consideration as behavior, and thus, the TRA as well as the TPB build the ideal core (Marangunić & Granić, 2014).

After starting the implementation of information systems in companies, the TAM is created specifically for the information technology context, contrary to the TRA and TPB, which derive from the psychological context (Momani & Jamous, 2017). Y. Lee et al. (2003) group the kinds of information systems into four categories: communication systems, such as email, general-purpose systems, like computers and the internet, office systems, and specialized business systems. From its first publication more than 30 years ago until now, the TAM is possibly one of the most frequently mentioned theoretical models in the area of information management (Wu, 2009). Referring to Momani and Jamous (2017) the progress of this model can be divided into three stages: first, the adoption stage with a high quantity of applications tested; second, the validation stage with scientists monitoring the measurement of technology acceptance by applying various technologies; and third, the extension stage, with scientists presenting additional variables and links between the hypotheses.

Moreover, a lot of research models are based on TAM and show the feasibility in different contexts of information and communication technology, for example, in m-government, in order to predict the citizens' behavioral intention to use government apps (B. W. Wirtz et al., 2019). Furthermore, in the health care area P. J. Hu et al. (1999) successfully prove the application of TAM by investigating physicians' decisions to accept telemedicine technology at public hospitals. Cheung and Vogel (2013) apply the TAM in the field of e-learning for forecasting user acceptance of collaborative learning technologies supporting students' project work.

The TAM faces limitations by not considering social effects or intrinsic motivations on technology adoption and therefore rather suits technologies in the area of work than, for example, in the customer setting where emotions are required (Taherdoost, 2018). Figure 3.3 shows the construct of the technology acceptance model (TAM).

FIGURE 3.3: **Technology acceptance model (TAM)**

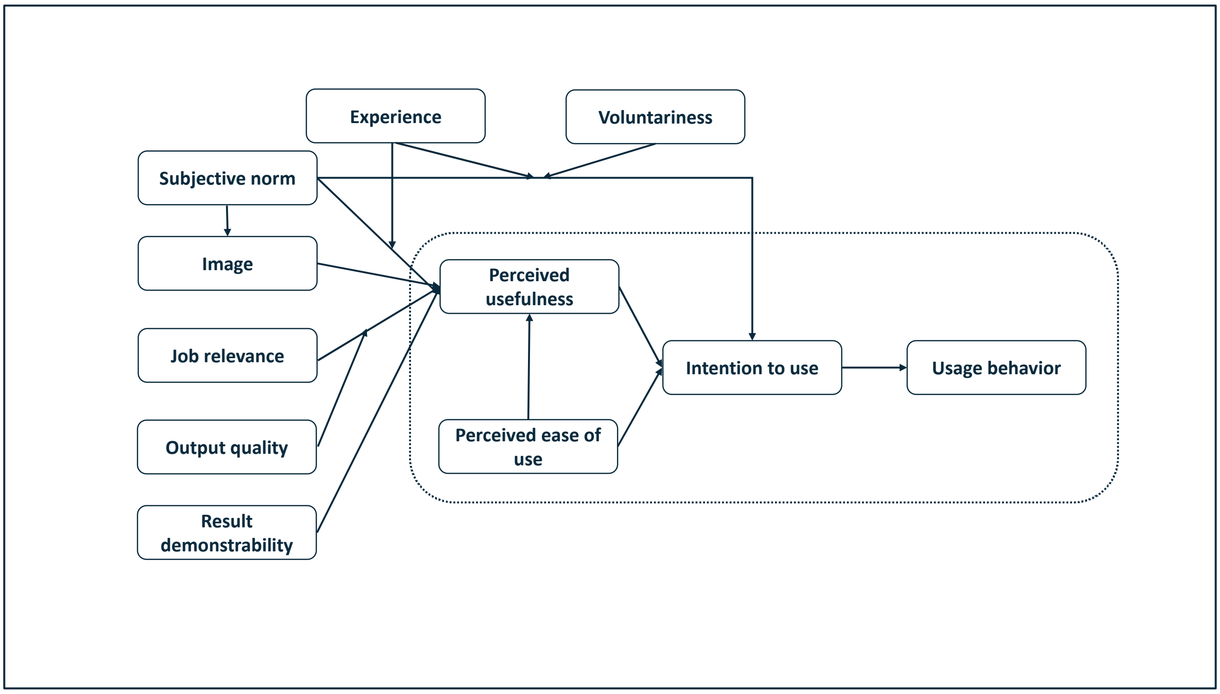



Source: Davis (1989)

Due to the importance of perceived usefulness, Venkatesh and Davis (2000) extend the TAM by the TAM2 in order to examine the social point of view and the factors affecting perceived usefulness. These variables involve subjective norm, which is the impact of other people on the person's choice of using a certain application; the image, which presents a favorable standing of a person among other people; the job relevance, referring to the extent to which a user can apply a technology; output quality, considering the appropriate performance of the job; and the result demonstrability, signifying the creation of concrete output (Venkatesh & Davis, 2000). Subjective norm has a direct influence on image, perceived usefulness, and intention to use, whereas experience and voluntariness function as moderators (Venkatesh & Davis, 2000).

Referring to Momani and Jamous (2017) the extension from TAM to TAM2 due to some constructs of former theories and the use of moderators improves the model and leads to a substantial enhancement in technology acceptance. Figure 3.4 shows the construct of the technology acceptance model 2 (TAM2).

FIGURE 3.4: **Technology acceptance model 2 (TAM2)**

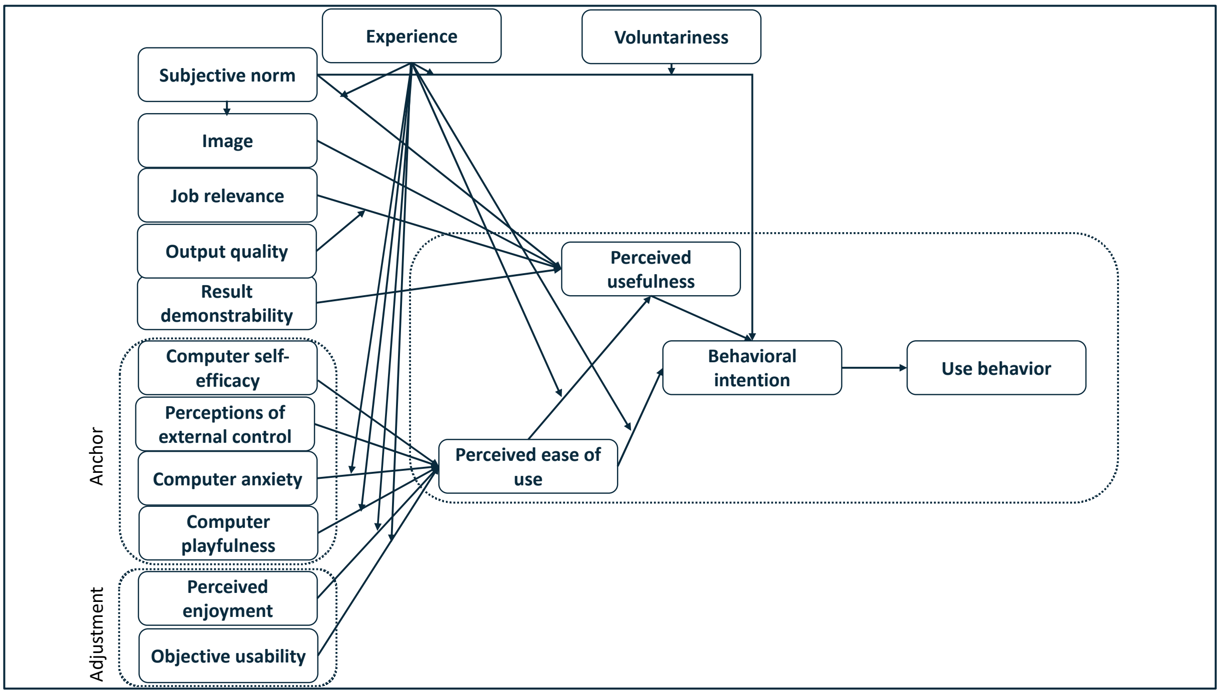



Source: Venkatesh and Davis (2000)

Even though the TAM and the TAM2 are created to forecast the individual information technology (IT) adoption and use, several companies fail to implement new technologies and systems due to insignificant adoption rates and little utilization by their personnel (Venkatesh & Bala, 2008). Therefore, Venkatesh (2000) creates a model forecasting the determinants of the perceived ease of use, claiming there are anchors linked to the person's beliefs concerning computers and their utilization as well as adjustments playing a pivotal role after the person gains experience with the computer.

Venkatesh (2000) groups the determinants affecting perceived ease of use into two clusters: first, the anchor considering computer self-efficacy, perceptions of external control, computer anxiety, and computer playfulness; and second, the adjustment, including perceived enjoyment and objective usability. Based on TAM2 and the determinants of perceived ease of use, Venkatesh and Bala (2008) develop TAM3, a model considering additionally the interventions effecting positively the determinants of IT adoption and use and, thereby, empowering successful implementations in companies. Figure 3.5 shows the construct of the technology acceptance Model 3 (TAM3).

FIGURE 3.5: **Technology acceptance model 3 (TAM3)**




Source: Venkatesh and Bala (2008)

A further model deriving from the TAM is the Igbaria's model (IM) created in 1996, postulating perceived usefulness as extrinsic motivation and perceived fun as intrinsic motivation affecting technology usage and technology satisfaction, while actual behavior is influenced by perceived usefulness, computer anxiety and satisfaction, as well as perceived fun in a direct and indirect way (Taherdoost, 2018). The main appliance of this model is in the information and communication technology sector, and the investigation of Igbaria et al. (1996) concentrates on the usage of microcomputers.

### *3.1.4. The social cognitive theory (SCT)*

The social cognitive theory (SCT) deriving from social studies and created in 1986 by Bandura, considers the social impact comprising the internal and external social reinforcement and the prior experience of a person, which generates expectations of output linked to the performance of a particular behavior (Momani & Jamous, 2017). The outcome expectancies can be differentiated by physical, social, and self-evaluative beliefs about the effects of one’s own acting (Conner & Norman, 2005). Referring to Venkatesh et al. (2003) SCT is one of the most influential theories of human behavior based on performance-related and personal consequences of the behavior as well as the self-assessment of the capability to achieve a task, the liking, and the anxious reactions regarding using a technology. Compeau and Higgins (1995) further developed this theory, adapted it to the use of computers, and created a model for technology acceptance and use of technology to examine the self-efficacy and its influence on behavior. The SCT is mainly used in the area of mass communication and media effects studies; for example, Huesmann et al. (2003) apply the SCT to investigate the relation between TV-violence viewing and aggression from childhood to adulthood. Moreover, the SCT is used in the public health sector, Luszczynska and Schwarzer (2015) provide an overview of the applications of the SCT, ranging from adherence to medication and rehabilitation to physical exercise to addictive behaviors.

### *3.1.5. The innovation diffusion theory (IDT)*

Another theory, the innovation diffusion theory (IDT), developed by Rogers, initially applicable for any innovation from the 1960s on and later adapted for the IT field in 1995, is based on the attributes perceived usefulness, ease of use, image, visibility, compatibility, results demonstrability, and voluntariness of use (Venkatesh et al., 2003). Firstly, the IDT exists of five key attributes, which are relative advantage, compatibility, complexity, trialability, and observability, and Moore and Benbasat (1991) extend it by adding the voluntariness of use and image.

According to Momani and Jamous (2017) it is one of the oldest theories of social studies, aiming to forecast how a person decides to adopt an innovation; nonetheless, it does not consider the social encouragement or resources of a person. Many studies exist applying the IDT in various fields, including sociology, communications, and education, such as the study by Dooley (1999), which sheds light on the adoption of educational technology in schools and also in the field of public health (Haider & Kreps, 2004). Compared to other adoption models, it rather concentrates on organizational, environmental, and system characteristics; however, it is less useful for forecasting results and has less explanatory power (Taherdoost, 2018).

### *3.1.6. The unified theory of acceptance and use of technology (UTAUT)*

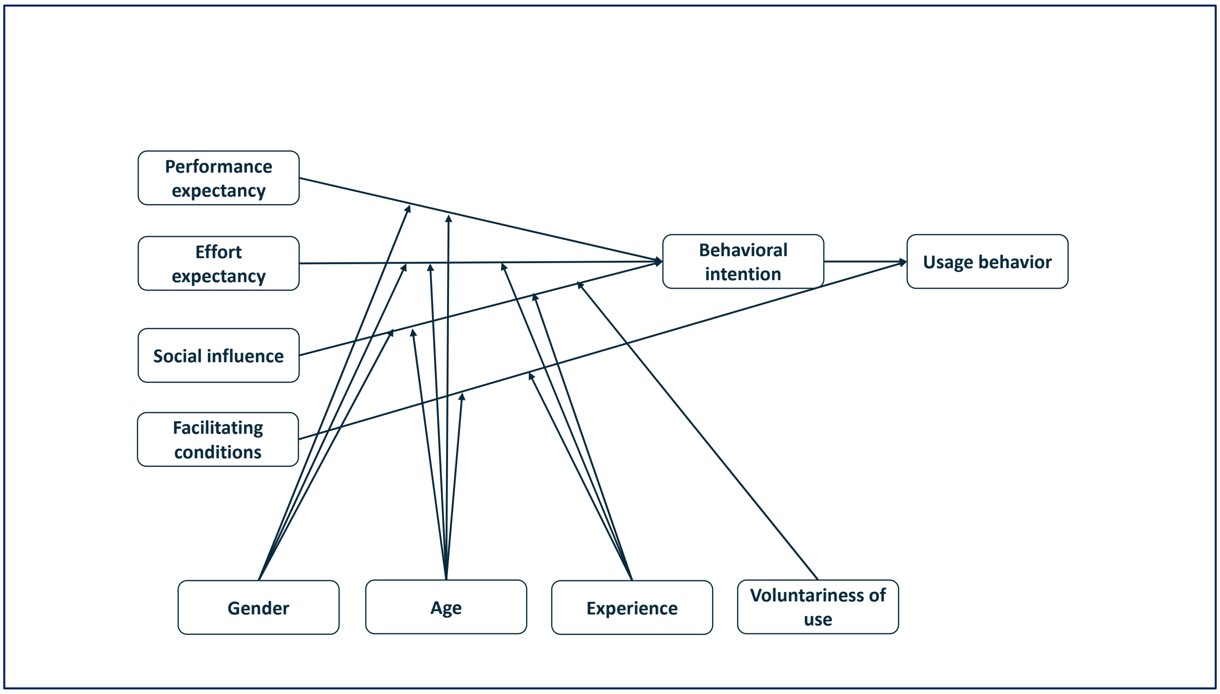
In order to explain the intention to use a system or a technology in a company context, Venkatesh et al. (2003) propose the unified theory of acceptance and use of technology (UTAUT) by uniting eight models and theories into one and adding the moderating variables gender, age, experience, and voluntariness of use. The models and theories are the TRA, TAM, motivational model (MM), TPB, combined TAM and TPB (C-TAM-TPB), the model of PC utilization (MPCU), IDT, and the SCT (Venkatesh et al., 2003). The main variables having a direct impact on the behavioral intention are performance expectancy, which is the individual's belief that utilizing a system helps to improve performance, effort expectancy, meaning the ease related to the use of the technology, and social influence, presenting how much a person perceives other important people to believe he should or should not use a certain technology; whereas the variable facilitating conditions refers to the believe that a technological and organizational framework is in place that facilitates the use of the system, and just as behavioral intention, having a direct impact on the technology use (Venkatesh et al., 2003).

A substantial part of studies in psychology confirms that motivation theory in general explains a person's behavior, and researchers adapt it to their context (Venkatesh et al., 2003). Deci and Ryan (1995) create the self-determination theory (SDT), suggesting self-determination as a human quality. From the SDT derives the extrinsic motivation, comprising external, introjected, identified, and integrated forms of regulation as sorts of self-determinations, whereas the intrinsic motivation relates to intrinsic regulation (Momani & Jamous, 2017). The motivational model (MM) is based on extrinsic motivation, created through external rewards, such as perceived usefulness, and intrinsic motivation, built on the will to perform the task per se, such as perceived enjoyment (Taherdoost, 2018). Davis et al. (1992) apply the motivational model in the corporate IT context and report that usefulness and enjoyment are essential determinants for technology acceptance.

Taylor and Todd (1995) developed the model combined TAM and TPB (C-TAM-TPB) by combining the determinants of TPB, including attitude toward behavior, subjective norm, and perceived behavioral control, with the perceived usefulness of TAM. Through this combination, the model is able to justify user behaviors for using new technologies with outstandingly high fitness (Taylor & Todd, 1995).

The model of PC utilization (MPCU) originates mainly from Triandis' (1977) theory of human behavior; however, Thompson et al. (1991) adjust the model for the field of IS and utilize it to forecast PC use. It exists of the core constructs job-fit, defined by the belief that utilizing a technology can enrich the job performance; complexity, presenting the perceived difficulty to comprehend and utilize; long-term consequences, meaning a promising output in the future; affect toward use, involving the feelings linked by a person with a specific act; social factors, comprising certain interpersonal arrangements a person has agreed on with others in certain social circumstances; and facilitating conditions, which help to accomplish a task with ease (Thompson et al., 1991). Figure 3.6 shows the construct of the unified theory of acceptance and use of technology (UTAUT).

FIGURE 3.6: **Unified theory of acceptance and use of technology (UTAUT)**



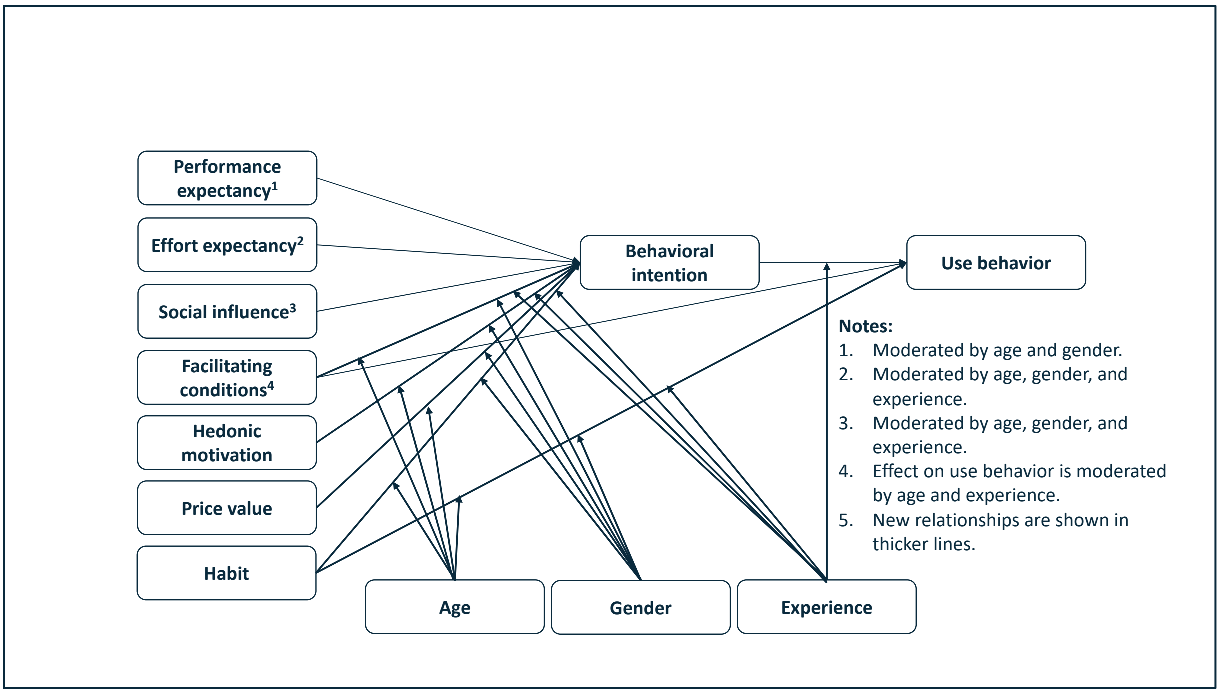

Source: Venkatesh et al. (2003)

### *3.1.7. The extended unified theory of acceptance and use of technology (UTAUT2)*

Venkatesh et al. (2012) extend the unified theory of acceptance and use of technology (UTAUT) to investigate technology acceptance and use in a consumer setting. In the extended unified theory of acceptance and use of technology (UTAUT2) three significant constructs are added: hedonic motivation, which comprises the fun resulting from a technology; price value, considering the balance between perceived benefits and financial expenses; and habit, the extent to which a person manages to achieve a task unconsciously by learning (Venkatesh et al., 2012). The UTAUT2 explains how the variables age, gender, and experience moderate the influence on behavioral intention as well as use behavior (Venkatesh et al., 2012). The moderator variables can be of interest for certain strategies, as they are able to increase or decrease the outcome of a relationship (Hess, 2022).

Referring to Tamilmani (2021) the UTAUT2 investigations can be divided into four categories involving the UTAUT2 general citation, the application, the integration, and the extension of the model. The main category of general citations counts more than 500 studies (Tamilmani, 2021). The UTAUT2 application covers different areas in the field of IS, whereas the consumer presents the original setting; however, there are also studies in the organizational setting. For instance, Mtebe et al. (2016) examine the elements affecting teachers' usage of multimedia enriched content in secondary schools in Tanzania. All variables, besides the performance of expectancy, have a noteworthy effect on the teachers' acceptance and use of multimedia enhanced content (Mtebe et al., 2016). Oliveira et al. (2016) combine UTAUT2 with the innovation features of the diffusion of innovation (DOI) and with perceived security to investigate the main determinants of mobile payment adoption in Portugal and the intention to recommend the technology. The UTAUT2 extension includes external variables and utilizes the UTAUT2 as a base (Tamilmani, 2021). Alalwan et al. (2017) extend the UTAUT2 by the external variable trust in order to investigate the determinants affecting behavioral intentions and adoption of mobile banking in Jordan, all variables are significant, except for social influence on behavioral intention to adopt. Figure 3.7 shows the construct of the extended unified theory of acceptance and use of technology (UTAUT2).

FIGURE 3.7: **Extended unified theory of acceptance and use of technology (UTAUT2)**




Source: Venkatesh et al. (2012)

## 3.2. The general model: Service robot acceptance model (sRAM)

For the purpose of this study, the general service robot acceptance model (sRAM) serves as the theoretical base, as it assesses customer perceptions, beliefs, and behaviors linked to service robots (J. Wirtz et al., 2018). This model not only incorporates the influential and proven model TAM; moreover, it adds the less examined social and relational dimensions driving service robots' acceptance (Fernandes & Oliveira, 2021).

The conceptual sRAM hypothesizes that the actual use of service robots is defined by the customer acceptance of service robots and influenced by not only the functional elements perceived ease of use, perceived usefulness, and subjective social norms, but also by the social-emotional elements perceived humanness, perceived social interactivity, and perceived social presence, as well as the relational elements trust and rapport (Fuentes-Moraleda et al., 2020). Additionally, it considers needs and role congruency (Abrams et al., 2021). In sum, the sRAM establishes the customers' technology acceptance as a construct explained by the three elements: functional, social-emotional, and relational.

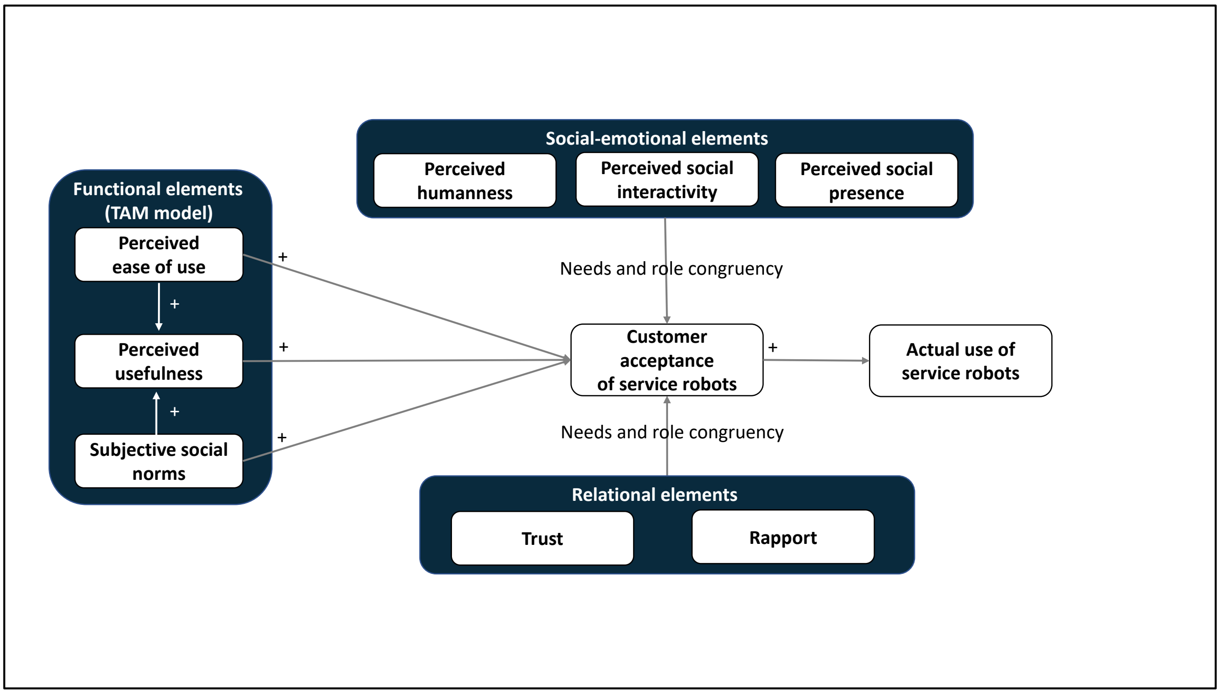
Fernandes and Oliveira (2021) apply the sRAM in the context of service encounters by undertaking a quantitative study focusing on millennials, whereas the functional, social-emotional, and relational elements successfully explain the user acceptance; however, the variable humanness may not drive adoption, but user experience as well as preferred human interaction have an impact as moderators. Whereas Fuentes-Moraleda et al. (2020) examine the main interaction between hotel service robots and humans, including reception, baggage, and room service, by creating a hotel-specific sRAM through an exploratory statistical analysis. The study proves the usefulness of the model and shows that, independent of the elements, any mistake by the service robot causes negative feelings among the hotel customers, and technical improvement is needed, especially for the relational abilities of the service robots. Furthermore, Amelia et al. (2021) investigate the drivers of customer acceptance of frontline service robots in retail banking by a qualitative approach applying the UTAUT and the sRAM based on the themes utilitarian aspect and social interaction by three additional themes: the customer responses toward frontline service robots, including likeability, enjoyment, and psychological comfort, as well as the theme customer perspective of the company brand, and the theme individual and task heterogeneity. The individual differences involve privacy risk, prior experience with self-service technologies, technology anxiety, and need for human interaction (Amelia et al., 2021). Moreover, Al-Makhmari et al. (2023) combine the sRAM and the UTAUT by exchanging the functional elements of the sRAM with the functional elements of the UTAUT and adding perceived intelligence to the social elements in order to explore the enabling factors of acceptance of the voice assistant Siri. This ongoing survey will be examined with a large-scale study of respondents of diverse genders, ages, and educations (Al-Makhmari et al., 2023). Abrams et al. (2021) undertake a theoretical and empirical investigation on technology acceptance models for autonomous delivery robots by creating the correlational model for existence acceptance, revealing there are two different types of acceptance: on the one hand, the usage-related acceptance as given in the sRAM, and on the other hand, the existence acceptance, which in contrast might not be triggered by or predict use.

In contrast to other technology acceptance models, the sRAM stands out for various reasons, to begin with, it considers the user perceptions, beliefs, and behaviors explicitly linked to service robots, and it reflects the main difference to former technologies, which is AI (J. Wirtz et al., 2018). Nonetheless, the core of the model is based on one of the most prominent and proven models, the TAM (Marangunić & Granić, 2014). Furthermore, the sRAM is more accurate by considering the extraordinary features of voice technology, including hands-free interactions, voice-based user interfaces, and voice control (McLean & Osei-Frimpong, 2019). By examining the social-emotional and relational elements, it provides more generalizability and a more holistic scientific approach (Fernandes & Oliveira, 2021). However, the main distinction from other technology acceptance models is taking the needs and role congruency regarding social-emotional as well as relational elements into account (Abrams et al., 2021). Meaning consumers may not need a high level of perceived humanness in order to accept voice shopping. J. Wirtz and Mattila (2001) posit that needs congruency occurs if the service performance meets the customers' needs and postulate the needs congruency as an important variable for the prediction of satisfaction. In the case of voice shopping needs, congruency can be achieved if the social-emotional VA performance meets the social-emotional needs of a consumer. Additionally, the role congruency by Solomon et al. (1985) considers the intra-role congruence, which is the extent to which a service provider understands his role within an organization, and the inter-role congruence, which presents the level to which service provider and customer have a mutual understanding of service roles, which are based on a cluster of social evidence. Both parties should perform consistently within their roles and according to their role script, deriving from the expected ideal service as well as the expectation toward the behavior of the service robot (Stock & Merkle, 2017). In the voice shopping setting, consumers might evaluate the interaction with the VA on these aspects, too.

Furthermore, the role theory can be applied to the relational elements as well; for example, when a consumer starts a conversation with the VA, he takes over the customer role, and the predefined and scripted conversation begins (Giebelhausen et al., 2014). Referring to Rhee and Choi (2020) the role of Alexa can be seen as that of a personal assistant, speaking in a pleasant, respectful, and formal way and providing suggestions based on the data received by the customer. If the VA performs its role related to trust and rapport according to the expectations of the customer, it's more likely the customer accepts the VA and uses voice shopping.

Merkle (2021) implemented in its service robot acceptance model the expectation disconfirmation theory and role theory. This model supposes customers subconsciously depend on other referrals to evaluate the handling of service robots (Merkle, 2021). Figure 3.8 shows the service robot acceptance model (sRAM).

FIGURE 3.8: **Service robot acceptance model (sRAM)**




Source: J. Wirtz et al. (2018)

### *3.2.1 Functional elements*

In comparison to the social-emotional elements and the relational elements, the functional elements are very well known and have been proven in numerous TAM studies (Davis, 1989). The functional elements present one of the three main elements of the sRAM, including the variables perceived ease of use, perceived usefulness, and subjective social norms (J. Wirtz et al., 2018). The relations between the functional elements and the relations to the customer acceptance are all positive, as the more perceived ease of use, perceived usefulness, and subjective social norms, the higher the customer acceptance (Schepers & Wetzels, 2007). There is evidence that utility plays a more pivotal role than a low level of complexity in the adoption of new technologies, and by growing experience with a specific technology, other variables overweigh the ease of use (Schepers & Wetzels, 2007). J. Wirtz et al. (2018) suppose that service robots accomplish functional tasks successfully and therefore lead to customer acceptance of service robots. This functional service robot acceptance includes the perceived degree of a service robot being useful and easy to use by a customer (Merkle, 2021). Nevertheless, J. Wirtz et al. (2018) differentiate between the adoption of service robots and self-service technologies and expect a faster adoption rate for service robots due to their customer guidance.

According to McLean and Osei-Frimpong (2019) the drivers of AI in-home voice assistants are mainly driven by utilitarian benefits, presenting in the sRAM the perceived usefulness and perceived ease of use and symbolic benefits referring to subjective social norms. The results of this quantitative survey focusing on the Amazon Echo in-home voice assistant show users are attracted by this technology due to the convenience and the usefulness (McLean & Osei-Frimpong, 2019). Moreover, Fernandes and Oliveira (2021) confirm functional elements are the key drivers for users, specifically perceived usefulness, which is affected by perceived ease of use and subjective social norms. If the purpose of a technology is utilitarian, the customers primarily appreciate rapidity and convenience (Fernandes & Oliveira, 2021). The survey by Fuentes-Moraleda et al. (2020) reveals hotel guests predominantly comment on the functional elements, in this case referring to interaction with the service robot at the reception, the room service, and the luggage management. Functions of a service robot that accelerate procedures such as check-in or luggage storage are of main interest to travelers (Fuentes-Moraleda et al., 2020). In the retail banking sector, the functional dimensions of frontline service robots are of high importance for customers, as they expect technical quality in the first place (Amelia et al., 2021). The results of Amelia et al. (2021) reveal that users consider the frontend service robots to be mainly useful and beneficial for performing tasks. Al-Makhmari et al. (2023) consider effort expectancy, performance expectancy, social influence, and perceived enjoyment as part of the functional elements and hypothesize these functional variables have a positive effect on the user acceptance of digital voice assistance. In the model for existence acceptance, Abrams et al. (2021) prove that the functional element of general perceived usefulness is the second utmost correlation; however, the general perceived usefulness rather addresses the society than the individual.

The acceptance of the user depends on the robot's performance in meeting the functional needs and is linked to its competence (Fernandes & Oliveira, 2021). The competence of a service robot is linked to the perceived capabilities, including effectiveness, cleverness, and ability (Fiske et al., 2007). Therefore, the ability of a service robot to work likewise a person without having efforts in accomplishing a duty might positively affect the way how customers equal them with humanoid alternatives (L. Lu et al., 2019). Furthermore, L. Lu et al. (2019) deliver insights by creating and validating a six-dimensional service robot integration willingness scale, among the 36 items, seven of them cover performance efficacy, representing the anticipated effort and abilities necessary for the utilization of technologies, and further seven items cover social influence. The research of Chattaraman et al. (2019) focuses on older adults and assesses whether a VA should interact social- or task-oriented. The characteristics of a task-oriented conversation style with a VA include more formal and solely on-task interaction in order to reach functional objectives; nonetheless, referring to natural conversations, people tend to combine task-oriented and social-oriented styles (Chattaraman et al., 2019). J. Wirtz et al. (2018) map service delivery examples based on the complexity of emotional-social and cognitive-analytical tasks and functional needs, such as purchasing a train ticket, renting a vehicle, booking a courier service, or checking out in a grocery store are simple emotional-social and simple cognitive-analytical tasks that can be perfectly delivered by a service robot as these tasks demand consistency, competence, rapidity, convenience, and profitable service.

There are investigations shedding light on the functional features of VAs, such as the study by Hoy (2018) and Bentley et al. (2018). The study by Bentley et al. (2018) examines the functional characteristics of VAs by focusing on the smart speaker Google Home in 88 households in the United States in order to achieve more insights into the daily use of VAs considering the number of commands per day, the length of commands, the time, and the type of command.

### *3.2.2 Social-emotional elements*

Persons have shown their interest in talking to computers since the invention of the first computer (Hoy, 2018). Robots are transforming from being purely technical and util to being reactive and interacting with persons in a social way (Breazeal, 2003). Additionally, more and more users are not technically skilled, and therefore, their actions are based on casual intuition (Mathur & Reichling, 2016). Along with artificial intelligence, not only functional elements are necessary to reach technology adoption, but the role of social-emotional elements is increasing as well (Stock & Merkle, 2018). Moreover, the scientific work on robots and humans can be divided into the functional acceptance of robots and the social acceptance of robots as a conversational companion comparable to a relation to a human or a pet (Heerink et al., 2010).

The social-emotional elements based on the sRAM exist of perceived humanness, the extent of humanlike behavior of a VA; perceived social interactivity, the acting of a VA according to accepted social norms; and perceived social presence (J. Wirtz et al., 2018), the degree to which a user has the impression of being in social company (van Doorn et al., 2017). In contrast to the functional elements, for the social-emotional elements, it does not necessarily imply that the more, the higher the acceptance (Schepers & Wetzels, 2007). Therefore, Tinwell et al. (2011) focus on the risk of the uncanny valley effect, which implies arousing a negative response from the user by approaching human appearance or behavior while deviating from the human standard. Findings of the study by Tinwell et al. (2011) highlight that this effect differs by the type of emotion that is transferred, and disgust, fear, sadness, and surprise evoke negative responses; however, this does not count for anger and happiness.

One basic dimension of social perception is warmth, which incorporates goodness, honesty, perceived pleasantness, and supportiveness (Fiske et al., 2007) and referring to the sRAM, it is related to the social-emotional elements (J. Wirtz et al., 2018). Furthermore, Abrams et al. (2021) cluster the social-emotional elements in social attributes (warmth, competence and discomfort) and basic emotions (surprise, joy, fear, anger, disgust and sadness). Due to the design of the delivery robot, the effect of the social-emotional elements is low and not comparable to the social abilities of a service robot (Abrams et al., 2021). The results of Gursoy et al. (2019) indicate emotions define acceptance and rejection of VAs by creating and empirically testing the theoretical model of artificially intelligent device use acceptance (AIDUA) to clarify VA acceptance in service encounters. The model consists of three stages, and in the primary appraisal stage, anthropomorphism has a positive influence on the perceived effort expectancy, which is part of the secondary appraisal, and an antecedent of emotion, which leads to the outcome stage and either willingness or objection to the use of VAs (Gursoy et al., 2019). In the 36-item service robot integration willingness scale of L. Lu et al. (2019) items of anthropomorphism and items on emotions are fundamental factors, where emotions reveal the most noticeable positive influence on the users' willingness to utilize and anthropomorphism is the most noticeable inhibiting factor.

Fernandes and Oliveira (2021) assess the social-emotional dimensions perceived humanness, social interactivity, and social presence and disclose that the main social drivers of digital voice assistants' acceptance in service encounters are perceived social presence, which is affected by social interactivity. Furthermore, perceived humanness shows no direct or indirect influence on the adoption of VAs for frequent users; however, infrequent users of VAs reveal a significant negative effect of perceived humanness (Fernandes & Oliveira, 2021). Referring to Sheehan et al. (2020), perceived humanness is playing a mediating role, and customers with an outstanding need for human interaction demonstrate a stronger link between perceived humanness and technology adoption. The personification of the VA is related to the sociability level of interactions, whereas households with multiple members interact more and thus, rather personify the VA (Purington et al., 2017).

Amelia et al. (2021) relate social interaction between an individual and a frontline service robot with social-emotional elements and include animacy/humanness, social intelligence, the skill to communicate according to social standards, and social presence. Based on this paper, the theme social interaction causes reactions by customers and leads to user acceptance of frontline service robots in retail banking services (Amelia et al., 2021). Al-Makhmari et al. (2023) extend the social elements perceived humanness, perceived social interactivity, and perceived social presence by the variable perceived intelligence indicating the intelligence of a VA, which animates individuals to use them, and link it with anthropomorphism, as persons tend to relate intelligent technologies with humanlike features. The findings of Moussawi et al. (2021) confirm anthropomorphism and perceived intelligence of a VA lead to adoption.

By performing two experiments with older users, the results of Heerink et al. (2008) indicate that the social abilities of a robot, such as listening carefully and being pleasant, lead to a feeling of social presence, and due to higher enjoyment, acceptance increases. Additionally, in the context of elder care, Heerink et al. (2010) extent the UTAUT by variables linked to social interaction, such as perceived sociability and social presence, and confirm by testing a socially expressive and a neutral robot that one with stronger social traits is perceived as more enjoyable. Furthermore, Chattaraman et al. (2019) highlight that a person with high internet competency benefits more from a social-oriented interaction with a VA through greater social outcomes involving trust and perceived interactivity, which refers to perceived two-way and synchronous interactivity.

Referring to McLean and Osei-Frimpong (2019), social benefits including social presence and social attraction, based on traits such as pleasant behavior or providing the feeling of a friendship, have a positive impact toward the usage of in-home voice assistants. Moreover, social presence and social attraction differ according to household size and the positive effect of social presence on the use is higher in a small household than in a large household as well as the influence of social attraction is more significant for a small household (McLean & Osei-Frimpong, 2019). Especially in the field of tourism, the expectations of the customers are habitually high regarding social presence and social interaction in several situations, such as reception, luggage service, or bar service (Fuentes-Moraleda et al., 2020). Even though the social-emotional dimensions are less than the functional dimensions, the results of Fuentes-Moraleda et al. (2020) show a wow effect is given by the presence and service of a robot, particularly for European hotel guests, where service robots are less common. According to the study by Tung and Au (2018), there is a need for robots to socialize in the area of tourism and hospitality; however, the natural human-oriented perception, which explains the capability of a service robot to react properly to customers’ requests, still calls for improvement. Therefore, service robots cause positive and negative emotions through their presence and behavior (Tung & Au, 2018).

The conceptual framework of van Doorn et al. (2017) focuses on the emergence of automated social presence and suggests that, due to technological advancements in frontline experiences, in future consumers act rather socially with service robots and, moreover, build a relation with the service robot. The survey by Fang (2017) investigates consumer brand engagement with mobile apps by applying an empirical cross-sectional survey design, and the results reveal that social presence is crucial for building relations between customer and brand. The study by Han and H. Yang (2018) investigates the possibility of developing a sense of social relationship with VAs by applying the parasocial relationship theory, which suggests that humanlike interactions and seeing VAs like friends arouse the feeling of an interpersonal relationship and are important for the adoption of the technology.

Schweitzer et al. (2019) examine the relation that persons build with VAs and the implications of their roles, whether as a servant, a partner, or a master. The results differ and show that users who perceive VAs as servants are more open to utilizing the devices in the future, while those who perceive the VAs as partners are positively appealed at the beginning but tend to leave them later due to a deficiency of real emotional interaction, and users who perceive VAs as masters have rather negative experiences (Schweitzer et al., 2019).

#### *3.2.3 Relational elements*

Due to the advances in frontline service robots, besides the functional and social-emotional elements, the role of relational elements is growing (Stock & Merkle, 2018). As many customers still demand contact with a person, rapport seems vital, in particular for services that require social closeness, such as, for example, care for elderly people (Fernandes & Oliveira, 2021). Nevertheless, especially trust is essential, first because of the user data a costumer delivers to the VA (Chattaraman et al., 2019), and second, because users are very critical regarding algorithms and even more so when errors occur (J. Wirtz et al., 2018).

Based on the sRAM, the relational elements consist of the variables trust, the belief of a person that the VA acts dependable and elicits confidence and rapport, the conception of a person that interacting with the VA is pleasant and that a special relation with the VA prevails (J. Wirtz et al., 2018). The sRAM is among the few technology acceptance models that consider the relational elements as well (Fernandes & Oliveira, 2021). In accordance with the social-emotional elements, for relational elements counts as well, a high level is not necessarily better (J. Wirtz et al., 2018).

Relational needs, especially trust, are linked to warmth and are necessary in order to attain role congruence (Fiske et al., 2007). There are further qualities of warmth, such as kindliness, goodwill, honesty, reliability, and ethics, the two characters warmth and trust are related and seem to go hand in hand in the social field (Fiske et al., 2007).

Fernandes and Oliveira (2021) examine the relational elements trust and rapport, revealing that these elements are the second most significant ones driving VA adoption. However, for users without experience, the relational elements have a higher importance than for experienced users, and for young consumers, who prefer human interaction, relational dimensions have no strong effect (Fernandes & Oliveira, 2021). Heerink et al. (2010) expand the TAM by adding not only social-emotional elements, but also relational elements in the field of elderly care. In the Almere model, the relational element trust is added and shows a substantial weight on perceived sociability (Heerink et al., 2010). The existence acceptance model of Abrams et al. (2021) adds to the societal-functional and social-emotional elements the expected-interactional elements, including trust, besides interest and enjoyment, as well as threat, including emotional, cognitive, and physical threat. The survey by Alalwan et al. (2017) extends the UTAUT2 with the relational element trust, confirming a positive effect of trust on the behavioral intention of mobile banking customers.

Results of Fuentes-Moraleda et al. (2020) suggest that relational elements are the least important ones for tourists due to language deficits and unsuitable interactions of the robot by talking when not requested. Nevertheless, this information only provides evidence that further progress of the robots is needed in order to advance the relational skills, especially as there is interest given in communicating with service robots (Fuentes-Moraleda et al., 2020). Furthermore, after various positive and fruitful interactions between user and robot, trust can increase (Tung & Au, 2018). The study by Tung and Au (2018) even shows a change from feeling insecure and having doubts before the experience with the robot to sensing security and trust after the interaction.

Another study assesses the influence of perceived personalization, which is the comprehension of the consumers' wishes, and familiarity, which is the consumers' comprehension of the VA, on trust and differentiates between cognitive trust, thus involving rational expectations, and emotional trust involving feelings (Komiak & Benbasat, 2006). According to van Pinxteren et al. (2019), the relational element trust is driven by anthropomorphism, which is vital for the acceptance of service robots and can be positively influenced through humanlike appearance or social behavior. A further study examines the impact of the uncanny valley effect on the willingness to trust a robot, exhibiting the dependence on features such as emotion, gender, and facial expression (Mathur & Reichling, 2016). Findings of Wuenderlich and Paluch (2017) show the significance of authenticity perception as a vital factor for creating trust because customers rather assess the experience as less authentic when having the impression to communicate with a robot rather than with a person. The survey by Poushneh (2021b) reveals that perceived auditory control effects positively customers' trust in VAs. Additionally, a charismatic, nice, and honest voice is increasing the trust (Klaus & Zaichkowsky, 2020). Moreover, the study by Klaus and Zaichkowsky (2022) investigates why customers notice VAs as trusty and sheds light on the relation between robots and customer decision making, showing that trust arises from positive emotions when interacting via voice. Findings of Chattaraman et al. (2019) highlight social-oriented communication style increases trust, particularly for older consumers with high internet skills.

Referring to the study by Pavlou (2003) in the field of electronic commerce, the relational element trust not only affects intention but also shows a significant impact on the functional elements perceived usefulness and perceived ease of use as well. Considering the long-term acceptance of robots, the advantage of a robot in comparison to a person is the perceived credibility, as they do not take decisions based on their personal profit (Lu, L. et al., 2019). Additionally, it seems a customer rather forgives a person than a robot, and hence, the trust toward the VA decreases easily (J. Wirtz et al., 2018). Consequently, the more the user has the feeling that the VA acts and prioritizes in the users' greatest interests, the more increases the probability of adoption (J. Wirtz et al., 2018).

Users build initial trust by assessing the level of reliability based on the sensed quality of information they receive from the VA, especially for customers with less knowledge or experience the evaluation of given information is difficult (Qiu & Benbasat, 2009). The model of Moussawi et al. (2021) includes only the trust variable without considering rapport, and the results indicate no positive direct effect on the intention to adopt. Strictly speaking, only the initial trust is measured, as the persons in their study do not have former experience with VA behavior and, therefore, do not have a connection to the VA when using it for the first time (Moussawi et al., 2021).

According to J. Wirtz (2018) not only in elder care, social familiarity and connection are vital for delivering a satisfactory service, but also in education and high-risk financial services. In the field of robot acceptance, the importance of relational elements is identified, and therefore, Nomura and Kanda (2016) developed the Rapport-Expectation with a Robot Scale (RERS) revealing that persons who act with the robot as with another human being achieve higher scores. By gaining experience with the VA, the customers develop a feeling of comfort and consequently build rapport with the VA (Cerekovic et al., 2017). Nevertheless, the actual need for the relational element is reliant on the service task differentiating between the complexity of emotional-social and cognitive-analytical tasks, which should be either delivered by a person only, a robot only, or in a human-robot combination (J. Wirtz et al., 2018).

# CHAPTER 4: HYPOTHESES DEVELOPMENT

# 4. HYPOTHESES DEVELOPMENT

The fourth chapter focuses on the proposed sRAM approach as well as the influence of control, risk, and personalization on the relational elements, customer acceptance of voice assistants, and the actual use of voice shopping. The proposed model (Figure 4.1) seeks to explain how the functional elements of the TAM model, the social-emotional and relational elements, and their variables of sRAM can influence toward the customer acceptance of voice assistants and the actual use of voice shopping. Additionally, this chapter seeks to form an understanding of the influence of control and risk on the relational element trust as well as personalization on trust and rapport. The hypotheses proposed on the basis of the components of the model are presented and justified in the upcoming section.

## 4.1. Hypotheses related to functional elements

The functional elements of the sRAM include perceived usefulness, perceived ease of use, and subjective social norms, and the current state of research provides starting points that these elements seem to be fundamentally suitable for capturing and predicting VA acceptance (J. Wirtz et al., 2018).

### *4.1.1. Perceived usefulness*

One of the two main determinants of technology adoption in the generally accepted TAM model is the perceived usefulness, and Davis (1989) defines this determinant as the perceived extent to which a person believes that the utilization of a certain system or service advances the performance of a task. Additionally, perceived usefulness presents the degree to which a person believes that the use of technology is useful, helpful, and facilitates the output of a particular job (Venkatesh & Davis, 2000).

Perceived usefulness measures the utility of adopting the technology based on the users' expectation that the usage will make it easier to fulfill a duty (Sánchez-Mena et al., 2019).

Furthermore, this variable is determined by performance effectiveness, task productivity, and time efficiency (R. J. H. Wang, 2020). Drawing on this, new technologies, such as platforms, applications, and VAs, should enable users to complete tasks in a simple manner in order to increase efficiency and productivity (McLean et al., 2020). The technology acceptance theory implies that perceived usefulness and perceived ease of use in the first place effect attitude toward a new technology and then drive the intention to use (B. W. Wirtz et al., 2019). Even though usefulness usually appears to be present, if it is not given to the degree expected by the user, it may impede the technology adoption (J. Wirtz et al., 2018). Referring to the study of consumer acceptance of smart speakers via a mixed methods approach by Kowalczuk (2018) the majority of behavioral intention is explicated and effected by perceived usefulness. Furthermore, an investigation of the understanding of the user behavior of VAs applying the cross-sectional method approach demonstrates most of the intention to use is driven by perceived usefulness, and the content quality presents the largest influence on the perceived usefulness considering software- and hardware-based functional value (H. Yang & H. Lee, 2019). Moussawi et al. (2021) examine in a cross-sectional research of personal intelligent agents how perceptions of intelligence and anthropomorphism affect the intention to adopt and confirm that adoption is mainly influenced by perceived usefulness, respectively, perceived intelligence positively affects perceived usefulness.

According to Fernandes and Oliveira (2021) the influence of perceived usefulness is especially high for persons who use the technology on a regular basis, and with growing experience, the usefulness is perceived even more. Chattaraman et al. (2019) differentiate between the low internet skills and high internet skills of older persons, and according to this study, older persons with low internet skills need a task-oriented service robot to achieve a higher perceived usefulness, whereas older users with high internet skills need a social-oriented service robot to achieve a higher perceived usefulness. Referring to Fuentes-Moraleda et al. (2020), different traveler types have different requirements for hotel-specific service robots, the two groups with the highest correlation with usefulness are business travelers, who give special consideration to details and mainly focus on the usefulness, and couples, who value the usefulness of service robots and their efficacy. Additionally, users in the retail banking sector point out the usefulness of frontend service robots and consider the delivered support beneficial for customers in order to fulfill banking related tasks (Amelia et al., 2021). Abrams et al. (2021) distinguish the perceived usefulness of the individual from the perceived usefulness of society, which incorporates the common usefulness for a superior good. Thus, the belief in the usefulness of a technology, which helps to overcome tremendous problems within a society, has a positive influence on the individual (Abrams et al., 2021).

According to Fernandes and Oliveira (2021) perceived usefulness relates to the extent to which the user supposes that the interactivity with the robot provides benefits, and perceived ease of use indicates the degree to which the user thinks that using the robot would be effortless. Referring to J. Wirtz et al. (2018), the relation between the functional dimensions and user acceptance is positive, and the more useful, the higher the acceptance. Moreover, the given convenience of hands-free interaction and the possibility of multitasking have a positive influence on the customers' use of the technology (McLean & Osei-Frimpong, 2019).

Henceforth, the perceived usefulness of voice shopping can be hypothesized as the degree to which consumers think shopping by voice improves their lives due to convenience and saving time. Therefore, the following hypothesis arises:

H1: Perceived usefulness is positively related to customer acceptance of voice assistants.

### *4.1.2. Perceived ease of use*

The other main determinant of technology adoption of the TAM model is perceived ease of use (Davis, 1989). As the second most important variable, perceived ease of use is defined as an individual's perception of the simple and effortless operation of a given system (Davis, 1989). Ease of use refers to the skills used to meet the challenges posed by information systems (Venkatesh & Davis, 2000).

According to Saxena (2017) perceived ease of use indicates the level to which a user considers that using a certain service would be without efforts. Additionally, it shows the degree to which information technology is easy to understand and utilize, flexible, and logical (R. J. H. Wang, 2020). Likewise, the perceived usefulness and ease of use are given in the majority of new technologies, but the absence might signify a barrier to adopt (J. Wirtz et al., 2018). According to Venkatesh and Davis (2000), ease of use increases with the user experience; thus, the more frequent a person utilizes a technology, the higher the perceived ease of use. Based on this, a new technology should be easy to understand and to utilize, so that the user is empowered to finish a task without effort and achieve the necessary skills for further usage (McLean et al., 2020).

Chattaraman et al. (2019) disclose that perceived ease of use with technically low skilled older persons has more impact on the functional result if the VA applies a task-oriented conversation style. In the hotel industry, especially the traveler type, couples appreciate the ease of use of service robots facilitating the arrival procedure due to their reception service and luggage management (Fuentes-Moraleda et al., 2020). Even though the utilitarian benefit outweighs the level of ease related to utilization in the retail banking sector, the perceived ease of use is pivotal for the acceptance of a new technology (Amelia et al., 2021). Veríssimo (2018) explains in an empirical cross-sectional analysis design that the high usage intensity of medical mobile applications used by medical professionals is determined by perceived ease of use and perceived usefulness. While Belanche et al. (2019) state that attitudes toward robo-advisors are influenced by perceived ease of use, especially at the initial stages of the technology adoption process. Contrarily, McLean et al. (2020) reveal in a longitudinal study investigating attitudes toward mobile commerce applications that perceived ease of use stays steady from the adoption phase over the continuous use. This sheds light on continuous usage behavior, as the majority of surveys focus on the initial adoption phase (McLean et al., 2020).

Referring to H. Yang and H. Lee (2019) perceived ease of use should be taken into consideration only for users without experience, which is due to the similar interfaces of VAs hardly given. Furthermore, L. Lu et al. (2019) consider ease of use in the context of VAs as irrelevant, as the VA with humanlike intelligence leads the customer and there is no effort of learning required from the user. Moreover, Moussawi et al. (2021) assume personal intelligent agents are not difficult and challenging enough, and therefore, perceived ease of use has no influence on the intention to adopt.

However, based on the study by J. Wirtz et al. (2018) the adoption of service robots is faster due to the given perceived usefulness and perceived ease of use, as the robots not only direct the user through the process but they are also capable of recovering errors and offering alternatives, though, if these functional elements are not delivered as expected by the user, it could be an obstacle.

Applying perceived ease of use to voice shopping can be the time a customer needs for downloading the Alexa app and the registration. In addition, learning how Alexa and the shopping process function. Thus, it is expected:

H2: Perceived ease of use is positively related to customer acceptance of voice assistants.

Findings of the TAM imply that perceived ease of use might have an impact through perceived usefulness rather than directly on technology acceptance (Davis, 1989). The study by

Venkatesh and Bala (2008) confirms that perceived ease of use contributes to perceptions about usefulness. In the area of automated service technologies, perceived ease of use describes the nature of the customers' belief that the VA can be utilized effortlessly (Fernandes & Oliveira, 2021). However, the results of Fernandes and Oliveira (2021) indicate that for users preferring human interactions, this impact is lower.

Nevertheless, K. H. Seo and J. H. Lee (2021) suggest there is an indirect influence of perceived ease of use on the acceptance of service robots through perceived usefulness. Consequently, ease of use is considered a significant variable in the sRAM and seems to be an important predictor in determining perceived usefulness.

Built on this, if a consumer perceives the use of Alexa for shopping as not triggering efforts, it's more likely that he believes voice shopping to be useful, and consequently, the consumer becomes more willing to use Alexa for shopping. This leads to the hypothesis below:

H3: Perceived ease of use is positively related to perceived usefulness toward voice assistants.

#### *4.1.3. Subjective Norm*

The third functional element subjective norm constitutes in the TRA, described as a "person's perception that most people who are important to him think he should or should not perform the behavior in question" (Fishbein & Ajzen, 1975, p. 302). Followed later by the TPB in form of a direct antecedent to behavioral intention, and Ajzen (1991) defines subjective norm as a social variable to fulfill a certain behavior motivated by perceived social stress. Even though, it is not considered in the original TAM (Davis, 1989), Venkatesh and Davis (2000) extended the TAM by exploring social influences through subjective norm in the TAM2 and Venkatesh and Bala (2008) in TAM3, however, as a direct antecedent to image, perceived usefulness, and intention to use. In the UTAUT the subjective norm is replaced by social influence, which Venkatesh et al. (2003) explain as the perception how much other important persons believe someone should or should not utilize a technology. In the sRAM the subjective social norms have a direct influence on the perceived usefulness and the customer acceptance of service robots (J. Wirtz et al., 2018).

Due to the trendiness of AI technology, persons might accept VAs in order to enrich their status in society (McLean & Osei-Frimpong, 2019). According to McLean et al. (2020) the subjective norm is of high importance in the initial adoption stage; nevertheless, there is no significance in the later usage phase. This might be due to the acquired personal experience and knowledge over time (McLean et al., 2020). Schepers and Wetzels (2007) investigate in a meta-analysis of the TAM the subjective norm and moderation effects, revealing subjective norm has more influence on behavioral intention in Western studies than in non-Western studies. Belanche et al. (2019) examine the key drivers of robo-advisor adoption in the context of AI in FinTech by taking a sample of British, North American, and Portuguese potential users. This survey confirms the influence of subjective norm is considerably higher for customers from the UK and USA, than from Portugal as well as for customers with less familiarity (Belanche et al., 2019). Based on the TAM, Venkatesh and Morris (2000) identify gender differences in the technology adoption and continuing use at work by measuring reactions and behavior over a period of five months. The influence of subjective norm is more significant on women than on men, but compliant with other studies by time the impact decreases.

In the study by Abrams et al. (2021), the result of subjective social norms is unclear, as relatives and close friends received a higher acceptance rating than the general society. L. Lu et al. (2019) include social influence in the 36-item scale and refer to the degree to which the customers' social network has an impact on the user by believing the person should use service robots. As this scale reproduces the continuing willingness to integrate a robot in the service environment, the effect of social influence is limited (L. Lu et al., 2019). Nonetheless, considering the present environment, social influence comprises the extent to which a user’s social group thinks using AI services is of relevance and congruency with group norms (Gursoy et al., 2019).

Transferred to the setting of voice shopping, friends or family who use Alexa can have a direct impact on someone’s acceptance of voice shopping. Subsequently, the following hypothesis is formed:

H4: Subjective social norms are positively related to customer acceptance of voice assistants.

Based on former research, subjective norm can have an indirect impact through perceived usefulness (Venkatesh & Davis, 2000). The findings of Gursoy et al. (2019) emphasize the direct effect of social influence on performance expectancy leading to AI device use acceptance in service delivery (Gursoy et al., 2019). Especially users who prefer human interactions show an indirect effect on VA acceptance through perceived usefulness; nevertheless, there is no direct influence of subjective social norms toward VA acceptance (Fernandes & Oliveira, 2021). In the current context, the belief of an important person in the VA’s usefulness can persuade someone to adopt this belief (Blut et al., 2016; Fernandes & Oliveira, 2021).

Therefore, if a friend praises the usefulness of buying products via voice, a consumer may start thinking that Alexa is indeed useful. Hence, it is proposed:

H5: Subjective social norms are positively related to perceived usefulness toward voice assistants.

### 4.2. Hypotheses related to social-emotional elements

Not only the functional elements but also the social-emotional elements are essential to drive the acceptance of VAs (Fernandes & Oliveira, 2021). These elements of the sRAM involve perceived humanness, perceived social interactivity, and perceived social presence (J. Wirtz et al., 2018).

#### *4.2.1. Perceived humanness*

Perceived humanness presents one of the three social-emotional elements of the sRAM and can be defined as humanlike qualities in behavior or form (J. Wirtz et al., 2018). Humanness can be seen as uniquely human characteristics that do not apply to animals, and as typical characteristics of human nature that also apply to animals (Haslam et al., 2008). When a person tends to recognize humanlike representors in all kinds of non-human objects, animals, and others in order to justify an action, anthropomorphism occurs (Duffy, 2003).

Former research on perceived humanness has mainly concentrated on embodied robots and physical features such as looks or gestures, whereas there is less known about the perception of humanlike behavior of VAs such as Alexa considering voice, language, and conversational rules (Doyle et al., 2019). Typical humanlike behaviors can be being eloquent, humorous, and humble, as well as caring, pleasant, and cheerful (Moussawi et al., 2021). Especially understanding, giving contextual responses, and being able to have natural conversations, such as remembering information from previous dialogues, describe the main distinction of VAs (Mari, 2019). The tendency of individuals to humanize objects shows an effect on the consumer behavior and therefore, in marketing, the awareness and interest in anthropomorphism increase (van Doorn et al., 2017). Additionally, marketers use the humanness and friendliness of a VA to promote the VA as a “digital buddy” (Han & H. Yang, 2018). Consequently, service robot research needs to examine when a consumer humanizes and why a consumer humanizes a service robot and how the anthropomorphism affects the service experience (van Doorn et al., 2017).

Aggarwal and McGill (2007) distinguish three types evoking anthropomorphism: the first type are persons striving for a relationship and by humanizing they are trying to fill this gap; the second type are individuals wanting to feel more familiar with things they possess less knowledge about; and the third type proposes persons humanize as part of a strategy and they see it as a bet that the world is anthropomorphic (Guthrie, 1995). Moreover, Guthrie (1995) differentiates different forms within this good bet: the partial, when an individual recognizes human characteristics but does not refer to it as a whole human; the literal, when a person believes the thing or creature is a real human; and the accidental, when someone sees a human component in a thing by coincidence, such as a face in an object. In the case of VAs, specific characters or functions, as for example, natural language may evoke partial perceived humanness; thus, the costumer recognizes certain anthropomorphic attributes in the VA, but does not recognize the complete VA as human (Fernandes & Oliveira, 2021). Based on the results of Aggarwal and McGill (2007) the influence of humanizing is not simply related to anthropomorphic traits, the different types have to be considered as well.

Previous research on humanness moved from physical human appearance to non-physical perceptions of humanness, investigating speech interfaces and their anthropomorphic traits (Doyle et al., 2019). According to Blut et al. (2021) the positive impact of humanness on the intention to use a robot is higher for non-physical robots than for physical robots and rather for female robots than for non-female robots. Therefore, the design of in-home VAs has rather an anthropomorphized appearance than in the past and is meant to play a pivotal role in the consumer's daily life (McLean & Osei-Frimpong, 2019). Due to the VAs' voice skills and the ability to show reactions and humor while interacting with a person, the perception of humanness can occur, independent of the physical features (Moussawi et al., 2021).

With the continuous developing technology virtual characters become more genuine and anthropomorphic characters tend to face the risk of the uncanny valley (Tinwell et al., 2011). The uncanny valley theory implies, the more similar a synthetic face appears human, the more it is favored; however, only until a certain level before it seems almost identical to a human face (Mori, 1970/2012). Beyond this level, the social robot can cause the opposite reaction and instead of appearing familiar it gives a creepy and strange impression (Duffy, 2003). Thus, minor differences can cause big changes (J. Wirtz et al., 2018). However, if the robot cannot be distinguished from a human, the likeability of the robot is as high as of a human (Mori, 1970/2012).

Through AI service robots entering the customer communication, the difficulty arises for the client to differentiate between a bot and a human employee; therefore, customer perceptions of AI-based service agents are influenced by perceived authenticity, which has a positive effect on the attitude and the behavioral consequences (Wünderlich & Paluch, 2017). The survey by Doyle et al. (2019) shows consumers differentiate speech-based VAs from humans and perceive them in social terms as more fake, restricted in their interpersonal skills, and rather formal. Findings of Amelia et al. (2021) reveal customers in the retail banking sector pay attention not only to the social interaction and communication, but also to the size of a frontline service robot; nevertheless, qualities such as voice, face, and replies impact the level to which a person enjoys interacting with the robot. Findings of the study by Goudey and Bonnin (2016) on the impact of anatomical anthropomorphism on companion robots highlight that users react more positively to a partly human appearance than to a full anthropomorphic appearance. Referring to Duffy (2003) the appearance and behavior of a social robot should not be too humanlike, rather balanced between robotic and anthropomorphic in order to be accepted and preventing the uncanny valley.

Blut et al. (2021) undertake a meta-analysis of physical robots, chatbots, and other AI in order to comprehend anthropomorphism with a focus on service provision, as there are contrary opinions on the impact of humanness on the use intention of robots. Depending on the relation a customer has with a VA, humanness either brings fortification for the relationship or weakening (Schweitzer et al., 2019). Złotowski et al. (2015) shed light on the advantages and disadvantages of the phenomenon of anthropomorphism, even though there is a necessity for a humanlike impression of a robot, the expectations of the users of robots with a humanlike appearance are more demanding in comparison to machine-like robots. Anthropomorphism may arouse positive feelings for persons, such as enjoyment and pleasure or negative feelings such as dissatisfaction and irritation, especially when a robot does not perform as expected by misunderstanding a command or an event that arises (Tung & Au, 2018).

According to Breazeal (2003) the capability of a robot to interrelate with a person in a human way is an essential functionality. Additionally, humanness is a significant factor in AI and individuals' service robots use behavior (van Doorn et al., 2017). The more social uses of the VA take place, the more humanizing occurs (Purington et al., 2017). Al-Makhmari et al. (2023) suppose a positive effect of perceived humanity on the user and the acceptance of VAs as the human traits support the relationship building between them. The study by Melián-González et al. (2019) investigates the intentions to use chatbots for travel and tourism, suggesting a positive relation between chatbots' humanness and the intention to use a chatbot. The results of Moussawi et al. (2021) disclose the positive indirect effect of perceived anthropomorphism through perceived enjoyment on the intention to adopt.

In the AIDUA, anthropomorphism does not only have a positive influence on the perceived effort expectancy of AI devices, but it also implies a negative impact on the perceived performance expectancy, which Gursoy et al. (2019) explain by the effort of the users to defend their concerns by the assumption that the AI devices are not probable to function as expected. The study by Fernandes and Oliveira (2021) assesses humanness is not generally positive, even though customers with a low technical affinity show a higher tendency for humanness, it depends on the likeability of the anthropomorphic device. Results of S. Y. Kim et al. (2019) suggest humanizing consumer robots maximizes the perceived warmth, but nevertheless it minimizes the liking due to uncanniness. Individuals who perceive a high level of humanness in VAs tend to feel threatened by VAs with humanlike features concerning the human uniqueness (Rosenthal-von der Pütten & Krämer, 2014). Results of L. Lu et al. (2019) indicate anthropomorphic appearance may have a negative effect on the consumer, especially for intelligent products, and it might differ depending on the service sector, for instance, in restaurants and retail stores the influence of humanness is negative toward the willingness to use a service robot, due to the dominance of interpersonal interaction.

According to Sheehan et al. (2020) humanness of customer service chatbots serves as mediator between the chatbot communication and the adoption intent, examining an error-free chatbot, a seeking clarification chatbot, and an error chatbot; while the first two chatbots don’t show any difference, the last chatbot diminishes the perceived humanness and the intention to adopt due to miscommunication. Additionally, perceived anthropomorphism can be a partial mediator between perceived intelligence and enjoyment (Moussawi et al., 2021).

A further topic receiving attention in the research of technology-human relations is the role of anthropomorphism in developing trust (Lankton et al., 2015). Referring to J. Wirtz et al. (2018) service robots with humanlike characteristics evoke more likely trust in the customer. Nonetheless, Moussawi et al. (2021) examined perceived intelligence has a positive influence on initial trust, but not perceived humanness of a VA. The study by Fuentes-Moraleda et al. (2020) confirms hotel service robots with humanlike behavior foster trust and lead to a satisfying customer experience. The study by van Pinxteren et al. (2019) investigates humanoid service robots in order to understand the implications in service marketing by differentiating between look and social performing qualities, and suggests humanness has a positive effect on the trust of a consumer as well as the intention to use and enjoyment. However, persons with lower technical skills and little experience feel less comfortable interacting with robots and therefore may humanize more, and thus, the appearance features are more important, while for experienced users the social-functioning features have a higher impact (Pinxteren et al., 2019). Han and H. Yang (2018) emphasize the positive influence of humanness of VAs on the relation between VA and consumer and the further use. There exist concerns that users might experience disappointment if their expectations about the anthropomorphic qualities are too high (J. Wirtz et al., 2018). Nonetheless, McLean and Osei-Frimpong (2019) outline perceived humanness of a VA induces social reactions and accordingly has a positive impact on the use of the technology.

Thus, if a user perceives Alexa as natural and humanlike, it leads to the hypothesis below:

H6: Perceived humanness is positively related to customer acceptance of voice assistants.

#### *4.2.2. Perceived social interactivity*

A further social-emotional element of the sRAM poses the perceived social interactivity, which embraces users' perception that a VA adheres to accepted social standards by showing adequate actions and feelings and in order to lead to broad adoption of VAs, perceived social interactivity has to comply with the requirements and the perception of VAs' acting and social abilities (J. Wirtz et. al, 2018). Breazeal (2003) describes social interaction as a dance between persons, pointing out the significance of the timing and the way of interacting. Therefore, the perceived social interaction presents the level to which the users sense they can speak with the VA mutually and harmoniously (Chattaraman et al., 2019).

The first touchpoint with a company or a brand is mainly the interaction with the frontline service employee, and a positive output is critical for further success, which applies for frontline service robots as well (Amelia et al., 2021). Therefore, J. Wirtz et al. (2018) argue that a successful interaction compels proper performance and emotions. According to Breazeal (2003) the social interaction of a VA is crucial for giving a competent impression to the costumer, whereas the anthropomorphic appearance does not influence the perceived competence. Nonetheless, in order to generate positive user responses and create a significant intercommunication between VAs and humans, social interaction skills are essential (van Doorn et al., 2017). In the field of robotics, a substantial amount of research is focusing on the ability of a robot to act socially, due to a high impact on acceptance (Heerink et al., 2008). As social abilities Heerink et al. (2008) consider cooperation, understanding, showing decisiveness, competence, responsibility, self-control, and increasing trust. Even in the educational sector the possibilities of social robots are examined to support and motivate students in studying through social interaction (Alam, 2022). Furthermore, the utilization of social robots in mental health, addressing mainly elderly people with dementia and psychological well-being is investigated presenting amplified pleasure and positive social interactions (Scoglio et al., 2019).

It is assumed that the preferences for social interaction differ among users (Sheehan et al., 2020). Moreover, the success of the social interaction style of a VA may vary depending on the product or service offered (Chattaraman et al., 2019). The study by Amelia et al. (2021) assesses the interaction with the VAs is comparable to interactions between humans. As robots possess more and more anthropomorphic characteristics, the assessment of them is based on social norms originating from human-human interactions (Sundar et al., 2017). Referring to Duffy (2003) within the human-robot interaction the humanization of robots is significantly higher than of any other technology.

According to Al-Makhmari et al. (2023) the interest and interaction with a VA rises if the customer has the feeling of interacting with a human. Referring to Purington et al. (2017) personification and social interaction are related in the case of the Amazon Echo, and the more personification, the more social interaction takes place. In this case, the device is personified due to the given name Alexa, and in order to work a social interaction is required (Purington et al., 2017). In order to keep social interactions between humans and robots pleasant and worthwhile the users require a certain level of anthropomorphic traits, particularly for social robots (Duffy, 2003). Anthropomorphic traits, such as voice, being able of having a conversation, and performing traditional social roles, support the feeling of interacting with a robot as with a human being (Chattaraman et al., 2019). The ability of a robot to copy human behavior steadily affects consumers, for example, VAs are capable of remembering former talks, thus giving the impression of consistency by referring to a correlated detail within the human-robot conversation (Mari et al., 2020). Users are able to have long talks with VAs, and these talks can arouse very enjoyable positive emotions due to the social interaction (Klaus & Zaichkowsky, 2020). Especially the perceived spontaneity deriving from surprising responses of a robot encourages the relationship building through the sense of nearness (Han & H. Yang, 2018). However, the focus should be on those traits that smoothen the social interaction whenever needed, including social, emotional, and autonomous communication, avoiding the uncanny valley, using natural movement, balancing form and function, and creating a unique identity of the robot (Duffy, 2003). Moreover, social interactions with VAs may be a new possibility for humans to express themselves, thus, the robot may play the role of an extended self (Belk, 2013).

The study by Chi et al. (2020) investigates the application of AI devices in service encounters and the hospitality industry, pointing out the importance of the quality of the social interaction, and by improved social abilities of VAs the users' need for social interaction may augment. According to Sheehan et al. (2020) there is a correlation between the necessity for human interaction and the relation between anthropomorphism and adoption intent; therefore, a highly humanized robot may fulfil the social needs of persons with a high demand for human interaction. Results of McLean and Osei-Frimpong (2019) suggest social interactions may be rather needed in a household with less people in order to reduce the solitude and boredom. In general, the perceived auditory sense of VAs, the capability to identify the customer's voice and react to the request, drives the perceived auditory social interaction, giving the user the impression of being in control of the VA and therefore increasing the trust in a VA (Poushneh, 2021b). Pagani et al. (2019) investigate social interaction combining touch and voice, revealing that adding voice to touch stays difficult and lowers the involvement with a platform; however, regarding the moderating effect of privacy concerns adding voice to touch lowers these concerns between platform engagement and brand trust.

The survey by Amelia et al. (2021) reveals due to the chance to relate, react, and be involved with a VA the consumers respond positively. Furthermore, social interaction activates the sympathy, pleasure, and emotional wellbeing and eventually leads to acceptance of frontline service robots in retail banking services (Amelia et al., 2021). The analysis of a study of social robots reveals elderly persons are willing to interact socially with robots, while familiarity increases the perceived sociability and hedonic factors influence the long-term acceptance (de Graaf et al., 2015). Moreover, the interaction style impacts the users' perception, in a further experiment of elderly people the results disclose playfulness increases the social attractiveness (Sundar et al., 2017). Thus, if social skills and behavior are shown, users may be more attracted to interact with a VA, and therefore, the social appeal may rise (McLean & Osei-Frimpong, 2019). Results of Han and H. Yang (2018) show social attraction, consisting of social or individual appealing characteristics, has a positive influence on the human-robot relationship, which consequently leads to user satisfaction and the intention of continuous use of the robot. Based on the survey by Amelia et al. (2021) humanness, social intelligence, and social presence are part of social interaction and have a positive influence on the consumer replies toward VAs.

Nonetheless, it might be a challenge for consumers to receive a service by a robot, which used to be offered by a person and leading to the impression of devaluation, additionally, users might reject the service of a VA due to their partiality for social interaction (Chi et al., 2020). Results of Gursoy et al. (2019) indicate that consumers' need for social interaction and especially, the need for human contact and sharing of emotions can have a negative impact toward the acceptance of VAs. Furthermore, in the health sector social interactions might be disturbing for the user, and a task-oriented communication might be more appropriate (Chattaraman et al., 2019).

Even though Fernandes and Oliveira (2021) do not confirm the direct influence of perceived social interactivity on VA acceptance, findings highlight perceived social interactivity has an indirect effect mediated by perceived social presence.

It is worth noting that VAs are capable to imitate humanlike interactions, as for instance, responding to their name, using “I” in order to make a reference to themselves, as well as picking up on related details during the talk (Mari et al., 2020). Considering Chattaraman et al. (2019) due to the VAs’ communication skills, the users perceive them as social human beings, which motivates the users to react socially and accordingly influences their behavior. Additionally, this social interaction with the device increases the satisfaction of the consumer (Purington et al., 2017).

Referring to this, having a pleasant shopping conversation with a VA might have a direct effect on the user’s acceptance of voice assistants and the actual use of voice shopping. Thus, proposing the hypothesis:

H7: Perceived social interactivity is positively related to customer acceptance of voice assistants.

#### *4.2.3. Perceived social presence*

Perceived social presence embodies the third social-emotional element of the sRAM and is expected to influence the customer acceptance of service robots and, subsequently, the consumer behavior and the actual use of service robots (J. Wirtz et al., 2018). Humans are anthropomorphizing robots; however, the level of humanizing depends on the social presence, which Heerink et al. (2008) define as the perception of being in company of somebody or as the degree to which a person perceives being surrounded by another social entity. J. Wirtz et al.

(2018) describe social presence as the impression that somebody is looking after you. Lankton et al. (2015) refer to the capability to communicate social signals, which a VA does through its social nature and interactions. In the field of AI, it can be explained as the competence of a service robot to talk to persons and give them the impression of relating with an actual social entity (McLean & Osei-Frimpong, 2019).

Heerink et al. (2010) argue robot acceptance research can be divided into two categories: on the one hand in functional acceptance and on the other hand in social acceptance, while the social behavior of a robot in the elderly care plays a pivotal role regarding the acceptance and use. Robots are in use in several sectors, such as health, aerospace, and tourism, and part of their success depends on the social skills to behave responsively and act in a natural and intuitive way with persons (Breazeal, 2003).

Various theories, such as the social presence theory, clarify the factors determining the extent of anthropomorphic appearance of a technology (Lankton et al., 2015). The social presence theory postulates that the traits of a technology effecting the perception of warmth and sociability are built on the level of feeling someone being psychologically nearby (Lankton et al., 2015). Although the service output may be the same, the manner of seeing and accepting a VA differs from person to person depending on the perception of the social presence of the VA (Belanche et al., 2019).

Independent of a virtual robot or a physical robot, the communication skills of a VA while interacting with a customer function like an anthropomorphic trait that elicits social presence; consequently, the customers react with a social behavior and interact with the robot like with other humans (Chattaraman et al., 2019). The model of Verhagen et al. (2014) shows as determinants of social presence, friendliness and expertise most probably leading to more social online service encounters and service encounter satisfaction, particularly with a socially oriented interaction style. Qiu and Benbasat (2009) examine product recommendation agents presenting that the anthropomorphized embodiment and voice-based speech have a positive impact on the customers' perceived social presence, leading then to more perceived enjoyment.

According to J. Wirtz et al. (2018) social presence shows an impact on the creation of trust between parties, as people who meet in person are more likely to build trust. Due to social presence trust can grow, as it minimizes uncertainty and risk and leads to a positive attitude toward the technology (N. Kumar & Benbasat, 2006). Moreover, the survey by Chattaraman et al. (2019) reveals social-oriented robots enhance trust, especially for older consumers with advanced internet skills, and with their social presence they can overcome the distrust.

The study by Fernandes and Oliveira (2021) examines in general a positive direct impact of social presence on the acceptance of VAs; however, by dividing the users according to their preferences, the group preferring human-robot interaction shows no direct influence on the acceptance, whereas the group favoring human-human interaction presents no indirect influence through perceived trust and rapport. According to Chattaraman et al. (2019) social presence influences customers who prefer a human-technology service only if it supports building a relation with the VA based on trust and rapport, thus, if the users' ambition is a mutual, trustworthy, and pleasant communication.

Referring to McLean and Osei-Frimpong (2019) the main player for a successful technology is social presence, serving as a motivating factor and only enabled by the progressions in AI using machine learning and natural language processing for comprehending the consumers and especially their preferences. Due to social presence, the users may communicate with a VA as they do with a real person (Chattaraman et al., 2019). Based on this, Al-Makhmari et al. (2023) suppose that social presence has a positive effect on the consumer as well as on the acceptance of VAs. The study by Amelia et al. (2021) confirms the majority of participants see the VA as a partner and behave in a social manner by thanking the VA for the service, which implies the aptitude for building a human-robot connection.

Customers experiencing a VA more frequently rather value the social presence and see the VA as easy to interact with, collaborative, competent, and trustworthy (Fernandes & Oliveira, 2021). Anthropomorphic characteristics of a machine-generated voice are specifically important for the perceived social presence (Purington et al., 2017). Results of K. M. Lee and Nass (2003) indicate the perception of social presence rises by customizing the robot's voice and adjusting it according to the customers' personality; therefore, an extrovert person senses more social presence with an extroverted voice, and an introvert person perceives a higher social presence with an introverted voice. However, in general, it can be said that an extroverted character stimulates and maximizes the perceived social presence and is supportive, especially in situations where favorable social behavior is needed (K. M. Lee & Nass, 2003). Prior research reveals in the field of branded mobile applications that social presence helps to increase the consumer brand engagement and, consequently, the repurchase intention and continuous usage through relationship building based on social cues (Fang, 2017). The perceived sense of emotional closeness with an app considering warmth and human interaction evokes a positive impression toward a brand; accordingly, the consumers are more willing to spend more energy and time with the technology, thus, building a connection with it and considering the brand more often (Fang, 2017). Heerink et al. (2008) examine the robot acceptance for elderly people by adding the variables perceived enjoyment, perceived sociability, and social presence, and findings highlight perceived sociability provides a feeling of social presence during a human-robot interaction and consequently has a positive effect on enjoyment, thus leading to an increased acceptance, followed by usage.

Nevertheless, the timing of the verbal as well as the non-verbal behavior presents a difficult challenge for social robots, and further development is needed, as for example, in the educational context (Alam, 2022). Additionally, the high expectancies of the customers toward the social presence of a VA can be very demanding (Fuentes-Moraleda et al., 2020). Moreover, for customers who prefer experiencing a personal service, using a VA can be less pleasing (Fernandes & Oliveira, 2021). Furthermore, persons who do not often use a technology and are therefore confronted with various online barriers rather tend to feel disaffection and nervousness when communicating with humanoid robots (Chattaraman et al., 2019). Even though the results of Heerink et al. (2010) suggest a higher perceived sociability has a positive effect on the social presence and on perceived enjoyment, there is no effect of social presence on the perceived enjoyment leading to intention to use.

Fernandes and Oliveira (2021) shed light on the indirect impact of social presence on consumer acceptance of VAs being mediated by the relational variables perceived trust as well as rapport. Furthermore, perceived social presence works as a mediator of perceived social interactivity (Fernandes & Oliveira, 2021). The study by van Doorn et al. (2017) creates a conceptual framework and concentrates on how automated social presence influences the service customer outcome through social cognition, including warmth and competence, as well as psychological ownership, including receptiveness, attractiveness, and manipulability. Additionally, it considers customer attributes such as relationship orientation, anthropomorphization, and technology readiness playing a moderating role between automated social presence, social cognition, and psychological ownership (van Doorn et al., 2017).

According to Heerink et al. (2010), if a robot seems to have social abilities, the perceived social presence grows. The skill of a VA having a humanlike conversation arouses the feeling of social presents and, in addition, causes a social response from the customer (Chattaraman et al., 2019). Transferring this to voice shopping, if a consumer is able to have a natural conversation with a VA as with another human, he senses a social presence. Thus, if the VA shows appropriate emotions during the shopping process, the consumer can have the feeling of another person being present. Additionally, J. Wirtz et al. (2018) argue that the perceived social presence of a system has a positive impact on the acceptance as well.

The more the user perceives Alexa as a social entity, the more might increase the acceptance of using the VA for voice shopping. Hence, it is expected:

H8: Perceived social presence is positively related to customer acceptance of voice assistants.

### *4.2.4. Hedonic motivation*

Referring to Davis et al. (1992) besides the usefulness of a new technology the enjoyment is vital for the technology acceptance, and thus, Venkatesh and Bala (2008) include the perceived enjoyment as an essential variable in the TAM3. Perceived enjoyment is explained as the degree to which the interaction of utilizing the computer is perceived as enjoyable by itself, independent of any expected outcome (Davis et al., 1992). Thus, enjoyment can be seen as a common behavioral belief as it is dependent on the pleasure while utilizing a technology (Lankton et al., 2015). Venkatesh et al. (2012) add the variable hedonic motivation to the UTAUT2, which can be explained as the feeling of enjoyment or amusement of a person when utilizing a technology (Melián-González et al., 2021). Hedonic motivation (positive emotions) in the field of voice shopping is defined as the degree someone perceives the use of a VA during the procedure as enjoyable, diverting, and agreeable (Zaharia & Würfel, 2021).

Hedonic or entertaining characteristics of a robot can be pleasure or fun while interacting or communicating with the robot, which can evoke the same feeling as having a pleasant talk with someone or playing a game (Heerink et al., 2008). Hedonic factors are features users feel while communicating with an AI device, and the study by de Graaf et al. (2015) counts to those enjoyment, in form of having fun; attractiveness, meaning the appearance of the robot; anthropomorphism, thus, humanlike characteristics; sociability, meaning the capability to show social behavior and companionship, hence, seeing the robot as a friend. Based on the study by H. Yang and H. Lee (2019) hedonic value exists out of perceived enjoyment and its subfactors, visual attractiveness and content quality, and particularly that visual attractiveness is more positively related to perceived enjoyment than content quality.

Even though the influence of enjoyment on the utilization of a technology are postulated in the TAM3 and the UTAUT, nevertheless, this may vary according to the situation (Venkatesh et al., 2012). Persons who are intrinsically driven are usually inspired by hedonic values such as amusement and diversion (Moussawi et al., 2021). A former study on websites exposes social attributes stimulate the social perception, and indirectly through arousal, flow, and pleasure the hedonic value increases; however, the impact of arousal is higher on hedonic value for women (L. C. Wang et al., 2007). The study by Qiu and Benbasat (2009) shows social presence having an impact on perceived enjoyment as well as perceived sociability (Heerink et al., 2010). Furthermore, the perceived enjoyment functions as an antecedent of perceived ease of use instead of being driven by it (Heerink et al., 2010). Perceived security can function as a driver for hedonic motivation, as for example, in the area of electronic banking (Salimon et al., 2017).

Moreover, trust is related to hedonic motivation, as the less risk and doubt a person perceives, the more comfort the person feels and, therefore, enjoys the technology (Lankton et al., 2015). Results of van Pinxteren et al. (2019) indicate a strong effect of perceived trust on users' perceived enjoyment and the influence of perceived enjoyment on the users' intention to utilize humanoid service robots.

The model of Al-Makhmari et al. (2023) extends the functional elements by the variable perceived enjoyment and expects a positive direct influence on the user acceptance of VAs. According to Venkatesh et al. (2012) hedonic motivation is the key factor in technology acceptance.

Based on the analysis of Heerink et al. (2008) even though in elderly care the utilitarian benefits play a pivotal role for the intention to use a robot, the perceived enjoyment has a strong influence as well. In the Almere model the direct effect of perceived enjoyment on the intention to use is confirmed (Heerink et al., 2010). Another study points out in order to increase the use of VAs, it is vital that possible consumers perceive the hedonic value rather than the utilitarian value (H. Yang & H. Lee, 2019).

By applying the uses and gratification theory (U&G theory) in the field of mobile apps, hedonic benefits have a positive impact on satisfaction as well as buying intents (Alnawas & Aburub, 2016). Moreover, by combining UTAUT2 and cultural moderators in the area of mobile banking in Africa earlier literature indicates a positive result of hedonism on behavioral intention (Baptista & Oliveira, 2015). Findings of Alalwan et al. (2017) confirm hedonic motivation has a positive impact on the adoption of mobile banking customers in Jordan due to perceived joyfulness, entertainment, fun, and satisfaction in utilizing new technologies. The extended sRAM of Amelia et al. (2021) adds as a further dimension below the theme customer responses toward frontline service robots the enjoyment of interaction leading to customer acceptance in retail banking services.

The service robot integration willingness scale of L. Lu et al. (2019) considers the emotional and hedonic benefits as elemental factors of the scale showing a noticeable outcome on the willingness of the users, especially when evaluating long-term service robot acceptance.

Referring to Kowalczuk (2018) the variable perceived enjoyment has a significant impact on the intention to use a smart speaker. Findings of Rzepka et al. (2020) highlight one among the three advantages of voice shopping is enjoyment. The communication and interaction with the VA during the buying process with a smart speaker can be entertaining for the customer (Zaharia & Würfel, 2021). The survey differentiates between the intention to buy a product and the intention to gather information; however, hedonic motivation is showing a positive effect on both (Zaharia & Würfel, 2021). Furthermore, the study by K. Lee et al. (2019) explains besides the factors compatibility and perceived security, hedonic motivation has a meaningful effect on satisfaction, which leads to continuous use of VAs.

Furthermore, in the existence acceptance model, enjoyment is part of the expected-interactional elements showing a direct positive effect on existence acceptance (Abrams et al., 2021). In the field of chatbots for travel and tourism, Melián-González et al. (2021) examine and confirm a positive effect of adding enjoyment and the hedonic view. Referring to Chi et al. (2020) hedonic motivation is a vital element for customers assessing service robots in the hotel sector. Yet, the extraordinary expectations of the hotel guests regarding experiences with actual shared emotions have to be taken into consideration (Fuentes-Moraleda et al., 2020). Considering the artificially intelligent device use acceptance (AIDUA) theory, hedonic motivation has an impact on the adoption in hospitality services, where the clients appear to have high standards for hedonic benefit (Lin et al., 2020). As soon as a customer believes that the utilization of a technology is giving pleasure, the later assessment of the user experience is most probably positive (Lin et al., 2020).

The study by Gursoy et al. (2019) investigates hedonic motivation as an antecedent of consumers' willingness to accept the utilization of AI devices in the primary appraisal phase, showing a positive relation between hedonic motivation and performance expectancy, leading via emotion to the willingness to accept.

Nevertheless, there is no relation between hedonic motivation and effort expectancy (Gursoy et al., 2019). The survey by McLean and Osei-Frimpong (2019) grounded in U&G theory and technology acceptance models, reveals even though acceptance variance is influenced by social benefits, hedonic advantages have no impact on the motivation of the consumers to use a VA, only in small households it may encourage the users. This might occur due to the absent human interaction, which is given in large households (McLean & Osei-Frimpong, 2019).

Results in the field of electronic banking indicate hedonic motivation being a mediator between perceived usefulness, perceived security, and the adoption of electronic banking (Salimon et al., 2017). Another study assesses the hedonic value of users' social communication with a VA, and the results expose perceived enjoyment has an indirect effect on the usage intention via perceived usefulness (Qiu & Benbasat, 2009). For AI driven devices hedonic consumer beliefs are deriving from the perception of intelligence via the perception of anthropomorphism, leading to perceived enjoyment and directly influencing positively the intention to adopt (Moussawi et al., 2021).

In the specific context of VAs, the customer can have an extensive chat with a VA, this interaction can provoke an entertaining positive emotion (Klaus & Zaichkowsky, 2020). Furthermore, VAs are capable of making jokes, which may arouse an emotional bond between the VA and the customer, similar to having a conversation with a friend (Han & H. Yang, 2018). Build on this, the consumers' voice interaction with the VA while shopping can be entertaining. Moreover, customers tend to rely on VAs with a pleasant, enjoyable, and delightful voice (Klaus & Zaichkowsky, 2020). Referring to K. Lee et al. (2019), voice shopping might be mainly determined by enjoyment, as it is only an alternative way to the existing and well-established online shopping.

Therefore, the factor hedonic motivation is considered and added to the original sRAM, showing there might be further meaningful variables influencing the voice shopping acceptance. This leads to the following:

H9: Hedonic motivation is positively related to customer acceptance of voice assistants.

## 4.3. Hypotheses related to relational elements

The third part of elements of the original sRAM, which appears to gain more importance for the customer acceptance, consists of the relational elements trust and rapport (Stock & Merkle, 2018).

### *4.3.1. Trust*

Trust presents one of the two relational elements of the sRAM and is the second most vital driver and confirmed variable in technology acceptance (Fernandes & Oliveira, 2021). Overall, studies differentiate between various forms, levels, objects, and sources of trust, based on the study by Welter (2012) there exists personal trust in other individuals on a micro level, collective trust in the company on a meso level, and international trust in the government on a macro level. Table 4.1 gives an overview.

TABLE 4.1: **Forms, levels, objects and sources of trust**

| **Forms** | **Level** | **Object** | **Source** |
|---|---|---|---|
| Personal trust | Micro | Relationship, person | Emotions, intentions, goodwill, benevolence, characteristics of persons, experiences, knowledge, competencies |
| Collective trust | Meso | Community (e.g., kinship, ethnic group, profession)<br>Organization (e.g., network, firm, association)<br>Industry | Characteristics of groups, information, reputation, recommendation certification, professional standards |
| Institutional trust | Macro | Cultural rules (e.g., norms, codes of conduct, values)<br>Formal regulations (e.g., laws, certification, licenses)<br>Business infrastructure (e.g., business courts, administration, financing organizations)<br>Government | |

Source: Welter (2012)

Trust can be seen as a multidimensional concept, as objects and sources of personal and collective trust interrelate; for example, persons and relationships between persons are part of communities and organizations; accordingly, personal trust can stimulate collective trust, whereas the sources of collective and institutional trust are comparable (Welter, 2012).

The study by Lankton et al. (2015) confirms in general the importance of trust and the ability of persons to trust in technology; however, differentiates between two forms of trust: humanlike trust including goodwill, honesty, and capability, and system-like trust including treats such as usefulness, dependability, and functionality.

J. Wirtz et al. (2018) describe trust as a multidimensional construct and distinguish between benevolence, considering the robot acts with the best of intentions for the customer, perceived competence, and arising from the IS literature emotional trust, the level of feeling safe and comfortable while being dependable on the robot.

Considering Siau and W. Wang (2018) there are three ways of seeing trust: first, as a bundle of beliefs including benevolence, competence, honesty, and probability; second, as a trusting intention; and third, combining the first two. The study by Komiak and Benbasat (2006) explains the trusting beliefs as cognitive beliefs, resulting from noticed interactions and linked to features of trust, such as competence or integrity. Furthermore, attributes such as competence and integrity are regarded as strongly linked with customer trust in the trustee (Chattaraman et al., 2019).

Former research points out that, especially for engagement with technology, trust is an essential antecedent (B. Lu et al., 2016). Referring to commerce and cyber transactions, trust is fundamental for being successful, and without trust a business or buying a product or a service might not take place (D. J. Kim et al., 2008). Especially in the e-commerce context trust shows its significance, as there can be a lot of uncertainty (Pavlou, 2003). Furthermore, with the arise of human-robot relations the creation of trust is crucial (Pitardi & Marriott, 2021). Even if service robots can be beneficial for customers and companies, missing trust impedes the technology acceptance (van Pinxteren et al., 2019). Moreover, it is vital for users that the technology works dependable and does not extradite them to any risky situation, evoking anxiety and minimizing the willingness to adopt (Al-Makhmari et al., 2023). In the decision making process customers' trust in the goodwill of the technology is important, independent if it's a low involvement decision or a high involvement decision (Klaus & Zaichkowsky, 2022). Additionally, trust is critical when it comes to brand management, and consumers prefer spending money on a service or product of a brand they trust, even if they have to pay more for this preferred brand than for other brands in which they trust less (Chaudhuri & Holbrook, 2001).

Users have various ways to perceive and develop trust in a technology; mostly, they link trust to the personality of the user interface of the technology, other options are relating with the hardware, the software, or the producer (Klaus & Zaichkowsky, 2022). Trust in AI and trust in other technologies are designated by human and environmental characteristics; nevertheless, the technology characteristics differ regarding performance, process, and purpose (Siau & W. Wang, 2018).

By giving attention to trust in the field of AI, the creating of initial trust as well as the building of continuous trust are relevant (Siau & W. Wang, 2018). According to the research of Q. Yang et al. (2015) examining the relation between trust and risk in the field of online payments in China, the building of initial trust is crucial to overcome the insecurities toward financial transactions, and therefore, at the beginning trust functions as an antecedent of perceived risk. In the context of mobile banking, trust can be seen as the gathering of consumer beliefs of benevolence, honesty, and capability that could have a positive effect on the willingness to use mobile banking for monetary transfers (Alalwan et al., 2017). Referring to Poushneh (2021b) trust in the specific environment of VAs can be explained as the level to which users perceive the VA as honest and genuine and that the VA accomplishes tasks in a reliable way.

The belief that a technology functions dependably has a positive effect on the feeling of confidence during the service experience (J. Wirtz et al., 2018), thus, by providing confidence to the customer, the doubts decrease and the willingness to accept the technology increases (Fernandes & Oliveira, 2021). The survey by Fuentes-Moraleda et al. (2020) reveals trust is vital in human-robot interaction; however, errors by robots, such as communication mistakes, especially in translations, but also in the service itself, as for example, long waiting times for a room service, can cause insecurity and lower the trust level. Therefore, the correct performance of the VA by comprehending the requests and delivering the adequate answers raises the level of trust and consequently improves the relation between the customer and the VA (Han & H.

Yang, 2018). Furthermore, the study by Heerink et al. (2008) assesses the perceived sociability as a construct in a technology acceptance model and lists gaining trust as a social ability, and in order to achieve trust the following VA features are required, such as confessing errors, using the users' names, or memorizing other particular details. Additionally, there are various contextual aspects necessary for trust building, including specific traits of customers such as the preference for personal contact, self-effectiveness, and service settings (Wuenderlich & Paluch, 2017).

The study by Touré-Tillery and McGill (2015) focuses on the different levels of trust users have toward human and anthropomorphized messengers, revealing users with a low level of interpersonal trust rather pay attention and tend to believe a humanlike messenger than a person, as they expect a lack of goodwill in people. Whereas customers with a high level of interpersonal trust react almost equal to an anthropomorphic messenger as well as to a person, because for customers it is not of importance who is trying to talk them into something; however, they expect a person acting in goodwill, and therefore, they pay more attention to humans (Touré-Tillery & McGill, 2015).

In general, humanlike features seem to have a positive influence on trust to a particular degree because of the uncanny valley theory (Tinwell et al., 2011). Former research indicates the uncanny valley theory has an impact on the customers' trusting behavior and users assess the social trustworthiness by evaluating small signs and gestures in the same manner as with humans (Mathur & Reichling 2016).

Referring to Pitardi and Marriott (2021) drivers of users' trust are the two traits social presence and social cognition, which is the information processing of other persons. Considering research in social cognition, in general, persons distinguish others by liking, including trustworthiness and warmth, as well as by respecting, involving competence and efficacy (Fiske et al., 2007). According to J. Wirtz et al. (2018) trust can be created through social presence.

Furthermore, findings of Fernandes and Oliveira (2021) confirm besides the strong direct influence, perceived trust is functioning as mediator between perceived social presence and the customer acceptance of VAs.

Referring to Klaus and Zaichkowsky (2022) trust can be linked to the feelings users develop by interacting with a VA, in particular if the communication is perceived as human. Another study suggests interaction quality as a vital factor in order to build trust and explains it as “the extent to which the influence of intelligent application has on human in the AI-based technology context” (Nasirian et al., 2017, p. 4). Additionally, customers feel empowered by activating a VA via command and herewith, effecting engagement behaviors more precisely, inducing positively the degree of trust and at the same time decreasing the perceived level of risk (Q. Yang et al., 2015).

The study by Pavlou (2003) integrates trust and perceived risk in the research model based on TAM and highlights the importance of trust toward the acceptance of e-commerce, first in an exploratory study, followed by a confirmatory study. The results of B. Lu et al. (2016) confirm the strong direct effect of trust on purchase intention of customers and separate the variables in trust in seller and trust in marketplace, as both relations are necessary before making a buying decision. Findings of Abrams et al. (2021) suggest a positive influence of trust toward existence acceptance for autonomous systems.

However, referring to McLean et al. (2021) trust as an AI feature evokes doubts and leads to a negative behavior, as customers have an uncomfortable feeling regarding financial security and personal data, consequently, VAs are affecting consumer brand engagement and limiting the brand engagement. Results of Moussawi et al. (2021) indicate the consumers’ perception of intelligence effect the perception of initial trust; however, there is no direct relation from initial trust to intention to adopt, probably due to missing experience, which might be necessary for developing solid initial beliefs of trust. Therefore, experience seems to play a pivotal role in trust building and by getting used to a technology or a robot, the customer develops trust and feels more secure (Tung & Au, 2018). Moreover, technology readiness may play a moderating role, as a user with a high technology readiness rather tends to be open to new things and thus indicates more trust in a technology, and therefore, warmth and competence are positively influenced (van Doorn et al., 2017).

It is worth noting that using VAs involves entrusting power to a robot, and therefore, fulfilling the relational needs of a customer is essential to achieve acceptance (Fernandes & Oliveira, 2021). Trust is inevitable (Klaus & Zaichkowsky, 2022) and connected to the sentiments the customer feels by interacting with the VA, and especially social skills enable a VA to gain more trust of a consumer (van Doorn et al., 2017). Principally in the field of voice shopping, trust is essential because the VA embodies the individual requirements and preferences of a user (Komiak & Benbasat, 2006).

Referring to this, if the VA is able to convey a trustworthy feeling and gives the impression of taking care of the shopping process, the consumer will be more willing to adopt. Therefore, a further hypothesis is raised:

H10: Trust is positively related to customer acceptance of voice assistants.

#### *4.3.1.1. Control*

To investigate the drivers of trust and rapport further antecedents need to be examined. This research focuses on the antecedents control, risk, and personalization. Many researchers put forward definitions of the term control from different approaches, for example, perceived control implies the perception of a person that the produced result derives from their own actions (Ajzen, 1991). Whereas another study describes perceived behavioral control as either the perceived ease of use or the effort of using something, as for example, the web, and relies on the possibilities and occurrences accessible to the user (Hoffman & Novak, 1996).

Considering the study by Fiske et al. (2007) warm behavior is rather understood as controllable, whereas competent behavior is perceived as not being under direct personal control. In the field of self-service technology perceived control is defined as “a belief in one’s ability to command and exert power over the process and outcome of a self-service encounter” (Collier & Sherrell, 2010, p. 492).

Prior studies indicate one of the main antecedents of trust presents control (Poushneh, 2021b), being a paramount factor in enhancing the customers’ confidence (Hoffman & Novak, 1996). In the area of digital devices users have to cope with more and more challenges in comprehending the technical features, interacting and communicating with them, and thus, they need to perceive control over the digital device (Schweitzer et al., 2019). Additionally, it is examined as a prerequisite for successful adoption, as a user may hesitate to use or continue using a technology, if he does not perceive control over the technology (Taylor & Todd, 1995). Consequently, control fosters the link between the technology and the user (Venkatesh, 2000). Control is considered as an essential ingredient for outcome responsibility, especially in the service encounters with robots (Jörling et al., 2019). Due to the digital disruption, changes in the decision making are given considering low and high involvement decisions, where control and trust are vital, and by positive experience with low involvement decisions, the high involvement decisions may be more facile (Klaus & Zaichkowsky, 2022).

Former technology acceptance models apply different types of control. The theory of planned behavior (TPB) by Ajzen (1991) considers the perceived behavioral control directly influencing the intention as well as indirectly the behavior via the intention. The study by Venkatesh (2000) applies control in a different way than the TPB and sheds light on control as a determinant of perceived ease of use in the TAM and the more familiar a user becomes with a technology, the more the perception of the external control grows and positively affects the perceived ease of use. Thereby, differentiating between internal control, including computer self-efficacy, and external control, including facilitating conditions (Venkatesh, 2000).

The TAM3 considers as an anchor the perceptions of external control and its impact on perceived ease of use (Venkatesh & Bala, 2008). Additionally, the model combined TAM and TPB (C-TAM-TPB) involves the perceived behavioral control in order to predict user behavior (Taylor & Todd, 1995). Whereas the conceptual framework of Poushneh (2021b) focuses on the perceived auditory control and its consumer responses, referring to the degree to which a customer has the impression of being in control while having an audio communication with a VA.

The study by Welter (2012) sheds light on the duality of trust and control and its interdependencies that occur between trust and control across diverse contexts. Table 4.2 gives an overview.

TABLE 4.2: **Interdependencies of trust and control across trust contexts**

| **Function of trust in relation to control** | **Complement** | **Substitute** |
|---|---|---|
| High-trust contexts: | | |
| Institutional trust | Institutional trust complements legal regulations (control at macro level) and functions as an informal, culturally based sanctioning mechanism | Institutional trust can substitute for personal trust in business relationships if entrepreneurs prefer control instead of trust |
| Personal trust | Complements institutional trust and control mechanisms, works as additional control mechanism at individual level (reputational and social control) | Can substitute for control mechanisms at the micro level if business partners forgo contracts |
| Low-trust contexts: | | |
| Institutional trust | Not applicable | Not applicable |
| Personal trust | Not applicable | Substitutes for lack of institutional trust and control mechanisms (legal sanctions), works as sanctioning mechanism, but does not imply less reliance on control in form of contracts |

Source: Welter (2012)

Institutional trust and personal trust, respectively, trust and control are able to complement and substitute each other (Welter, 2012). The study by van Doorn et al. (2017) relates the need for control to manipulability, which is part of psychological ownership and effecting the service and customer outcomes. From an AI point of view, consumers perceive control differently and depending on the type of service robot, as for example, heaters, automobiles, and lawn mowers can cause diverse perceptions (Jörling et al., 2019). In the context of automated technologies at the service frontline, the utilization and application of them involve assigning the control to a service robot (Fernandes & Oliveira, 2021). There is a link between assigning the buying decision to VAs and the feeling of control, because the relation to the VA is comparable to the relation of a supportive friend (Klaus & Zaichkowsky, 2020).

VA users are able to create a feeling of power because the communication between them and the VA is without any negativity and discussions; moreover, the reactions and interactions of the VA are fast (Klaus & Zaichkowsky, 2020). Functional intelligence, sincerity, and creativity have a positive impact on the users' perceived control, leading to a voice interaction flow experience during the voice interaction with a VA (Poushneh, 2021a). Social interaction, especially via voice, functions as a driver of perceived control and accordingly has a positive impact on trust, as for example, the prompt replies by a VA transmit a feeling of control, and by receiving this perceived auditory control the level of trust in the VA rises (Poushneh, 2021b).

Findings highlight in the self-service technology control has more impact through the mediating variables of speed of transaction, exploration, and trust in service provider (Collier & Sherrell, 2010). Considering online retail business, the customers perceive a certain degree of control, as they can decide when and what kind of content of the given website to see (L. C. Wang et al., 2007). The survey by Q. Yang et al. (2015) investigates in the field of online payment in China the relation between perceived risk and trust by applying perceived risk, perceived usefulness, and perceived ease of use as a construct of perceived behavioral control and showing the effect on trust in online payment systems. According to a study investigating active control in branded mobile applications, a high level of interactivity indicates that the person is able to control the interaction with these apps, and consequently evocates a positive brand perception (Fang, 2016). Thus, active control has a positive influence on interactivity, which leads to consumer brand engagement and either continuance intention of using the app or repurchase intention of the brand (Fang, 2016).

The study by Amelia et al. (2021) reveals facilitating conditions, which besides resources and knowledge exist out of control, are dependent on the situation. Furthermore, task complexity can have an impact on control, by increasing task complexity, the perceived control over the situation decreases (Amelia et al., 2021). In IS research, some users face the anxiety that technology may rule their daily life and they may lose control of these technologies, leading to a higher need for improved system behavior control (Moussawi et al., 2021). Another study addresses the influence of autonomous robots on the social acceptance, their perception as a threat to persons, security, and resources, as well as the evoking negative attitude due to the feeling of losing control over the robot (Złotowski et al., 2017). In the context of service robots, the technology autonomy of robots lowers the perceived behavioral control and, herewith, the perceived responsibility for positive effects, nevertheless, the possibility to interfere the autonomy raises the perceived behavioral control and the perceived responsibility (Jörling et al., 2019).

The capability to control can increase the individuals' privacy concerns, as the vulnerability of revealed information discloses the loss of control and therefore raises the perceived privacy risk (Bansal et al., 2016). When it comes to users' security and data privacy, the control of personal data is limited and can have a negative effect on the adoption (Chi et al., 2020). According to Rzepka et al. (2020) the limited control is one of the main costs of voice commerce, and the principal disadvantages arising from using a VA are the missing manual input modality, the risk of understanding something incorrectly, and the possible improper use by others. Besides the impact on trust, perceived auditory control empowers the users to communicate with the VA and elicits a feeling of pleasure with the brand, however, an unforeseen reply causes a feeling of surprise, diminishing the power of perceived auditory control (Poushneh, 2021b).

Referring to Pavlou (2003) control can be seen as a part of trust, respectively, as trust in the control mechanism; moreover, risk is related to control, as perceived risk can reduce the perceived behavioral control and therefore, rather leading to a negative intention to transact.

Customers need to perceive control over the VA, as they face more and more difficulties in understanding the technical features, especially considering the social-emotional intelligence (Schweitzer et al., 2019). Based on Q. Yang et al. (2015) it is notable that the consumers' perceived control has a positive effect on trust. Furthermore, social interactions via voice drive perceived control, and consequently cause a positive impact on trust (Poushneh, 2021b). The VA replies quickly to commands and questions, does not discuss, and the conversation takes place without any negativity, therefore the user develops a sense of power (Klaus & Zaichkowsky, 2020).

By activating the VA through keywords, the user might feel more in control and consequently rather trusts Alexa and the voice shopping process. Leading to the following hypothesis:

H11: Control is positively related to trust toward voice assistants.

#### *4.3.1.2 Risk*

Risk presents a further critical antecedent in predicting technology acceptance, and moreover, it is an essential factor, especially in e-commerce, due to the structure and environment of the internet and the corresponding transactions (Pavlou, 2003). A person identifies a situation as a risk when a setting seems to bring undesired results and when the incidents of these results are not controllable; consequently, the level of risk depends on the severity of the consequences and their controllability (Koller, 1988). Based on this understanding of perceived risk, a user expects that not only the likelihood of each interaction is unsure but also the result of each interaction (Dowling & Staelin, 1994). Generally, risk is defined as "felt uncertainty regarding possible negative consequences of using a product or service" (Featherman & Pavlou, 2003, p.

453), whereas in e-services perceived risk is defined as “the potential for loss in the pursuit of a desired outcome of using an e-service“ (Featherman & Pavlou, 2003, p. 454).

Referring to Koller (1988) the level of risk within a situation influences the level of trust a person builds toward a communication partner. For customers risk counts as one of the most important factors when purchasing a new brand or product (Grewal et al., 1994). Furthermore, the user perception toward risk is one of the major barriers and challenges for technology acceptance (Pavlou, 2003) and especially, the financial transfers are perceived as uncertain for the users (Q. Yang et al., 2015). Moreover, perceived risk is being recognized as significant and a generally conversed theme, mainly in the data privacy and data security context (Haug et al., 2020). Therefore, the importance of reducing risk of privacy and security is significantly high (Han & H. Yang, 2018).

In the area of economics, the subject risk gains attention in the early 1920s and researchers apply the variable in their decision making theories (Dowling & Staelin, 1994). In the marketing literature the perceived control appears for the first time in the 1960s, followed by literature on risk taking, information handling, and risk as an explanatory factor in the field of consumer behavior (Dowling & Staelin, 1994).

A review on consumer behavior literature distinguishes between six types of perceived risk: financial, performance, physical, psychological, social, and time risk (Jacoby & L. B. Kaplan, 1972). Referring to the study by Q. Yang et al. (2015) the perceived risk can be grouped into either system-dependent risk, which is positively linked to trust and includes functional risk, security risk, time risk, and social risk, or transactional risk, which is negatively linked to trust and includes economic risk, privacy risk, service risk, and psychological risk.

The study by Featherman and Pavlou (2003) sheds light on the perceived risk facets and concerns of customers in e-services, who focus mainly on the time efficiency and, thus, the possible risk of losing time. The seven perceived risk facets involve the performance risk, financial risk, time risk, psychological risk, social risk, privacy risk, and overall risk, presenting a common measure of perceived risk when the evaluation of all criteria takes place together (Featherman & Pavlou, 2003).

Research in the field of self-service technologies reveals human or technical mistakes during transactions bear a possible risk for users; however, considering tasks with low complexity, there might be a positive effect on the behavior, as the avoidance of mistakes can have a motivational impact on task performance (Blut et al., 2016).

Research in the field of AI and VAs reveals that risk bears a negative impact on the behavioral intention to use a VA (Kowalczuk, 2018). Additionally, referring to voice shopping, Zaharia and Würfel (2021) extend the UTAUT2 by perceived risk and supposing a negative impact on the behavioral intention of purchase and the behavioral intention of information. The study by Zaharia and Würfel (2021) clusters the risk in functional risk of the technologies, such as the understanding of voice commands, financial risk referring to payments, as well as personal risk considering data privacy and security, demonstrating all three types of risk have an impact on the factor trust.

Functional risk or performance risk can be described as the probability that a product will not work as anticipated or will not deliver the wanted output (Grewal et al., 1994). From an AI point of view, the functional risk that technology users are perceiving might be a false interpretation of a voice command by a VA (Zaharia & Würfel, 2021). In the online payment setting users are concerned with steadiness and dependability, especially in the initial stage, and therefore, functional risk is significant (Q. Yang et al., 2015).

A further critical facet of risk is the financial risk, which can be defined as the possible economic expense linked with the first buying price and the following maintenance and repair costs of the product (Grewal et al., 1994). Studies in financial services extend this type of risk by the possible returning monetary loss because of deception or overpriced rates by service suppliers (Featherman & Pavlou, 2003). Considering voice shopping, financial risk is given due to buying activities connected with the shopping procedure (Blut et al., 2016). For instance, a financial fraud can occur by another user buying a product without authorization (Haug et al., 2020).

The third vital facet of risk and key impediment is personal risk existing of data privacy risk, such as recordings and storing of data, as well as security risk, such as stored bank account data (Kowalczuk, 2018). Referring to Han and H. Yang (2018) privacy and security can be defined jointly as consumers anxiety about illegal access to VAs by other parties and possible damage from revealing private customer data to VAs. In general, data privacy can be defined as a sort of control over the possible usage of personal information (Bélanger & Crossler, 2011). Data privacy risk involves the probable loss of control over data related to a person and utilized without this person’s knowledge or permission, for example, the use of someone’s identity to undertake illegal transactions (Featherman & Pavlou, 2003). Bansal (2017) distinguishes between privacy and security by defining security as the safeguard from malicious players who intend to abuse data for several reasons, such as gaining additional income. Security risk can be related to cybercriminals and explained as the potential data leakage caused by third parties (Bansal, 2017). In online payments Q. Yang (2015) includes technical and delivery concerns in security risk, bearing in mind a safe financial transaction.

The notion of information privacy started in the mid-1980s and besides the area of information systems, further studies in law, management, marketing, psychology, and others examine this subgroup of privacy (Bélanger & Crossler, 2011). Revealing personal information means, on the one hand, receiving more advantages such as personalized services, but on the other hand, risking the abuse of their information by others (Pal et al., 2020).

There are several possibilities to gain user information on the internet, especially internet services require personal data such as age and gender; however, the most significant advantage of these data is the quantity, which can be gathered and then provided to third parties (Hess, 2022). According to Bawack et al. (2021b) publishers of web platforms are often confronted with the split between online privacy and low-priced services due to monetized user data. The main problem for VA user derives from the lack of knowledge, how the gathered customer information is utilized (Bawack et al., 2021a).

In the early technology acceptance process privacy plays a more pivotal role, than security (Haug et al., 2020). Findings highlight privacy concerns have a negative impact on the users' intention to adopt to a technology (Hoy, 2018). In comparison to other e-commerce channels, voice shopping implies more privacy concerns due to the continuous listening status of the VAs (Bawack et al., 2021b). Moreover, results of Bawack et al. (2021b) suggest privacy concerns during voice shopping are mediated by users' trust and have an impact on consumer experience performance. The study by McLean and Osei-Frimpong (2019) outlines the moderating role of perceived privacy risk of utilitarian benefits as well as social benefits on the usage of VAs.

Considering users' continuous intention to use a VA, privacy and security risk are critical factors influencing the parasocial relationship negatively (Han & H. Yang, 2018). Therefore, companies and brands have to reduce the privacy and security risk perception (Klaus & Zaichkowsky, 2020). Results of K. Lee et al. (2019) suggest perceived security has an impact on user satisfaction and via habit on group harmony, but after the technology adoption, security concerns are less weighted on the user satisfaction.

Nonetheless, security outlines a critical problem for VAs due to accessibility of others and abusing the access in a malevolent approach, such as acquiring private information, ordering a product, or applying unwanted commands (Hoy, 2018). Security issues in the area of VAs can be distinguished between two kinds of incidents: first, the voice squatting, which means hijacking a voice command; and second, voice masquerading, which comprises eavesdropping talks through impersonation of a service or skill (Zhang et al., 2018). Moreover, due to the insecure access control of the VA Alexa, there are three security vulnerabilities discovered: the weak single-factor authentication, no physical presence-based access control, and insecure access control on the Alexa-enabled device cloud (Lei et al., 2017).

Considering the three main types of risk (functional, financial, and personal) and based on several applied studies, it can be summarized as follows: firstly, consumers might have less trust in a VA, as they perceive a functional risk through wrong interpretation of their voice commands (Zaharia & Würfel, 2021). Secondly, voice shopping bears a potential for financial risk because of the transactions related to the buying process (Blut et al., 2016). Amongst others, an unauthorized person may buy a product very quickly and easily without any effort (Haug et al., 2020). Thirdly, it is notable that personal risk is a major barrier and involves data privacy and security concerns, especially due to the microphone, the recording of the voice commands, and the saved bank account information (Kowalczuk, 2018). Consumers are frequently concerned if their personal data are secure and ethically correct used by other parties (Pal et al., 2020). The shoppers are set out to the risk of data abuse, particularly as they do not know exactly how the gathered data is utilized except for improving the shopping activity, the product, and the service (Bawack et al., 2021a). Although the VA producers Amazon, Apple, Google, and Microsoft take these scruples into consideration, there exists a threat for data to be taken, revealed, or used to denounce persons (Hoy, 2018). Bearing in mind VAs are still in the early majority phase and new to most of the people, the user expectations are not clear for all, therefore, the related mentioned risks may inhibit them to utilize a VA (Haug et al., 2020). Klaus and Zaichkowsky (2020) advise to reduce the perception of personal risk in order to achieve a higher acceptance.

The lower the perceived risk, the higher the trust of the consumer in the VA. Therefore, suggesting the hypothesis:

H12: Risk is negatively related to trust toward voice assistants.

#### *4.3.1.3. Personalization*

The days of mass advertising are numbered, customers are shifting from an anonymous quantity, roughly characterized by some market research data, to an individual dialog to learn more about customers' needs, desires, and shopping behavior (Peppers et al., 1996). Thus, in order to stay competitive marketers constantly apply personalization, if procurable (Ball et al., 2006). With the support of database systems, the gathered user information can be converted into user profiles, helping to predict the user behavior of either a single person or groups (Hess, 2022). The idea of personalization is creating a fit with the consumers' preferences and, herewith, convincing more than with a standardized offer, which might not fit (Rhee & Choi, 2020). A study in the field of fintech investigating robo-advisors describes personalization as a special feature of robo-advisors in comparison to human advisors (Faloon & Scherer, 2017). With regard to VAs, perceived personalization is the level to which a VA comprehends and reflects the individual opinion of a consumer (Mari et al., 2020).

For most of the companies and brands data works as an essential currency and base for successful business, and especially the quantity of data and their evaluation empowers companies to provide personalized contents, services, and products (Hess, 2022). Generally, all firms pursue via the use of data the personalization in form of individual price offers, products, or services for specific customers or customer groups (Morlok et al., 2017). In services personalization presents a powerful tool in order to retain customers (Ball et al., 2006).

The increasing awareness of individual customer approach and one-to-one marketing, which is more effective and less expensive, takes personalization of communication, products, and services to a noticeable level, moving from product marketing to customer marketing (Peppers et al., 1996). The shift from a goods centered view to a service centered view of marketing brings herewith the creation of customer relationships, which are customized and fit the customers' particular requirements, thus generating a competitive advantage and value (Vargo & Lusch, 2004). The personalization of human-computer interaction has improved significantly in the last decade due to the growing amount of user data, advanced computing power, and machine learning reproducing the intricate user behavior, focusing on the users' interest, and the adequate content and action (Sarikaya, 2017). Therefore, by looking at marketing and sales purposes, AI is utilized for delivering a more precise targeting and a tailor-made communication (A. Kaplan & Haenlein, 2019).

There exist different types of personalization, such as service personalization, which can be defined as "any creation or adjustment of a service to fit the individual requirements of a customer (Ball et al., 2006, p. 391). In the case of VAs, service personalization can take place in form of personalized time management, supporting and managing users private and work life in order to be more efficient (Sarikaya, 2017). Another form of personalization is product related personalization, which results in recommended product features being consistent with the consumer's buying preferences; thus, perceived personalization provides the consumer with the feeling of considering their individual needs (Komiak & Benbasat, 2006). The study by M. K. Lee et al. (2012) distinguish between three research groups in personalization: the first group focuses on social and personal interaction; the second concentrates on the design of the system according to the customer preferences; and the third, emphasizes personalized interaction based on iterated encounters.

The personalization of online contents can be achieved through adjustments by the user, such as manual filtering of content, by collaborative filters, or preconfigured rules of the marketer (V. Kumar et al., 2015). Results suggest that personalized messages not only have a positive influence on the attitude toward a product on the web, but that personalized content also has an impact on consumers in a voice-based e-commerce context and independently of product involvement (Rhee & Choi, 2020). In the field of mobile advertising, personalization belongs to one of the most significant antecedents having an impact on the consumers' attitude toward mobile advertising and in this research predominantly female consumers (Xu, 2006). Results of Alalwan (2020) support the benefits of personalization by concentrating on mobile food ordering apps in Jordan and demonstrate the possible enhancement of customers' experience, which can be simply realized by mobile technology. Findings of Smith (2019) concentrate on the generation of digital natives and highlight that for this generation personalization plays a less important role; however, they expect from personalized mobile ads not only to be entertained but also to receive information.

Nevertheless, the main advantage of personalization, especially for marketers, presents the possibility of addressing prospective customers exclusively and consequently building or enhancing the relationship with the customers based on received information such as demographics, preferences, context, and content (Xu, 2006). Research in AI discloses a great advancement in services enabled by mass personalization existing of huge user data amounts, collaborative personalization including service robots collaborating with machines, adaptive personalization, which means adjusting the service according to the monitored consumer behavior, relationship-based personalization, and data-based personalization, deriving from peer data (M. H. Huang & Rust, 2018). The capability of processing huge amounts of data and, herewith, acquiring the customer preferences over time shows the significant impact of AI (M. H. Huang & Rust, 2018). Due to this progress, the user can be personified by four dimensions, which are user profile, digital activity, physical location, and time, leading to a better consumer understanding (Sarikaya, 2017). Therefore, in the area of marketing and sales, AI is essential and beneficial for personalized approaches and interaction (A. Kaplan & Haenlein, 2019). The study by Verhagen et al. (2014) combines the technological basics of personalization with an anthropomorphic service robot style encouraging perceived personalization and showing characteristics of a robot, such as friendliness and expertise, influencing the personalization and, thus, the service encounter satisfaction. A further study sheds light on the personalization of robots for elderly persons in smart homes to be applied by elderly persons, relatives or carers and their willingness to use (Saunders et al., 2016). Generally, AI brings the personalized recommendations forward and many companies and brands apply AI to offering personalized music and movie recommendations (A. Kaplan & Haenlein, 2019).

Comprehending the customer requirements and desires in the fast growing and competitive marketing surrounding is indispensable, and therefore, the benefit of VAs is the capability of learning consumers' preferences and based on these providing recommendations (V. Kumar et al., 2015). Additionally, personalization of the present situation allows VAs to develop context awareness (Mari et al., 2020). The perceived personalization involves the degree to which VAs realize and embody a customer's individual view (Mari et al., 2020). Through personalization individual consumer experience can be enriched while using VAs, hereby, the customer personality presents a crucial factor within the e-commerce sector (Bawack et al., 2021b). Furthermore, through improved understanding of the users' needs and behaviors, VAs progressively affect their behavior and patterns (Simms, 2019). Referring to the privacy calculus framework and the continuous use of VAs, personalization brings a perceived benefit in exchange for personal data, and remarkably, in the VA and IoT ecosystem the customer can receive more benefits the more personal data is revealed (Pal et al., 2020).

Moreover, personalization is one of the principal advantages of voice shopping respective using VAs (Tuzovic & Paluch, 2018). Within voice shopping the personalization can reach a next level, as information can be taken also from the tone of voice, which is not feasible in written conversations (Bawack et al., 2021b). Besides, voice shopping along with personalization empower businesses to develop new goods and services in addition to improving the current offerings (Simms, 2019).

Research indicates personalized services have a positive impact on the customers' loyalty through trust and satisfaction (Ball et al., 2006). In the context of recommendation agents perceived personalization has a positive effect on cognitive trust and leads via emotional trust toward the intention to adopt (Komiak & Benbasat, 2006). The study by Marinkovic and Kalinic (2017) examines the drivers of satisfaction in mobile commerce and analyses the moderating effect of personalization on the relationships between satisfaction and the antecedents trust, social influence, perceived usefulness, mobility, and perceived enjoyment. Additionally, further findings highlight trust functions as a mediator between personalization and user experience (Bawack et al., 2021b).

Particularly, voice shopping offers a high capability for personalized services (Bawack et al., 2021b). According to Rhee and Choi (2020) personalization through a VA that suits the consumers' preferences has a positive influence and, consequently, is more convincing. This can occur through advanced personalization, as the user will feel less difference between the VA product suggestion and the own choice, leading to increased trust (Komiak & Benbasat, 2006). Referring to Irfan et al. (2019) personalization is an antecedent of trust as well as rapport and influences positively.

Accordingly, if a customer receives personalized shopping recommendations from Alexa, which match with his expectations, he might be more trustful. Taking this into account, the following is hypothesized:

H13: Personalization is positively related to trust toward voice assistants.

Based on the findings above, personalization is not only vital to create trust but also fundamental for establishing rapport between the robot and the customer, particularly in the long term (Irfan et al., 2019). Building and maintaining rapport is essential in order to deliver prosperous services by service robots, and former investigation reveals personalized services increase the feeling of rapport, engagement, and cooperation by running an experiment with a snack delivery robot (M. K. Lee et al., 2012). Furthermore, M. K. Lee et al. (2012) show that personalization has a positive effect on how users connect to the service and the VA. Customers are not exclusively asking for a communicative device, they are looking for VAs delivering enhanced and tailor-made experiences (Schweitzer et al., 2019). The research of Irfan et al. (2019) suggests, personalization has a positive effect on rapport, thus, by providing personalized communication, rapport can be increased and the bond between VA and user strengthened.

Therefore, personalized interactions within the shopping process might enhance the customer's rapport. Thus, proposing the hypothesis:

H14: Personalization is positively related to rapport toward voice assistants.

#### *4.3.2. Rapport*

Rapport presents the second relational element of the sRAM, and even though it is a significant dimension, it is less examined within the research of technology acceptance (Fernandes & Oliveira, 2021). Rapport is known as the feeling of being connected and in harmony with your conversational partner while having a pleasant talk (L. Huang et al., 2011). Many researchers have put forward definitions of the term rapport from different contexts, for example, educational background, roommate relations, interview settings, therapist-client relationships, general interactions, sales relationships, and service settings (Gremler & Gwinner, 2000). Based on these diverse definitions and within the customer-employee relationship, rapport can be described, firstly, as the consumers' view of having a pleasant communication with a service worker, and secondly, as an individual relation between two interaction partners (Gremler &

Gwinner, 2000). Considering the context of VAs, rapport can be described as a special link between the consumer and the VA involving the impression of a pleasant encounter, as for example, acting according to the customers' needs, taking care and being polite (J. Wirtz et al., 2018). Rapport building behavior involves eye contact, smiling, initiating an enjoyable dialog, attentive service, and knowledge sharing, and service encounters can be seen as social interactions, which are affected by the presence or absence of these behaviors (Giebelhausen et al., 2014).

For the creation and growth of a relation and fruitful personal interactions, the factor rapport is indispensable (Cerekovic et al., 2017). Equally, among workers, rapport is vital for a professional and successful collaboration, but also between human and robot collaborators (S. H. Seo et al., 2018). There still exist a lot of customers demanding personal contact; thus, rapport is of high importance, particularly for services with social intimacy and familiarity (Fernandes & Oliveira, 2021). Within the service sector, clients emphasize an enjoyable relation with the service employee, especially in education, elderly care, and financial services of high risk, herewith, experiencing emotional and social advantage in form of rapport, engagement, and trust (J. Wirtz et al., 2018). Referring to the context of robotic services, building and maintaining rapport is an essential success factor (M. K. Lee et al., 2012).

Most of the former rapport investigations derive from psychology, marketing, and education (Cerekovic et al., 2017). The most renowned theoretical model is suggested by Tickle-Degnen and Rosenthal (1990) focusing on the non-verbal cues related to rapport and explaining the essence of rapport through the three dynamics: coordination, mutual attentiveness, and positivity, where at the initial state without experience positivity and mutual attentiveness are more important and later with more experience the coordination and the mutual attentiveness. The rapport literature deriving from human-human rapport covers more and more investigations of human-robot rapport and certain types of robots, such as collaborative robots, which are mainly applied in the industrial area (S. H. Seo et al., 2018). Most of the studies anticipate persons to create rapport with social robots; consequently, in order to measure rapport Nomura and Kanda (2016) developed the Rapport-Expectation with a Robot Scale (RERS) corresponding successfully with the users' behavior.

Thereby, research distinguishes between verbal and non-verbal behavior: verbal rapport building behavior involves giving compliments, being thankful, asking questions, answering with empathy, applying inclusive language, such as using names, and reacting open to criticism, whereas non-verbal rapport building involves outgoing posture, smiling, welcoming eye contact, kind body language, such as nodding, and keeping an appropriate corporal proximity (S. H. Seo et al., 2018). By applying non-verbal behavior, such as mutually showing kindness and attentiveness to each other, reacting adequate to the feelings of others, and radiating positivity, rapport can be built successfully (Tickle-Degnen & Rosenthal, 1990). Referring to professional context, a possibility to elicit a group feeling is imitating non-verbal rapport building behavior, such as tone of voice or facial expressions (Gremler & Gwinner, 2000). Findings highlight one of the rapport building behaviors smile has a positive effect on the customer-employee rapport, and moreover, customer-employee rapport is driving customer satisfaction (Hennig-Thurau et al., 2006). Nonetheless, besides non-verbal behavior, such as hand gestures, also verbal behavior, as for example, acknowledgement can enhance human-robot rapport (S. H. Seo et al., 2018). Furthermore, the survey by Li (2015) examines the effects of physical robots and virtual robots and points out through language-based communication users perceive a closer bond with a robot or virtual agent. For example, a service robot has the capability to arouse curiosity while interacting with a customer (Fuentes-Moraleda et al., 2020). Based on VAs' ability to apply verbal rapport building behavior, customer experience and relations can be enriched (Fuentes-Moraleda et al., 2020).

It is necessary to mention that there is no need for rapport building over time, even with only one interaction between the customer and the employee, rapport can emerge (Hennig-Thurau et al., 2006). Results indicate the presence of employee rapport is having an impact on customers' reactions, remarkably when technology is involved in the service, meaning if there is a high level of rapport, the technology works as a barrier between the customer and the employee, however, having a negative effect on the customer experience, but if there is a low level of rapport, the technology barrier works as an enabler providing a positive customer experience (Giebelhausen et al., 2014). Meaning, in case an employee is not keen on developing rapport with the client, the technology functions as support, leading the customer through the service encounter and improving the overall perception of the service experience (Bolton et al., 2018). Another investigation shows by applying the model of Tickle-Degnen and Rosenthal and emphasizing positivity, coordination, and mutual attention, also a virtual human is able to generate rapport with human customers when undertaking collaborative tasks (L. Huang et al., 2011).

Referring to the mapping of consumer needs toward robot abilities by J. Wirtz et al. (2018), although there is a low desire for rapport for complex cognitive/analytical and simple emotional/social tasks, such as insurance, the desire for rapport is high for simple cognitive/analytical and complex emotional/social tasks, as for example, sporting or entertainment services. The study by Cerekovic et al. (2017) assesses the influence of character and social signs of a person with a robot on the likelihood of rapport by differentiating between self-reported rapport and the rapport monitored by others. Results of the survey reveal the difference between VAs and other technologies is the anthropomorphic social presence, and with the friendly behavior of the VA, the user feels socially appealed and encouraged to communicate with; thus, rapport can be built, having a noteworthy effect on successful technology adoption (Cerekovic et al., 2017). Drawing on this, McLean and Osei-Frimpong

(2019) highlight the positive influence of social attractiveness as well as social presence on the utilization of an AI driven device. Contrarily, in another study investigating the influence of anthropomorphism on rapport as a relational mediator, results suggest that there is no positive effect, which may encourage human-robot rapport and so intention to use (Blut et al., 2021).

The higher the trustworthiness and the feeling the VA wants the consumers' best interest, the higher the possibility of customer adoption, however, there is still the dependency for certain services on the degree to which VAs can satisfy customers' need for rapport (J. Wirtz et al., 2018). VA research has demonstrated consumers are getting more used to talk with a VA and are having more conversations with a VA as with a human, which consequently leads to rapport between VA and user (Cerekovic et al., 2017). Based on this, the existence of rapport is essential and subsequently has a positive influence on the acceptance (Fernandes & Oliveira, 2021).

Bearing this in mind, in the context of voice shopping positing the following:

H15: Rapport is positively related to customer acceptance of voice assistants.

### 4.4. Actual use of voice shopping

One of the most studied areas of investigation in information systems is comprehending technology acceptance and use of information technology (Benbasat & Barki, 2007). Technology acceptance can be described as a positive assessment leading to the intention to use and eventually the actual use of technology (Beer et al., 2011). Yet, the behavioral intention to utilize a technology is more often examined than the actual usage (Turner et al., 2010). In the original TAM the actual use of a certain technology refers to a behavior; thus, in order to rationalize and anticipate the user behavior, parts of the TRA as well as the TPB serve as a foundation and are applied (Marangunić & Granić, 2014). Hereby, the TRA suggests the intention and willingness to utilize a technology are the core factors of users' actual behavior (Fishbein & Ajzen, 1975).

Nevertheless, instead of reflecting the intention to use, the conceptual sRAM implies that the customer acceptance of service robots leads to the actual use (J. Wirtz et al., 2018). Findings of Stock and Merkle (2017) reveal insights into consumers' acceptance of frontline service robots during service encounters by applying the TAM and the role theory. Specifically, robot acceptance can be outlined as the level to which the customer positively evaluates the frontline service robot regarding functionality and reliability (Stock & Merkle, 2017). Referring to J. Wirtz et al. (2018) the customer acceptance is linked to meeting the users' needs of the functional, social-emotional, and relational determinants, and consequently, leading to the actual use of voice shopping. Therefore, the understanding of users' behavior with service robots can be enriched by applying the sRAM (Fuentes-Moraleda et al., 2020).

The research of Legris et al. (2003) on the relation between TAM determinants and actual usage undertakes a comparison of previous work by distinguishing between studies measuring actual usage and those measuring behavioral intention to use. Another study demonstrates that there is one main group of empirical TAM studies presenting the involvement of consequence procedures, namely attitude, perceptual usage, and actual usage (King & He, 2006). The study by Turner et al. (2010) examines the accurateness of TAM as indicator of actual use and differentiates between objective forms and subjective forms of measuring actual usage, while objective forms can be evaluated through logs of usage of the technology itself, subjective forms are evaluated by individual opinions, mostly created by question-based surveys and involve self-measures of the intensity or frequency of utilizing a certain technology. Based on the findings, subjective measures of actual use occur more often than objective measures, possibly because of the requirement to utilize computer-recorded forms (Turner et al., 2010). A former investigation on the World Wide Web examining TAM and World Wide Web usage describes actual usage as a TAM dependent determinant and usually a self-declared quantity of frequency or time of using the application (Lederer et al., 2000). The intention to buy in the setting of online shopping acceptance can be explained as the choice to utilize the internet as a novel shopping channel (Bigné-Alcañiz et al., 2008).

Within the field of mobile shopping, the research of Bigné-Alcañiz et al. (2007) reveals that the frequency of mobile use has a positive influence on mobile shopping adoption, as well as length of mobile use has a positive influence on mobile shopping adoption. Additionally, the actual technology usage can be assessed by time, such as the time the person spends within a shopping app or mobile store or the frequency of utilizing a technology (Chong et al., 2012). Prior research on consumer acceptance and use of technologies demonstrates the impact of frequency due to the experience a consumer gains by using a technology more often and the effect of behavioral intention on technology use being moderated by experience (Venkatesh et al., 2012). Previous online and offline shopping literature predominantly covers shopping adoption and shopping intention as well as shopping frequency and shopping spendings, whereas, within the specific context of mobile shopping, the focus is mainly on the adoption and intention and less on the intensity, which involves frequency and spendings (Hou & Elliott, 2021). Therefore, the study by Hou and Elliott (2021) sheds light on the mobile shopping intensity and how demographics and motivations affect this intensity by demonstrating the impact of education and income level on the number of mobile buys, the frequency of mobile buys, and the sum of expenses.

The research of Abrams et al. (2021) makes a distinction between use-related acceptance, which is related to any possible person, and existence acceptance, which is related to any possible incidentally co-present person, thereby pointing out that, especially in the context of delivery robots, existence acceptance means not necessarily the intention to use or actual usage, as an incidentally co-present person might accept or refuse to accept the existence.

Furthermore, another study investigating the adoption of VAs emphasizes that the continuous intention to use a technology is a substantial behavior and a well-examined area of information systems (Han & H. Yang, 2018). Numerous investigations suggest the intention is more significant than the actual behavior; however, it is equally essential to identify if the intention really converts into users' actual behavior, therefore, another study on consumers' re-use behavior of VAs shows that the intention to re-use has a positive effect on actual usage (Moriuchi, 2021).

Narrowing down the latter relationship, the first applied sRAM studies in different contexts demonstrate the capability of forecasting consumer acceptance of, for example, the consumer acceptance of service robots in hotels (Fuentes-Moraleda et al., 2020) and service robots in retail banking (Amelia et al., 2021) as well as the study by Fernandes and Oliveira (2021) focuses on the acceptance of VAs in services, nonetheless, it is noteworthy to mention that these studies concentrate on the acceptance and do not examine the actual use of VAs.

The actual use of voice shopping can be categorized into two different kinds: first, the consumer buys a product again, which he already bought, thus being aware of what he wants to purchase before starting the voice shopping; second, the consumer buys a certain product for the first time, not being aware of what he wants to purchase (P. Hu et al., 2022).

Following the transition from website shopping to mobile shopping, voice shopping is the next level of the e-revolution; however, the key challenge of the actual use of voice shopping is that even if a user adopts a VA, it does not automatically signify that the user is going to apply the VA for voice shopping, as VAs are in use for a variety of non-commercial interactions (P. Hu et al., 2022). Driven by the increasing acceptance of AI in e-commerce, another study based on the TRA suggests a model proposing that the adoption of VAs for voice shopping is pushed through the behavioral intention of the customer (Bawack et al., 2021a). Therefore, the findings of Bawack et al. (2021a) present that the customer's intention to use VAs for voice shopping affects positively the actual use of voice shopping. Drawing on the findings above, not only the actual use but, more specifically, the intensity of voice shopping, including the frequency of voice purchases, may be of importance for firms to address voice shoppers (Hou & Elliott, 2021).

Hence, if a consumer accepts a VA, this will have a positive influence on the actual use of voice shopping, including the frequency of purchases. Considering this, the last hypothesis of the research model proposes:

H16: Customer acceptance of voice assistants is positively related to actual use of voice shopping.

### 4.5. The research model

With VAs entering consumers' daily lives, the desire grows for understanding why an AI-based technology is accepted or not. Even though the latest findings report an increase in user willingness to accept AI technologies, rejection toward change is still a meaningful obstacle to adoption (Chi et al., 2020).

Referring to Gursoy et al. (2019) research in the area of AI acceptance comprises different theoretical frameworks, mainly based on the TAM, UTAUT, or UTAUT2. Davis (1989) amended the TRA, which was created by Fishbein and Ajzen (1975) by developing the TAM. A model specific for the area of information technology, supplementing the TRA's attitude toward behavior with the two determinants perceived usefulness and perceived ease of use (Momani & Jamous, 2017). Nonetheless, it must be considered that the classical technology acceptance models were created to examine the adoption of non-intelligent technologies, which is insufficient for investigating the acceptance of AI technologies (Gursoy et al., 2019). Amelia et al. (2021) argue that more dimensions need to be included as AI technologies possess social abilities (e.g., speaking). Therefore, in the case of VAs and the adoption of voice shopping, the sRAM is used, which is suggested by J. Wirtz et al. (2018) and derives from the TAM. However, the sRAM considers in addition social-emotional and relational variables (Fernandes

& Oliveira, 2021). According to J. Wirtz et al. (2018) the customer acceptance is related to how good the VA meets the functional, social-emotional, and relational needs of the user and leads then to the actual use of voice shopping. The functional elements are associated with the usefulness and performance of the technology, whereas the social-emotional and relational elements are correlated with the interchange between the user and the VA (Amelia et al., 2021). Consequently, the sRAM enhances the understanding of customers' behavior with service robots (Fuentes-Moraleda et al., 2020). Herein, Alexa can be classified as a service robot by the definition of a "virtual AI software that works autonomously and learns over time" (J. Wirtz et al., 2018, p. 909).

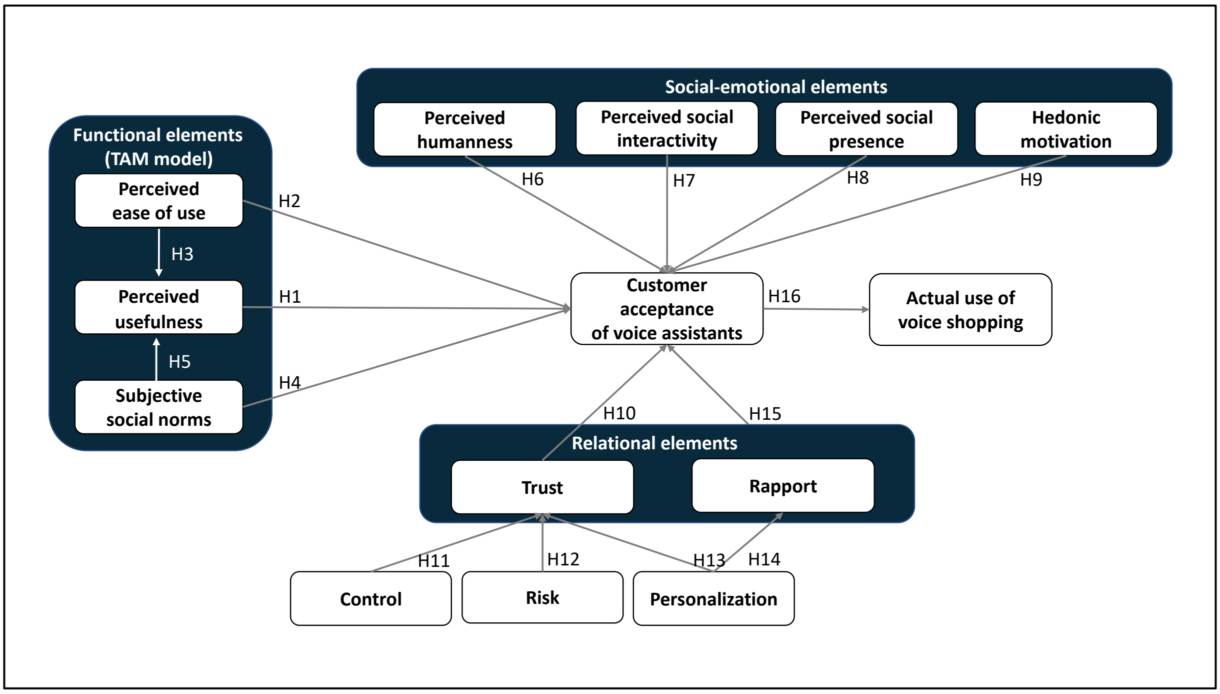
Additionally, Fiske et al. (2007) imply in the stereotype content model that warmth and competence are two basic dimensions of social perception, whereas warmth involves perceived pleasantness, supportiveness, honesty, and goodness, and competence comprises perceived intellect, proficiency, and efficiency. Social perception is vital as it mainly explains how persons characterize others and particularly triggers their behavior (Cuddy et al., 2008). Referring to the sRAM, warmth is related to the social-emotional and relational elements, while competence is related to the functional elements (J. Wirtz et al., 2018). Thus, user acceptance of voice shopping relies on the functional needs linked to competence and the social-emotional and relational needs linked to warmth. Furthermore, the sRAM incorporates the role theory by Solomon et al. (1985), which suggests both parties should act within their socially determined role to reach congruency and, hence, satisfaction. Thus, delivering according to the social-emotional as well as the relational needs of the consumer and considering the role congruency between him and the VA are vital for acceptance and not the level of those elements per se (J. Wirtz et al., 2018).

The first research models testing the conceptual sRAM empirically confirmed the ability to predict consumer acceptance of service robots in hotels (Fuentes-Moraleda et al., 2020), service robots in retail banking (Amelia et al., 2021), and the acceptance of digital VAs in service encounters, but not the actual use of them (Fernandes & Oliveira, 2021).

Referring to prior research, the proposed model includes hedonic motivation as a fourth social-emotional element, expecting a positive effect on consumer acceptance of VAs (Venkatesh et al., 2012). Furthermore, the model considers the antecedents control (Poushneh, 2021b), risk (Featherman & Pavlou, 2003) and personalization (Komiak & Benbasat, 2006) and their influence on the relational element trust as well as the effect of personalization on rapport (M. K. Lee et al., 2012), respectively, the effect of these relational elements on customer acceptance, followed by the actual use of voice shopping.

The research model is built on the hypotheses stated above. First, explaining the general concept of sRAM; second, adding the social-emotional element hedonic motivation; third, explaining and analyzing the antecedents control, risk, and personalization of the relational elements trust and rapport; and finally, clarifying the influence of these elements on the actual use through acceptance. Based on this set of theoretical relations, the conceptual model of this study is developed. Figure 4.1 summarizes the proposed model.

FIGURE 4.1: **The proposed model**



# CHAPTER 5: METHODOLOGY

# 5. METHODOLOGY

The current study incorporated various theoretical lenses in order to understand the constructs of the research model and determine the relationships between them. Among the main dimensions of the model are the acceptance and actual use of technology conceptualized from the sRAM of J. Wirtz et al. (2018) and analyzed by Fernandes and Oliveira (2021), the hedonic motivation developed by Venkatesh et al. (2012), control analyzed by Poushneh (2021b), risk developed by Featherman and Pavlou (2003), as well as personalization related to trust established by Komiak and Benbasat (2006), and personalization linked to rapport analyzed by M. K. Lee et al. (2012).

Functional, social-emotional, and relational elements are multidimensional constructs. Functional elements are considered to be a combination of three factors: perceived usefulness, perceived ease of use, and subjective norm, whereas social-emotional elements are hypothesized to comprise perceived humanness, perceived social interactivity, perceived social presence, and hedonic motivation. Relational elements include trust and rapport, while control, risk, and personalization are antecedents.

## 5.1. Sampling and data collection

The research focused on Amazon’s VA Alexa, as this was the only available VA in Germany offering voice shopping at the time of the investigation. Additionally, Alexa is the most common VA, also regarding the highest global sales market share (Voicebot, 2018). To assure statistically reliable results, an online questionnaire survey of a sample of participants in Germany was conducted including only people who experienced Alexa but not necessarily voice shopping. Germany was selected for the study, as 11% of the citizens use voice shopping weekly, exposing a potential for adoption that does not exist in many other European countries (PricewaterhouseCoopers, 2019). Since previous findings showed that users without experience are mainly neutral toward shopping related VA applications (Baier et al., 2018), this survey sought to appeal to innovative users who are accustomed to the abilities of VAs.

The empirical part of this study was carried out in Germany using an online form created via Lime Survey. The survey was applied in the months of June 2022 and July 2022 in order to collect data, validate the conceptual model, and test the research hypotheses. A random sample of respondents within whole Germany was the most suitable in order to undertake the survey. Respondents were targeted by distributing the survey link via social media platforms, such as Facebook, Instagram, and LinkedIn, but also via WhatsApp, email, and the platform Clickworker. 514 questionnaires were filled out to make sure the primary research is reliable and valid. As can be seen in Table 5.1, out of 514 filled out questionnaires, 499 (97.08%) were considered valid for the research analysis. In terms of gender, two participants indicated diverse (0.40%), approximately half of the participants were women (49.90%), thus, 249 were female respondents and, with 49.70% 248 male respondents. The target population were adults over 18 years old, experienced with the VA Alexa, and who have either used voice shopping in Germany or have not used voice shopping in Germany yet. In terms of age, there was no focus on a certain age category, even though there are studies only directed toward specific groups, as for example, Fernandes and Oliveira (2021) chose millennials due to their openness toward new technologies, as they rather tend to be early adopters and power users and show faster adoption rates in comparison to baby boomers. Moreover, other studies in the field of AI and robots targeted elderly people, due to the increasing elderly population. The predominant group of this survey was between 25 and 40 years old, with 53.11%, followed by the group between 41 and 56 years old, with a participation rate of 28.06%, while under the age of 24, 9.42% and over the age of 57, as well 9.42%, presenting the smallest groups. More than 32.46% of participants have used a VA at least once for voice shopping.

TABLE 5.1: **Sample demographics**

| **Characteristics** | **Percentage** |
|---|---|
| ***Gender*** | |
| Diverse | 00.40% |
| Female | 49.90% |
| Male | 49.70% |
| ***Age*** | |
| Under 24 | 09.42% |
| 25 - 40 | 53.11% |
| 41 - 56 | 28.06% |
| Over 57 | 09.42% |
| ***Voice shoppers*** | 32.46% |
| ***Non-voice shoppers*** | 67.54% |

## 5.2. Measures

The questionnaire consisted of four parts, however, only three parts had to be filled in by each group (voice shoppers and non-voice shoppers), because each had its own survey path to be able to differentiate the results of both groups. The first part concentrated on clarifying the main objective of the study. In the second part, before answering the variable sections of the form, the survey respondent had to indicate gender and age, followed by nine dimensions including 27 items, and ending with the question if the user already applied voice shopping. The third part addressed voice shoppers and was composed of the constructs based on the literature by measuring the dimensions of 15 items. While the fourth part addressed non-voice shoppers by measuring the dimensions of 12 items. The survey measures were initially drawn from the literature and adapted to fit the voice shopping context. The questions tackled the functional, social-emotional, and relational elements as well as the experience of the user. In order to ensure content validity, scales from former studies were used and adopted for voice shopping. The functional elements were measured by adopting studies by Chong et al. (2012), Davis (1989), and Venkatesh et al. (2012). The social-emotional scale was modified from Lu et al. (2019), Bartneck et al. (2009), Heerink et al. (2010), Poushneh (2021b), and Venkatesh et al. (2012). The relational scale was generated from the study by Bawack et al. (2021b), Chong et al. (2012), Heerink et al. (2010), Fernandes and Oliveira (2021), Pavlou (2003), Ball et al. (2006), as well as Xu (2006), and Taylor and Todd (1995). The acceptance was adopted from Taylor and Todd (1995). The actual use of voice shopping was adopted from Venkatesh et al. (2012) as well as Chong et al. (2012). The seven-point Likert scale was applied, ranging from strongly agree to strongly disagree. The English version of the questionnaire (Appendix A) was translated to German (Appendix B), and a pre-testing was undertaken with persons who had used Alexa before to guarantee the questions were clear and comprehensible. Table 5.2 shows the scale items.

TABLE 5.2: **Scales**

| **Variable** | **Item coding** | **Scale items** | **Source** |
|---|---|---|---|
| Subjective social norms | SN1<br>SN2<br>SN3 | People who are important to me think that I should use Alexa for voice shopping.<br>People who influence my behavior think that I should use Alexa for voice shopping.<br>People whose opinions I value prefer that I use Alexa for voice shopping. | Adapted from Venkatesh et al. (2012) |
| Perceived humanness | HU1<br>HU2<br>HU3 | I personally feel Alexa is natural.<br>I personally feel Alexa is humanlike.<br>I personally feel Alexa is lifelike. | Adapted from Lu et al. (2019) and Bartneck et al. (2009) |
| Perceived social interactivity | SI1<br>SI2 | I find Alexa pleasant to interact with.<br>I think Alexa is nice. | Adapted from Heerink et al. (2010) and |

| | | | |
|---|---|---|---|
| | SI3 | Alexa makes me feel like she wants to listen to me. | Poushneh (2021b) |
| Perceived social presence | SP1<br>SP2<br>SP3 | When interacting with Alexa, I felt like talking to a real person.<br>Sometimes Alexa seems to have real feelings.<br>I often think Alexa is a real person. | Adapted from Heerink et al. (2010) |
| Hedonic motivation | HM1<br>HM2<br>HM3 | Using Alexa is fun.<br>Using Alexa is enjoyable.<br>Using Alexa is very entertaining. | Adapted from Venkatesh et al. (2012) |
| Trust | TRU1<br>TRU2<br>TRU3 | I believe that Alexa is trustworthy.<br>I believe voice shopping with Alexa is as secure as online shopping with Amazon.<br>I believe that Alexa is reliable. | Adapted from Bawack et al. (2021b) and Chong et al. (2012) |
| Rapport | RAP1<br>RAP2<br>RAP3 | I consider Alexa a pleasant conversational partner.<br>I think there is a bond between Alexa and myself.<br>I relate well to Alexa. | Adapted from Heerink et al. (2010) and Fernandes and Oliveira (2021) |
| Risk | RISK1<br>RISK2<br>RISK3 | How would you characterize the decision to give a voice command to Alexa? (Very low risk/very high risk)<br>How would you characterize the decision to disclose financial information to Alexa? (Very low risk/very high risk)<br>How would you characterize the decision to disclose personal information to Alexa? (Very low risk/very high risk) | Adapted from Pavlou (2003) |
| Personalization | PERS1<br>PERS2<br>PERS3 | Alexa offers me products and services according to my preferences.<br>I feel that Alexa sends personalized messages to me.<br>I feel that Alexa is personalized for my usage. | Adapted from Ball et al. (2006) and Xu (2006) |
| Control<br>(Voice shoppers) | CON1<br>CON2 | Using Alexa for voice shopping is entirely within my control.<br>I am able to use Alexa for voice shopping. | Adapted from Taylor and Todd (1995) |

| | | | |
|---|---|---|---|
| | CON3 | I have the control to make use of Alexa for voice shopping. | |
| Control<br>(Non-voice shoppers) | Comment<br><br><br><br><br><br><br>CON1<br><br>CON2<br><br>CON3 | Even if you have not used Alexa for voice shopping, you might know someone who shared with you his impressions, or you heard about it in the media. Based on this, rate in which measure you believe that Alexa for voice shopping could be within your control.<br>Using Alexa for voice shopping would be entirely within my control.<br>I would be able to use Alexa for voice shopping.<br>I would have the control to make use of Alexa for voice shopping. | Adapted from Taylor and Todd (1995) |
| Perceived usefulness<br>(Voice shoppers) | PU1<br><br>PU2<br><br>PU3 | Using Alexa for voice shopping is more convenient than online shopping.<br>Using Alexa for voice shopping allows me to multitask.<br>Overall, I find Alexa for voice shopping useful. | Adapted from Chong et al. (2012) and Davis (1989) |
| Perceived usefulness<br>(Non-voice shoppers) | Comment<br><br><br><br><br><br><br>PU1<br><br><br>PU2<br><br>PU3 | Even if you have not used Alexa for voice shopping, you might know someone who shared with you his impressions, or you heard about it in the media. Based on this, rate in which measure you believe that Alexa for voice shopping could be useful.<br>Using Alexa for voice shopping would be more convenient than online shopping.<br>Using Alexa for voice shopping would allow me to multitask.<br>Overall, I would find Alexa for voice shopping useful. | Adapted from Chong et al. (2012) and Davis (1989) |
| Perceived ease of use<br>(Voice shoppers) | EOU1<br><br>EOU2<br><br>EOU3 | Learning to operate Alexa for voice shopping is easy for me.<br>I find it easy to get Alexa to do what I want her to do.<br>Overall, I find Alexa for voice shopping easy to use. | Adapted from Davis (1989) |

| | | | |
|---|---|---|---|
| Perceived ease of use<br>(Non-voice shoppers) | Comment | Even if you have not used Alexa for voice shopping, you might know someone who shared with you his impressions, or you heard about it in the media. Based on this, rate in which measure you believe that Alexa for voice shopping could be easy to use. | Adapted from Davis (1989) |
| | EOU1 | Learning to operate Alexa for voice shopping is easy for me. | |
| | EOU2 | I would find it easy to get Alexa to do what I want her to do. | |
| | EOU3 | Overall, I would find Alexa for voice shopping easy to use. | |
| Customer acceptance<br>(Voice shoppers) | ACC1 | Using Alexa for voice shopping is a good idea. | Adapted from Taylor and Todd (1995) |
| | ACC2 | Using Alexa for voice shopping is pleasant. | |
| | ACC3 | I like the idea of using Alexa for voice shopping. | |
| Customer acceptance<br>(Non-voice shoppers) | ACC1 | Using Alexa for voice shopping is a good idea. | Adapted from Taylor and Todd (1995) |
| | ACC2 | Using Alexa for voice shopping would be pleasant. | |
| | ACC3 | I like the idea of using Alexa for voice shopping. | |
| Actual use<br>(Voice shoppers) | USE1 | I will continue using Alexa for voice shopping in the future. | Adapted from Venkatesh et al. (2012) and Chong et al. (2012) |
| | USE2 | I am always using Alexa for voice shopping whenever I want to buy something. | |
| | USE3 | How frequently are you using Alexa for voice shopping? (Yearly / more than once a day) | |

### 5.3. Data analysis

After the primary research was finished, the data were depured and analyzed. To contrast the hypotheses, structural equation modeling based on variances (PLS-SEM) was estimated. According to recent research (Sarstedt et al., 2023) the classical need to explain when PLS-SEM should be used instead of covariance-based SEM (CB-SEM) with guidelines as those provided by the same authors (Hair et al., 2011) is less necessary each time, as “PLS-SEM has clearly emancipated from its covariance-based counterpart” (Sarstedt et al., 2023, p. 265). PLS-SEM does not need to be treated as an “attractive alternative” to the CB-SEM approach (Rigdon, 2012; Rigdon et al., 2017). With their different statistical objectives and methodological requirements, both methods are complementary rather than competitive. As Sarstedt et al. (2023, p. 265) point out, “researchers should therefore emphasize PLS-SEM’s causal predictive nature and its ability to obtain meaningful solutions in complex models with many indicators and relatively small sample sizes (Hair et al., 2019b)”.

Accordingly, this is the reason that led us to estimate our model using PLS-SEM, as we are dealing with a complex model (Figure 4.1) with 14 latent variables structured at different nomological levels and measured by 54 indicators. While CB-SEM assumes an explanatory perspective to test theories, PLS-SEM is causal-predictive as the method focuses on in-sample prediction in estimating statistical models whose theoretical structures are intended to deliver causal explanations (Chin et al., 2020).

To estimate the model presented in Chapter 4 we followed the steps indicated by Hair et al. (2022). Firstly, the PLS path model was estimated, but no attention was given to the structural paths as the reflective measurement model was first assessed. Once reliability, convergent and discriminant validity were confirmed, the results of the structural model were assessed and the hypotheses tested accordingly.

### *5.3.1. Measurement model assessment*

To evaluate measurement and the structural model, the model presented in Chapter 4 was estimated with the following algorithm settings. As all the latent variables were related reflectively to their scale items, model A (correlation weights) between the construct and its indicators was used to compute the construct scores. Path weighting scheme was used to determine the relationships in the structural model, as this approach "attempts to produce a component that can both ideally be predicted (as a predictand) and at the same time be a good predictor for subsequent dependent variables" (Chin, 1998, p. 309).

The original PLS-SEM algorithm has been used instead of new approaches like the consistent PLS-SEM (PLSc-SEM) (Bentler & Huang, 2014; Dijkstra, 2014). Although the latter produces highly similar results to CB-SEM according to simulation studies (Dijkstra & Henseler, 2015a; Dijkstra & Henseler, 2015b) it also has similar problems such as inferior robustness and highly inaccurate results in certain configurations (Sarstedt et al., 2016), but what is more important and the reason we have followed to use PLS-SEM instead of CB-SEM, is that the correction factor introduced by PLSc-SEM makes it very difficult to assess a model's out-of-sample predictive power.

The model was estimated using SmartPLS 4 (Ringle et al., 2022) so the default options of this software were chosen for the rest of the algorithm settings. The initial values of the weights were fixed to +1 as all the indicators had the same orientation, a stop criterion of $1 \cdot 10^{-7}$ was chosen, and the maximum number of iterations was established at 300.

To evaluate the significance of parameters, as PLS-SEM does not assume the data are normally distributed, the parametric significance tests arising from the regressions that the algorithm performs cannot be used. Instead, PLS-SEM relies on a non-parametric bootstrap procedure (Chernick, 2008) to test the significance of the coefficients. A large number of samples are drawn from the original sample with replacement at random, and the model is estimated for each of those bootstrap samples. Then the bootstrap standard error of each parameter is used to calculate the t statistic to evaluate its significance. Following the indication of Hair et al. (2022), 10.000 subsamples were extracted, and the percentile method for constructing confidence intervals was used.

To evaluate the psychometric properties of the measurement model, the steps proposed by Hair et al. (2022) were followed. Firstly, the indicator reliability (size of the outer loading) was checked. Apart from being significant according to the bootstrap results, a size of 0.70 was required. However, to preserve content validity, if necessary, indicators between 0.40 and 0.70 were taken into account for elimination only when removing the indicator led to a growth in the internal consistency reliability or convergent validity.

To assess internal consistency reliability, Cronbach's alpha (Cronbach & Gleser, 1965) was provided as the lower bound for internal consistency, the composite reliability rho_b (Fornell & Larcker, 1981) was calculated as an upper bond, and the reliability coefficient rho_a (Dijkstra, 2014) as a good compromise between those two measures (Hair et al., 2019a). All these indicators should usually be higher than 0.70, although in exploratory research values between 0.60 and 0.70 are deemed acceptable, and values higher than 0.95 are not desirable (Hair et al., 2022).

Convergent validity is the degree to which a measure correlates positively with other measures of the same construct (Ringle et al., 2022). Average variance extracted (AVE) (Fornell & Larcker, 1981) defined as the average of the squared outer loadings of each latent variable, was calculated to assess convergent validity. Values higher than 0.50 indicate that, on average, the construct accounts for over half of the indicators' variance and represents the benchmark that is followed.

Discriminant validity is the degree to which a construct is genuinely distinct from further constructs according to the scales chosen to measure them (Hair et al., 2011). Two criteria were followed. Firstly, Fornell and Larcker (1981) contrast the square root of the AVE values with the latent variable correlations, where each square root of the AVE of a latent variable should be higher than each correlation in which that latent variable is implied. The implicit idea is that a construct should have a higher variance with its indicators than with any other construct. Secondly, the heterotrait-monotrait ratio (HTMT) proposed by Henseler et al. (2015) was used using the upper limit of 0.90 as the benchmark (higher values would imply lack of discriminant validity).

As we wanted to determine if the model in Figure 4.1 applies to both the user and non-user samples, the validation of the measurement model must be applied in both samples. Accordingly, Table 5.3 and Table 5.4 show the reliability and convergent validity assessment for the user and non-user samples, respectively, and Table 5.5 and Table 5.6 the discriminant validity evaluation for the same two groups. It can be seen that in order to deal with discriminant validity issues, two items (PU2 and PU3) had to be deleted in the perceived usefulness latent variable and another two (SI1 and SI2) in the social interactivity construct. After these deletions, the results showed that the measurement models fit the above-mentioned benchmarks for reliability and validity.

TABLE 5.3: **Reliability and convergent validity assessment (Sample: Users)**

| Latent variable | Indicators | Convergent validity | | | | Internal consistency reliability | | |
|---|---|---|---|---|---|---|---|---|
| | | Standardized loading | | t-value (bootstrap) | AVE | Cronbach's alpha | Reliability rho_a | Composite reliability rho_c |
| Customer acceptance | ACC1 | 0.952 | ** | 98.30 | 0.863 | 0.920 | 0.921 | 0.950 |
| | ACC2 | 0.914 | ** | 46.86 | | | | |
| | ACC3 | 0.920 | ** | 54.17 | | | | |
| Control | CON1 | 0.869 | ** | 27.13 | 0.757 | 0.845 | 0.884 | 0.903 |
| | CON2 | 0.838 | ** | 12.66 | | | | |
| | CON3 | 0.902 | ** | 22.96 | | | | |
| Ease of use | EOU1 | 0.876 | ** | 31.93 | 0.780 | 0.861 | 0.890 | 0.914 |
| | EOU2 | 0.899 | ** | 51.94 | | | | |
| | EOU3 | 0.874 | ** | 33.08 | | | | |
| Hedonic motivation | HM1 | 0.927 | ** | 50.24 | 0.849 | 0.911 | 0.911 | 0.944 |
| | HM2 | 0.918 | ** | 41.06 | | | | |
| | HM3 | 0.920 | ** | 46.79 | | | | |
| Perceived humaness | HU1 | 0.922 | ** | 91.40 | 0.838 | 0.904 | 0.922 | 0.939 |
| | HU2 | 0.901 | ** | 38.43 | | | | |
| | HU3 | 0.922 | ** | 60.94 | | | | |
| Personalization | PERS1 | 0.829 | ** | 19.52 | 0.683 | 0.775 | 0.804 | 0.866 |
| | PERS2 | 0.851 | ** | 15.72 | | | | |
| | PERS3 | 0.798 | ** | 10.26 | | | | |
| Perceived usefulness | PU1 | 1,000 | ** | N/A | N/A | N/A | N/A | N/A |
| Rapport | RAP1 | 0.879 | ** | 42.68 | 0.728 | 0.816 | 0.847 | 0.889 |
| | RAP2 | 0.805 | ** | 21.86 | | | | |
| | RAP3 | 0.875 | ** | 31.30 | | | | |
| Perceived risk | RISK1 | 0.765 | ** | 11.29 | 0.721 | 0.803 | 0.810 | 0.885 |
| | RISK2 | 0.864 | ** | 26.35 | | | | |
| | RISK3 | 0.912 | ** | 42.32 | | | | |
| Social interactivity | SI3 | 1,000 | ** | N/A | N/A | N/A | N/A | N/A |
| Subjective social norms | SN1 | 0.965 | ** | 141.37 | 0.929 | 0.962 | 0.963 | 0.975 |
| | SN2 | 0.961 | ** | 104.59 | | | | |
| | SN3 | 0.966 | ** | 147.36 | | | | |
| Perceived social presence | SP1 | 0.924 | ** | 34.53 | 0.833 | 0.903 | 0.973 | 0.937 |
| | SP2 | 0.931 | ** | 35.88 | | | | |
| | SP3 | 0.881 | ** | 21.87 | | | | |
| Trust | TRU1 | 0.848 | ** | 31.20 | 0.752 | 0.835 | 0.838 | 0.901 |
| | TRU2 | 0.866 | ** | 29.47 | | | | |
| | TRU3 | 0.887 | ** | 41.90 | | | | |
| Actual use | USE1 | 0.971 | ** | 275.62 | 0.933 | 0.964 | 0.971 | 0.977 |
| | USE2 | 0.972 | ** | 277.17 | | | | |
| | USE3 | 0.954 | ** | 155.20 | | | | |

** p<0.01
N/A = Does not apply as latent variable is measured with one single item

TABLE 5.4: **Reliability and convergent validity assessment (Sample: Non-users)**

| Latent variable | Indicators | Convergent validity | | | | Internal consistency reliability | | |
|---|---|---|---|---|---|---|---|---|
| | | Standardized loading | | t-value (bootstrap) | AVE | Cronbach's alpha | Reliability rho_a | Composite reliability rho_c |
| Customer acceptance | ACC1 | 0.948 | ** | 124.24 | 0.882 | 0.933 | 0.933 | 0.957 |
| | ACC2 | 0.930 | ** | 88.59 | | | | |
| | ACC3 | 0.939 | ** | 113.95 | | | | |
| Control | CON1 | 0.891 | ** | 39.90 | 0.694 | 0.796 | 0.886 | 0.870 |
| | CON2 | 0.686 | ** | 9.34 | | | | |
| | CON3 | 0.905 | ** | 45.10 | | | | |
| Ease of use | EOU1 | 0.831 | ** | 20.15 | 0.823 | 0.896 | 0.978 | 0.933 |
| | EOU2 | 0.941 | ** | 75.09 | | | | |
| | EOU3 | 0.945 | ** | 99.45 | | | | |
| Hedonic motivation | HM1 | 0.962 | ** | 161.66 | 0.904 | 0.947 | 0.953 | 0.966 |
| | HM2 | 0.956 | ** | 164.52 | | | | |
| | HM3 | 0.935 | ** | 91.01 | | | | |
| Perceived humaness | HU1 | 0.896 | ** | 61.30 | 0.850 | 0.911 | 0.911 | 0.944 |
| | HU2 | 0.935 | ** | 92.78 | | | | |
| | HU3 | 0.934 | ** | 84.28 | | | | |
| Personalization | PERS1 | 0.852 | ** | 34.56 | 0.733 | 0.826 | 0.875 | 0.892 |
| | PERS2 | 0.863 | ** | 25.59 | | | | |
| | PERS3 | 0.852 | ** | 26.16 | | | | |
| Perceived usefulness | PU1 | 1,000 | ** | N/A | N/A | N/A | N/A | N/A |
| Rapport | RAP1 | 0.903 | ** | 84.38 | 0.757 | 0.840 | 0.861 | 0.903 |
| | RAP2 | 0.800 | ** | 30.04 | | | | |
| | RAP3 | 0.903 | ** | 82.90 | | | | |
| Perceived risk | RISK1 | 0.763 | ** | 20.26 | 0.757 | 0.835 | 0.846 | 0.903 |
| | RISK2 | 0.901 | ** | 55.03 | | | | |
| | RISK3 | 0.937 | ** | 110.64 | | | | |
| Social interactivity | SI3 | 1,000 | ** | N/A | N/A | N/A | N/A | N/A |
| Subjective social norms | SN1 | 0.971 | ** | 169.58 | 0.943 | 0.970 | 0.971 | 0.980 |
| | SN2 | 0.975 | ** | 200.51 | | | | |
| | SN3 | 0.968 | ** | 173.77 | | | | |
| Perceived social presence | SP1 | 0.920 | ** | 106.97 | 0.833 | 0.901 | 0.923 | 0.937 |
| | SP2 | 0.922 | ** | 62.24 | | | | |
| | SP3 | 0.897 | ** | 47.02 | | | | |
| Trust | TRU1 | 0.890 | ** | 67.56 | 0.780 | 0.859 | 0.860 | 0.914 |
| | TRU2 | 0.888 | ** | 64.80 | | | | |
| | TRU3 | 0.873 | ** | 52.40 | | | | |

**p<0.01
N/A = Does not apply as latent variable is measured with one single item

TABLE 5.5: **Discriminant validity (Sample: Users)**

| Latent variable | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1. Customer acceptance | **0.942** | 0.418 | 0.361 | 0.729 | 0.659 | 0.492 | 0.731 | 0.744 | 0.483 | 0.599 | 0.570 | 0.564 | 0.823 | 0.480 |
| 2. Control | 0.400 | **0.839** | 0.703 | 0.374 | 0.199 | 0.290 | 0.272 | 0.253 | 0.211 | 0.256 | 0.153 | 0.153 | 0.413 | 0.149 |
| 3. Ease of use | 0.350 | 0.549 | **0.899** | 0.364 | 0.236 | 0.479 | 0.280 | 0.247 | 0.110 | 0.283 | 0.103 | 0.121 | 0.353 | 0.096 |
| 4. Hedonic motivation | 0.686 | 0.354 | 0.346 | **0.946** | 0.634 | 0.510 | 0.465 | 0.747 | 0.323 | 0.659 | 0.461 | 0.475 | 0.717 | 0.283 |
| 5. Perceived humaness | 0.610 | 0.205 | 0.232 | 0.591 | **0.923** | 0.481 | 0.440 | 0.827 | 0.289 | 0.673 | 0.573 | 0.793 | 0.777 | 0.354 |
| 6. Personalization | 0.454 | 0.251 | 0.432 | 0.474 | 0.435 | **0.853** | 0.440 | 0.516 | 0.088 | 0.507 | 0.336 | 0.430 | 0.495 | 0.255 |
| 7. Perceived usefulness | 0.707 | 0.260 | 0.286 | 0.453 | 0.421 | 0.418 | **1.000** | 0.546 | 0.279 | 0.465 | 0.454 | 0.442 | 0.572 | 0.362 |
| 8. Rapport | 0.666 | 0.213 | 0.228 | 0.683 | 0.725 | 0.449 | 0.502 | **0.869** | 0.321 | 0.753 | 0.634 | 0.850 | 0.831 | 0.371 |
| 9. Perceived risk | -0.426 | -0.152 | -0.077 | -0.282 | -0.254 | -0.075 | -0.256 | -0.268 | **0.865** | 0.173 | 0.234 | 0.224 | 0.538 | 0.205 |
| 10. Social interactivity | 0.580 | 0.243 | 0.284 | 0.639 | 0.643 | 0.478 | 0.465 | 0.696 | -0.159 | **1.000** | 0.532 | 0.640 | 0.625 | 0.271 |
| 11. Subjective social norms | 0.545 | 0.119 | 0.094 | 0.442 | 0.540 | 0.319 | 0.448 | 0.565 | -0.211 | 0.524 | **0.972** | 0.628 | 0.588 | 0.459 |
| 12. Perceived social presence | 0.530 | 0.108 | 0.090 | 0.454 | 0.731 | 0.384 | 0.427 | 0.735 | -0.202 | 0.620 | 0.590 | **0.916** | 0.634 | 0.352 |
| 13. Trust | 0.740 | 0.385 | 0.329 | 0.649 | 0.690 | 0.441 | 0.531 | 0.714 | -0.453 | 0.581 | 0.538 | 0.570 | **0.885** | 0.391 |
| 14. Actual use | 0.458 | 0.141 | 0.076 | 0.272 | 0.333 | 0.232 | 0.356 | 0.332 | -0.186 | 0.268 | 0.445 | 0.331 | 0.357 | **0.966** |

Note: diagonal shows square root of AVE and lower triangle latent variable correlations (Fornell & Larcker, 1981). Upper triangle: HTMT ratios

TABLE 5.6: **Discriminant validity (Sample: Non-users)**

| Latent variable | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1. Customer acceptance | **0.939** | 0.399 | 0.304 | 0.731 | 0.652 | 0.430 | 0.701 | 0.739 | 0.508 | 0.592 | 0.485 | 0.594 | 0.787 |
| 2. Control | 0.379 | **0.833** | 0.700 | 0.358 | 0.188 | 0.275 | 0.274 | 0.222 | 0.206 | 0.225 | 0.122 | 0.142 | 0.396 |
| 3. Ease of use | 0.296 | 0.540 | **0.907** | 0.326 | 0.236 | 0.489 | 0.280 | 0.223 | 0.114 | 0.255 | 0.062 | 0.127 | 0.330 |
| 4. Hedonic motivation | 0.689 | 0.337 | 0.310 | **0.951** | 0.642 | 0.445 | 0.411 | 0.780 | 0.375 | 0.652 | 0.407 | 0.513 | 0.715 |
| 5. Perceived humaness | 0.601 | 0.197 | 0.234 | 0.600 | **0.922** | 0.445 | 0.361 | 0.837 | 0.310 | 0.662 | 0.490 | 0.801 | 0.790 |
| 6. Personalization | 0.405 | 0.227 | 0.448 | 0.424 | 0.408 | **0.856** | 0.422 | 0.490 | 0.076 | 0.494 | 0.289 | 0.418 | 0.439 |
| 7. Perceived usefulness | 0.678 | 0.252 | 0.282 | 0.402 | 0.344 | 0.404 | **1.000** | 0.485 | 0.244 | 0.462 | 0.364 | 0.404 | 0.510 |
| 8. Rapport | 0.661 | 0.172 | 0.192 | 0.714 | 0.733 | 0.428 | 0.446 | **0.870** | 0.344 | 0.758 | 0.588 | 0.853 | 0.806 |
| 9. Perceived risk | -0.448 | -0.167 | -0.101 | -0.332 | -0.272 | -0.064 | -0.224 | -0.290 | **0.870** | 0.160 | 0.217 | 0.231 | 0.543 |
| 10. Social interactivity | 0.571 | 0.206 | 0.260 | 0.635 | 0.632 | 0.469 | 0.462 | 0.700 | -0.148 | **1.000** | 0.483 | 0.666 | 0.589 |
| 11. Subjective social norms | 0.461 | 0.077 | 0.027 | 0.391 | 0.461 | 0.277 | 0.359 | 0.522 | -0.197 | 0.475 | **0.971** | 0.610 | 0.508 |
| 12. Perceived social presence | 0.553 | 0.110 | 0.092 | 0.486 | 0.735 | 0.373 | 0.387 | 0.733 | -0.208 | 0.642 | 0.570 | **0.913** | 0.650 |
| 13. Trust | 0.705 | 0.367 | 0.306 | 0.651 | 0.702 | 0.400 | 0.473 | 0.693 | -0.460 | 0.547 | 0.464 | 0.582 | **0.883** |

Note: diagonal shows square root of AVE and lower triangle latent variable correlations (Fornell & Larcker, 1981). Upper triangle: HTMT ratios

### *5.3.2. Evaluation of the structural model*

As Hair et al. (2022) point out, once we have confirmed that the construct measures are reliable and valid, before focusing on the hypotheses contrast, the structural model properties must be evaluated. Firstly, collinearity issues must be discarded, and secondly, the model's explanatory and predictive power must be established. Only after satisfactory results in this evaluation can the focus be translated to the structural path significance (hypotheses testing).

Regarding collinearity issues, it must be taken into account that the PLS-SEM algorithm divides the structural part of the model into different OLS regressions to estimate beta coefficients. In consequence, high collinearity among independent latent variables can have the same negative consequences on beta coefficient estimation as it has in any regression. The criterion usually used to deal with this issue is calculating the variance inflation factor (VIF). Hair et al. (2022) propose that values of 5 and above indicate critical collinearity issues, although some authors (Becker et al., 2015; Mason & Perreault, 1991) consider that these issues can also exist at lower VIF values of 3. The VIF values should ideally be close to 3 or lower (Hair et al., 2022).

As it can be seen in Table 5.7 VIF values in our model are far from 5 and the highest are, as recommended, close to 3, making us discard any collinearity issue in our model for both samples.

TABLE 5.7: **VIF values for the structural model (Sample: Users and non-users)**

| | Users | | | | | Non-users | | | |
|---|---|---|---|---|---|---|---|---|---|
| | 1.ACC | 7. PU | 8. RAP | 13. TRU | 14. USE | 1.ACC | 7. PU | 8. RAP | 13. TRU |
| 1. Customer acceptance (ACC) | | | | | 1,000 | | | | |
| 2. Control | | | | 1,088 | | | | | 1,081 |
| 3. Ease of use | 1,251 | 1,009 | | | | 1,243 | 1,001 | | |
| 4. Hedonic motivation | 2,440 | | | | | 2,562 | | | |
| 5. Perceived humaness | 3,091 | | | | | 3,236 | | | |
| 6. Personalization | | | 1,000 | 1,069 | | | | 1,000 | 1,055 |
| 7. Perceived usefulness (PU) | 1,573 | | | | | 1,486 | | | |
| 8. Rapport (RAP) | 3,847 | | | | | 3,924 | | | |
| 9. Perceived risk | | | | 1,025 | | | | | 1,029 |
| 10. Social interactivity | 2,453 | | | | | 2,504 | | | |
| 11. Subjective social norms | 1,804 | 1,009 | | | | 1,623 | 1,001 | | |
| 12. Perceived social presence | 3,107 | | | | | 3,164 | | | |
| 13. Trust (TRU) | 2,787 | | | | | 2,718 | | | |

We focused then on the explanatory power of our model. The Explanatory power of a model relates to its ability to fit the data at hand by quantifying the strength of the association indicated by the PLS path model (Shmueli, 2010; Shmueli & Koppius, 2011). As Hair et al. (2022) point out, the most widely used measure to assess the structural model's explanatory power is the coefficient of determination $R^2$, which is calculated as the squared correlation between a specific endogenous construct's actual and predicted values. It represents a measure of in-sample predictive power (Rigdon, 2012). As it can be seen in Table 5.8 for our key variable, customer acceptance, our model is able to explain more than 70% of its variance for both samples, which according to most rules of thumb can be considered moderate or high in explanatory power. For the rest of the dependent variables, the model exhibits low explanatory power, but they play an instrumental role in the prediction of customer acceptance; however, the objective of the model is not to predict them themselves.

In the same manner, the f2 effect size expresses the change in the R2 value when a specific explanatory variable is omitted from the model. If the omission of a construct leads to a substantial decline in the dependent constructs R2 value, this is evidence of the antecedent construct's substantial impact. Most of the time, low f2 effects are logically associated with non-significant antecedents. Values of 0.02, 0.15, and 0.35 indicate a predictor construct's small, medium, or large effect, correspondingly (Cohen, 1988). Focusing again on Table 5.8, it can be seen that the variables that exhibit a higher effect size on customer acceptance are perceived usefulness (large effect) and trust, with a similar profile in both samples. We had to elaborate on this result when calculating the significance of the parameters.

TABLE 5.8: **Explanatory power: f2 effect sizes, R2 and adjusted R2**

**(Sample: Users and non-users)**

| | Users | | | | | Non-users | | | |
|---|---|---|---|---|---|---|---|---|---|
| | 1.ACC | 7. PU | 8. RAP | 13. TRU | 14. USE | 1.ACC | 7. PU | 8. RAP | 13. TRU |
| 1. Customer acceptance (ACC) | | | | | 0.266 | | | | |
| 2. Control | | | | 0.090 | | | | | 0.079 |
| 3. Ease of use | 0.007 | 0.081 | | | | 0.000 | 0.093 | | |
| 4. Hedonic motivation | 0.096 | | | | | 0.134 | | | |
| 5. Perceived humaness | 0.004 | | | | | 0.007 | | | |
| 6. Personalization | | | 0.252 | 0.202 | | | | 0.224 | 0.164 |
| 7. Perceived usefulness (PU) | 0.333 | | | | | 0.384 | | | |
| 8. Rapport (RAP) | 0.002 | | | | | 0.001 | | | |
| 9. Perceived risk | | | | 0.258 | | | | | 0.260 |
| 10. Social interactivity | 0.001 | | | | | 0.004 | | | |
| 11. Subjective social norms | 0.014 | 0.242 | | | | 0.003 | 0.155 | | |
| 12. Perceived social presence | 0.000 | | | | | 0.003 | | | |
| 13. Trust (TRU) | 0.103 | | | | | 0.062 | | | |
| R2 | 0.738 | 0.261 | 0.201 | 0.424 | 0.210 | 0.722 | 0.203 | 0.183 | 0.398 |
| R2 adjusted | 0.733 | 0.257 | 0.199 | 0.420 | 0.208 | 0.714 | 0.198 | 0.181 | 0.392 |

The last step in the evaluation of the structural model before focusing on hypotheses contrast is analyzing the model's predictive power. For the model to be useful for managerial purposes, it needs to produce generalizable findings (Hair & Sarstedt, 2021). In the previous step, when we talked about explanatory power, we were evaluating the model with the same sample it was estimated, which is in-sample evaluation. In this step, we needed to test the model with data that were not used in the estimation process, what is called out-of-sample predictive power or simply predictive power (Chin et al., 2020; Sarstedt et al., 2017).

But the point is that we only had a data set that we have used for estimation. The approach that is usually followed, for instance, in Shmueli et al.'s (2016) PLSpredict approach, is separating the overall data set into a training and a holdout sample. The training sample is the portion of the overall data set used to estimate the model parameters, and the remaining portion is used to evaluate those results. A small divergence indicates high predictive power.

However, we applied a more recent approach to evaluate predictive power, the cross-validated predictive ability test (CVPAT), which represents an alternative to PLSpredict for prediction-oriented assessment of PLS-SEM results. The CVPAT was developed by Liengaard et al. (2021) for prediction-oriented model comparison in PLS-SEM. Sharma et al. (2023) extended the CVPAT for evaluating the model's predictive capabilities. Sharma et al. (2023) also provide guidelines for its use.

As described by Ringle et al. (2022), CVPAT applies an out-of-sample prediction approach to calculate the model's prediction error, which determines the average loss value. For prediction-based model assessment, this average loss value is compared to the average loss value of a prediction using indicator averages (IA) as a naive benchmark and the average loss value of a linear model (LM) forecast as a more conservative benchmark. PLS-SEM's average loss should be lower than the average loss of the benchmarks, which is expressed by a negative difference in the average loss values. CVPAT tests whether PLS-SEM's average loss is significantly lower than the average loss of the benchmarks. Therefore, the difference between the average loss values should be significantly below zero to substantiate the better predictive capabilities of the model compared to the prediction benchmarks.

Sharma et al. (2023) propose that the PLS-SEM predictions should always be significantly better than the naïve indicator-averages (IA) prediction benchmark to demonstrate predictive validity. In the case where the PLS-SEM predictions were significantly better than the linear model (LM) prediction benchmark, we could talk of strong predictive validity.

Table 5.9 shows the results of the CVPAT predictive validity test for both samples. To interpret them correctly, it is necessary to understand that the null hypothesis tested is that the loss of the proposed model is equal to the loss of the benchmark, and that the alternative hypothesis is that the loss of the proposed model is lower than the loss of the benchmark, being the benchmark the IA model and the LM model. Thus, the null hypothesis should be rejected for the model to show predictive validity. At the same time, a negative loss implicates that the model loss is smaller than the benchmark loss, indicating positive signs for a contrary conclusion. Results show how our model demonstrates predictive validity for both user and non-user samples, as the t test always allows to reject the null hypothesis when the benchmark is the indicator's average and the loss sign is negative. However, we cannot conclude that we have a model with strong predictive validity because, although the overall test is significant and it is also significant for nearly all the latent variables when compared to the linear model (LM) benchmark, the sign of the loss is positive, indicating a greater loss of our model than the benchmark's loss.

TABLE 5.9: **Predictive validity analysis: Cross-validated predictive ability test (CVPAT)**

| | Users | | | | Non-users | | | |
|---|---|---|---|---|---|---|---|---|
| | Indicators' average (IA) | | Indicators' average (LM) | | Indicators' average (IA) | | Indicators' average (LM) | |
| Latent variable | (Model - benchmark) loss | t value | (Model - benchmark) loss | t value | (Model - benchmark) loss | t value | (Model - benchmark) loss | t value |
| Customer acceptance (ACC) | -1,530 | 12.596 ** | 0.123 | 2.778 ** | -1.389 | 10.496 ** | 0.064 | 1.097 |
| Perceived usefulness (PU) | -0.754 | 6.140 ** | 0.248 | 2.722 ** | -0.584 | 4.163 ** | 0.233 | 1.831 * |
| Rapport (RAP) | -0.407 | 4.896 ** | 1.129 | 10.848 ** | -0.362 | 3.868 ** | 1.163 | 8.813 ** |
| Trust (TRU) | -0.924 | 8.317 ** | 0.512 | 6.466 ** | -0.874 | 6.598 ** | 0.530 | 5.242 ** |
| Actual use (USE) | -0.494 | 5.247 ** | 0.053 | 0.509 | | | | |
| Overall | -0.832 | 10.831 ** | 0.438 | 9.683 ** | -0.846 | 8.743 ** | 0.550 | 8.839 ** |

# CHAPTER 6: RESULTS AND DISCUSSION

# 6. RESULTS AND DISCUSSION

Once demonstrated in the previous chapter, the reliability and validity of the measurement model, as well as the absence of collinearity issues, explanatory power, and predictive validity of our structural model, it can be estimated, and the focus of the analysis can be translated to the hypotheses contrast.

To have a clear roadmap of the estimation process, it is important to remember that we tested a set of hypotheses in two different samples: users and non-users. That implies that not only the model had to be estimated in both samples, but also that a test on the path parameters' difference had to be applied to determine which of the differences are really significant. With this approach, we were able to not only contrast hypotheses but also determine differences in the behavior of our model between users and non-users.

It should be beard in mind that a final estimation for the user sample model had to be performed, as hypothesis H16 is specific to this sample.

## 6.1. Results

As stated before, a multigroup analysis (MGA) had to be performed in order to apply a statistical test for path differences and determine whether or not the difference between the two samples is significant. As Rasoolimanesh et al. (2016, p.769) indicate, "Hair et al. (2014) and Henseler et al. (2016) advocate for the testing of measurement invariance before performing MGA between two or more groups when using SEM. However, most methods of assessing SEM measurement invariance assume common factor models. PLS-SEM, on the other hand, is a composite model with latent variable scores calculated according to a composite model algorithm (Henseler et al., 2016). Henseler et al. (2016) suggested an alternative method, the measurement invariance of composites (MICOM), that is more suitable for PLS-SEM as a composite-based analysis technique. Given that the current study aims to compare a model over two groups via PLS-SEM, MICOM has been adopted. MICOM is a three-step process involving (a) configural invariance assessment; (b) the establishment of compositional invariance assessment; and (c) an assessment of equal means and variances."

To be able to compare the standardized coefficients of the structural model, configural and compositional invariance must be established, which is called partial measurement invariance (Henseler et al., 2016).

Configural invariance entails that a composite, which has been specified equally for all the groups, emerges as a unidimensional entity in the same nomological net across all the groups. Specifically, it must be fulfilled (Henseler et al., 2016): identical indicators per measurement model, as we assured in the measurement model validity, identical data treatment, which includes coding, reverse coding, and data handling (standardization and missing data handling), and identical algorithm settings or optimization criteria. All these requirements have been fulfilled in the previous steps.

Compositional invariance means that the prescription for condensing the indicator variables into composites is the same for all groups, that is, when the composite's scores are created equally across groups (Henseler et al., 2016). Henseler et al. (2016) propose a permutation method to establish compositional invariance. If compositional invariance applies, the correlation between the composite scores of the two groups must be c=1. If c is significantly different from 1, we must reject the hypothesis of compositional invariance. According to this permutation test, the indicator weights were estimated for each group. Correlation c was calculated between the composite scores. The data were randomly permuted a number of times, meaning that the observations were randomly assigned to the groups. For each permutation, the correlation $c_u$ was calculated. To test the hypothesis that c equals one, if c is smaller than the 5% percent-quantile of the distribution of $c_u$, the c=1 hypothesis must be rejected, because the deviation from one is unlikely to stem from the sampling distribution.

TABLE 6.1: **Results of measurement invariance using permutation (MICOM)**

| Constructs | Configural invariance (same algorithms for both groups) | Compositional invariance (correlation = 1) | | Partial measurement invariance established | Equal mean assessment | | | Equal mean assessment | | | Full measurement invariance established |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | C=1 | Confidence Interval | | Differences | Confidence interval | Equal | Differences | Confidence interval | Equal | |
| 1. Customer acceptance | Yes | 1,000 | [ 1,000 1.000 ] | Yes | -0.721 | [ -0.208 0.198 ] | No | 0.256 | [ -0.218 0.233 ] | No | No |
| 2. Control | Yes | 0.997 | [ 0.979 1.000 ] | Yes | -0.242 | [ -0.192 0.194 ] | No | 0.295 | [ -0.249 0.294 ] | No | No |
| 3. Ease of use | Yes | 0.997 | [ 0.993 1.000 ] | Yes | 0.004 | [ -0.199 0.201 ] | Yes | 0.324 | [ -0.299 0.328 ] | Yes | Yes |
| 4. Hedonic motivation | Yes | 1,000 | [ 1,000 1.000 ] | Yes | -0.463 | [ -0.201 0.210 ] | No | 0.486 | [ -0.243 0.282 ] | No | No |
| 5. Perceived humaness | Yes | 0.999 | [ 0.999 1.000 ] | Yes | -0.500 | [ -0.203 0.204 ] | No | 0.091 | [ -0.206 0.216 ] | Yes | No |
| 6. Personalization | Yes | 1,000 | [ 0.988 1.000 ] | Yes | -0.378 | [ -0.207 0.208 ] | No | 0.445 | [ -0.295 0.288 ] | No | No |
| 7. Perceived usefulness | Yes | 1,000 | [ 1,000 1.000 ] | Yes | -0.503 | [ -0.203 0.206 ] | No | 0.261 | [ -0.204 0.215 ] | No | No |
| 8. Rapport | Yes | 0.999 | [ 0.999 1.000 ] | Yes | -0.445 | [ -0.198 0.209 ] | No | 0.087 | [ -0.212 0.251 ] | Yes | No |
| 9. Perceived risk | Yes | 1,000 | [ 0.993 1.000 ] | Yes | 0.244 | [ -0.202 0.205 ] | No | 0.163 | [ -0.261 0.271 ] | Yes | No |
| 10. Social interactivity | Yes | 1,000 | [ 1,000 1.000 ] | Yes | -0.448 | [ -0.203 0.209 ] | No | 0.364 | [ -0.197 0.227 ] | No | No |
| 11. Subjective social norms | Yes | 1,000 | [ 1,000 1.000 ] | Yes | -0.733 | [ -0.194 0.200 ] | No | -0.078 | [ -0.201 0.221 ] | Yes | No |
| 12. Perceived social presence | Yes | 1,000 | [ 0.999 1.000 ] | Yes | -0.506 | [ -0.215 0.210 ] | No | -0.166 | [ -0.262 0.305 ] | Yes | No |
| 13. Trust | Yes | 1,000 | [ 0.999 1.000 ] | Yes | -0.522 | [ -0.206 0.205 ] | No | 0.298 | [ -0.217 0.233 ] | No | No |

Table 6.1 shows the results for the described MICOM procedure. It can be seen that the c correlation for each of the latent variables was always higher than the 95% confidence interval of the $c_u$ distribution, which confirms that it is not significantly different from 1 and compositional invariance can be confirmed. As configurational invariance was assured in the measurement model validation, partial measurement invariance is present, and a multigroup analysis (MGA) to evaluate our model in both groups can be performed.

Estimating the MGA is quite a simple process. The sample is divided into the two groups (users and non-users in our case) and the model is estimated for each of them. Path coefficients are always numerically different, but the question is whether their differences are statistically significant. As Hair et al. (2022) point out, research has proposed several approaches for comparing groups of data and establishing the statistical difference between the parameters. The parametric approach (Keil et al., 2000), was the first proposal, and it is a modified version of the independent sample t-test, which is used to compare means (but applied to the path coefficients) with both the homoscedastic and heteroscedastic versions. But apart from a bad performance (Klesel et al., 2019) it does not make sense to apply a parametric approach to a result arising from PLS-SEM, which does not assume any distributional assumptions about the data.

Accordingly, we applied two non-parametric approaches to test the difference on the structural paths: the permutation test (Chin & Dibbern, 2010) and the PLS-MGA proposed by Henseler et al. (2009). The permutation test randomly permutes observations between the groups and re-estimates the model for each permutation. Comparing the differences between group-specific path coefficients per permutation facilitates testing whether the path coefficients also differ among the population. The PLS-MGA test is based on bootstrap results. The test compares each bootstrap estimate for one group with all other bootstrap estimates of the same parameter in the other group. By counting the number of occurrences where the bootstrap estimate of the first group is larger than that of the second group, the approach derives a probability value for a one-tailed test.

Table 6.2 presents the hypotheses testing results. The table can be divided into two separate parts. The first one estimates our proposed model for the two sample groups, while the second part just performs the two tests to evaluate which paths are significantly different between users and non-users. Accordingly, it had to be analyzed in two consecutive steps. Firstly, we had to focus on the validation of our model in both samples and on checking which hypotheses hold or not for users and non-users. In a second step, we had to focus on the users' and non-users' differences where the test demonstrated those differences exist.

As hypothesized, perceived usefulness is a key determinant of customer acceptance of voice shopping for both users and non-users (H1: $\beta_{user} = 0.342$, $p<0.01$: $\beta_{nonuser} = 0.398$, $p<0.01$) demonstrating that if a clear added value is not perceived, voice shopping would difficultly be being adopted by users or would not have been adopted by non-users. However, ease of use played a different role for the two samples while it has been demonstrated to be important for users to adopt (H2: $\beta_{user} = 0.277$, $p<0.01$) it did not show a significant effect for non-users (H2: $\beta_{nonuser} = 0.005$, $p>0.05$) this difference being significant according to the two non-parametric tests performed. Those who have adopted voice shopping recognize ease of use is important in this process, while those who have not yet adopted voice shopping focus on the perceived value of using it but cannot yet assess the importance of ease of use as they assess it only from the media or colleagues' point of view (see Table 5.2 for the specific wording of the scales).

Social norms' non-significant effect on the acceptance of voice shopping (H4: $\beta_{user} = 0.056$, $p>0.05$: $\beta_{nonuser} = 0.038$, $p>0.05$) demonstrated that the social pressure is not focused directly on making people to adopt this technology but in showing consumers how useful it may be (H5: $\beta_{user} = 0.469$, $p<0.01$: $\beta_{nonuser} = 0.352$, $p<0.01$) and as we have demonstrated the significant direct effect of perceived usefulness on consumer acceptance, social norm, we had a clear indirect significant effect of social norm on customer acceptance via the mediating role of usefulness[1]. The effect of increasing the perceived usefulness of voice shopping thanks to perceiving it as an easy to use technology holds for both user and non-user samples (H3: $\beta_{user} = 0.194$, $p<0.05$: $\beta_{nonuser} = 0.272$, $p<0.01$).

Once analyzed the block of hypotheses related to functional elements, we move on to comment on the results regarding the social-emotional elements. The results are quite clear on the very limited effect of these elements on acceptance of voice shopping. Neither humanness (H6: $\beta_{user} = 0.053$, $p>0.05$: $\beta_{nonuser} = 0.080$, $p>0.05$) nor interactivity (H7: $\beta_{user} = -0.040$, $p>0.05$: $\beta_{nonuser} = -0.053$, $p>0.05$) nor social presence (H8: $\beta_{user} = -0.064$, $p>0.05$: $\beta_{nonuser} = 0.053$, $p>0.05$) had a significant effect on customer acceptance neither for users nor for non-users.

But there is an exception to the small effect of social-emotional elements on customer acceptance, and it is associated with hedonic motivation. While it had not a significant effect for actual users (H9: $\beta_{user} = 0.043$, $p>0.05$), it did have it on non-users (H9: $\beta_{nonuser} = 0.309$, $p<0.01$), demonstrating permutation. The PLS-MGA was used to test the significance of this difference. The results show an important difference between people who have not yet approached voice shopping and people who already engage in voice shopping. Non-users perceive that fun and entertainment could make it worthwhile to use VAs, while users know that this motivation can be neglected when compared to the objective usefulness of VAs.

The last block of hypotheses is related to the effect of relational elements and their antecedents. Trust in the technology was a prerequisite for customer acceptance for both users and non-users

[1] In order to not create a very complicated table 6.2 indirect and total effects significance have been omitted, however the indirect effect of social norm on acceptance has been calculated and it is significant ($\beta_{user} = 0.160$**; $\beta_{nonuser} = 0.140$**) as well as the total effect ($\beta_{user} = 0.216$**; $\beta_{nonuser} = 0.178$)

(H10: $\beta_{user}$ = 0.397, $p<0.01$: $\beta_{nonuser}$ = 0.217, $p<0.01$) while rapport did not matter for either sample (H15: $\beta_{user}$ = 0.019, $p>0.05$: $\beta_{nonuser}$ = 0.032, $p>0.05$) showing an objective approach to technology acceptance. Customers need to trust in the technology, but the creation of a theoretical “feeling of connection” is not relevant compared to the objective benefits of the technology.

The last result makes very relevant analyzing the way trust can be increased, showing our results that perceived control boosted it (H11: $\beta_{user}$ = 0.252, $p<0.01$: $\beta_{nonuser}$ = 0.227, $p<0.01$), so did personalization (H13: $\beta_{user}$ = 0.406, $p<0.01$: $\beta_{nonuser}$ = 0.323, $p<0.01$) while perceived risk deteriorated it (H12: $\beta_{user}$ = -0.361, $p<0.01$: $\beta_{nonuser}$ = -0.402, $p<0.01$). The managerial implications of this relevant result are presented later in this chapter. Although less relevant, as we have seen that the effect of rapport on customer acceptance was not significant, personalization also improved rapport (H14: $\beta_{user}$ = 0.445, $p<0.01$: $\beta_{nonuser}$ = 0.428, $p<0.01$).

Finally, it would be of little interest to delve into the determinants of customer acceptance if we could not demonstrate that this attitudinal variable has a behavioral consequence in actual use, such as increasing the frequency of use or a desire for continuous use in the future. According to the test on the user sample, acceptance demonstrated a strong and significant effect on actual use (H15: $\beta_{user}$ = 0.458, $p<0.01$) demonstrating the attitudinal-behavioral expected connection.

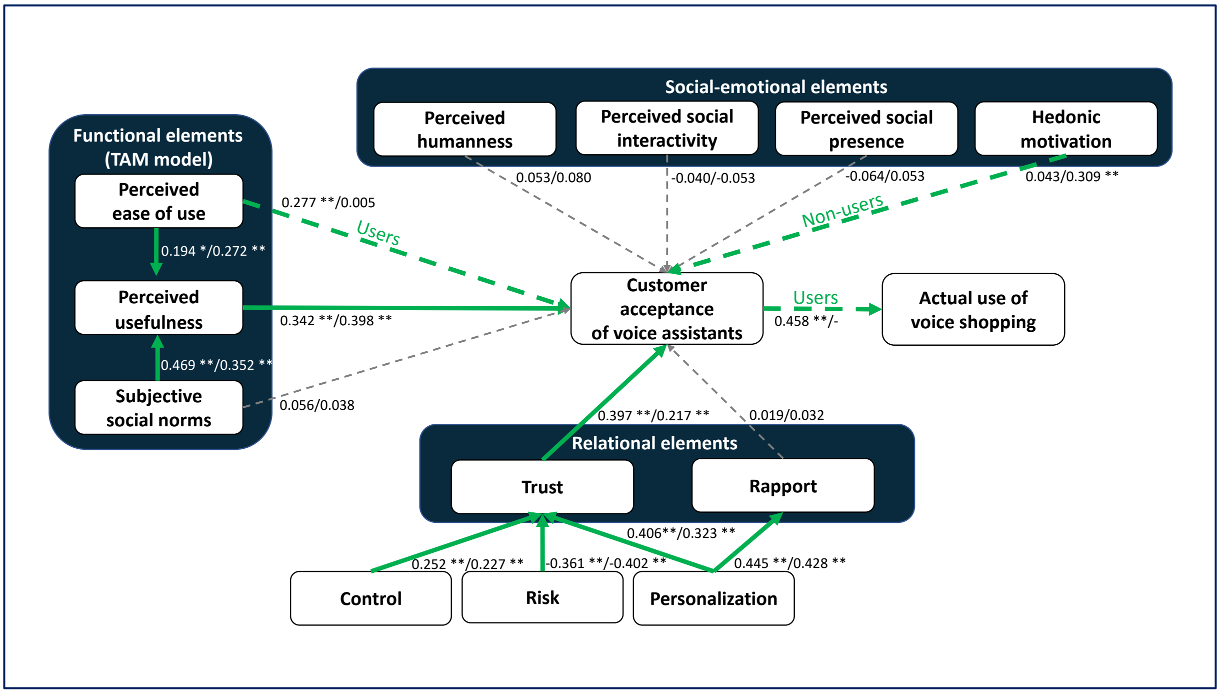
TABLE 6.2: **Results of hypotheses testing**

| | Hypothesis | Path coefficient | | Confidence interval (95%) | | Supported hypothesis (users/non-users) | Path coefficient difference | P value difference (one-tailed) | | Supported difference (MGA/Permutation) |
|---|---|---|---|---|---|---|---|---|---|---|
| | | Users | Non-users | Users | Non-users | | | Henseler's MGA | Permutation | |
| H1 | Perceived usefulness -> customer acceptance | 0.342 ** | 0.398 ** | [ 0.226 0.471 ] | [ 0.314 0.479 ] | Yes/Yes | 0.056 | 0.230 | 0.491 | No/No |
| H2 | Ease of use -> customer acceptance | 0.277 ** | 0.005 | [ 0.177 0.403 ] | [ -0.058 0.072 ] | Yes/No | -0.272 | 1.000 ** | 0.000 ** | Yes/Yes |
| H3 | Ease of use -> perceived usefulness | 0.194 * | 0.272 ** | [ 0.036 0.349 ] | [ 0.175 0.357 ] | Yes/Yes | 0.079 | 0.201 | 0.336 | No/No |
| H4 | Social norm -> customer acceptance | 0.056 | 0.038 | [ -0.077 0.193 ] | [ -0.034 0.115 ] | No/No | -0.018 | 0.594 | 0.820 | No/No |
| H5 | Social norm -> perceived usefulness | 0.469 ** | 0.352 ** | [ 0.308 0.601 ] | [ 0.252 0.442 ] | Yes/Yes | -0.117 | 0.905 | 0.183 | No/No |
| H6 | Perceived humaness -> customer acceptance | 0.053 | 0.080 | [ -0.097 0.194 ] | [ -0.042 0.201 ] | No/No | 0.027 | 0.391 | 0.822 | No/No |
| H7 | Social interactivity -> customer acceptance | -0.040 | -0.053 | [ -0.169 0.102 ] | [ -0.153 0.049 ] | No/No | -0.013 | 0.567 | 0.914 | No/No |
| H8 | Social presence -> customer acceptance | -0.064 | 0.053 | [ -0.212 0.087 ] | [ -0.056 0.163 ] | No/No | 0.116 | 0.109 | 0.250 | No/No |
| H9 | Hedonic motivation -> customer acceptance | 0.043 | 0.309 ** | [ -0.100 0.171 ] | [ 0.216 0.407 ] | No/Yes | 0.266 | 0.001 ** | 0.001 ** | Yes/Yes |
| H10 | Trust -> customer acceptance | 0.397 ** | 0.217 ** | [ 0.260 0.546 ] | [ 0.106 0.331 ] | Yes/Yes | -0.180 | 0.976 * | 0.075 | Yes/No |
| H11 | Control -> trust | 0.252 ** | 0.227 ** | [ 0.119 0.372 ] | [ 0.135 0.317 ] | Yes/Yes | -0.025 | 0.628 | 0.765 | No/No |
| H12 | Risk -> trust | -0.361 ** | -0.402 ** | [ -0.473 -0.236 ] | [ -0.498 -0.311 ] | Yes/Yes | -0.041 | 0.699 | 0.636 | No/No |
| H13 | Personalization -> trust | 0.406 ** | 0.323 ** | [ 0.265 0.522 ] | [ 0.240 0.402 ] | Yes/Yes | -0.083 | 0.857 | 0.295 | No/No |
| H14 | Personalization -> rapport | 0.445 ** | 0.428 ** | [ 0.297 0.566 ] | [ 0.327 0.510 ] | Yes/Yes | -0.017 | 0.584 | 0.837 | No/No |
| H15 | Rapport -> customer acceptance | 0.019 | 0.032 | [ -0.151 0.186 ] | [ -0.109 0.176 ] | No/No | 0.012 | 0.456 | 0.911 | No/No |
| H16 | Customer acceptance -> actual use | 0.458 ** | – | [ 0.389 0.523 ] | – – | Yes | – | – | – | – |

Note: In Henseler's MGA method, the p value lower than 0.05 or higher than 0.95 indicates at the 5% level significant differences between specific path coefficients across two groups.
**p<0.01; *p<0.05

Figure 6.1 summarizes the results of the proposed model and highlights the confirmed hypotheses with thick lines, while the ones confirmed by only one group are shown with thick dashed lines and the unconfirmed ones with thin dashed lines.

FIGURE 6.1: **Results of the proposed model**




## 6.2. Discussion

The outcome of this study has created new insights into the adoption of voice shopping in Germany by assessing the characteristics of the persons based on data collected from 499 people in Germany, drawing on the conceptual service robot acceptance model (sRAM) by J. Wirtz et al. (2018), which considers functional elements, social-emotional elements, and relational elements. Owing to the limitations of the investigation, these meaningful results should be translated with attention. This section gives a contemplation on the investigation process. The limitations and hypothetical consequences are argued, as are the implications for the interpretation of the findings. The section closes with respective recommendations for potential exploration.

The study reveals the primacy of objective antecedents comprising functional and relational elements over social-emotional elements, as well as the importance of trust. The results suggest that social-emotional elements are not relevant for the acceptance of VAs, which goes in line with the needs and role congruency (Schepers & Wetzels, 2007), showing Germans don't need a high level of perceived humanness, perceived social interactivity, or perceived social presence in order to accept VAs. One plausible explanation is the cultural context, as this survey focuses on people living in Germany and, consistent with the findings of Zaharia and Würfel (2021), demonstrates that for Germans, usefulness plays the most important role when obtaining information about a product or making a purchase. The survey provides a new insight into the impact of culture on customer acceptance of VAs and should be taken into account when considering how to address customers in Germany. Consequently, in the case of the VA Alexa, Amazon and other businesses should focus on the functional elements in order to increase the adoption in Germany.

The results indicate that perceived usefulness is a key determinant of customer acceptance of voice shopping for both users and non-users. In line with the hypothesis and coherent with existing literature (J. Wirtz et al., 2018) a clear added value makes people accept a VA, which is of even higher importance for non-voice shoppers. The results fit with the theory that in Western cultures, perceived usefulness appears to be more significant than perceived ease of use, whereas in non-Western cultures, it is the opposite (Schepers & Wetzels, 2007). Therefore, businesses should position Alexa as valuable and point out its usefulness.

Moreover, the data points out that ease of use plays a different role for users and non-users, with users recognizing its importance and non-users focusing on the perceived value of using the technology. Contrary to the hypothesized association, people who have not experienced voice shopping yet concentrate solely on the usefulness of the technology. Non-users are not able to assess the significance of the ease of use because by only hearing about the technology from someone they know and who shared the impressions or from the media is neither enough to consider it nor the same having done voice shopping oneself or just supposing how it might be. Nevertheless, the results confirm the study by Venkatesh and Davis (2000) by showing an experienced customer has a higher perceived ease of use. Although the direct impact of perceived ease of use on VA acceptance is irrelevant for non-users, the absence of perceived ease of use might be inhibiting (J. Wirtz et al., 2018). Hence, this determinant should be considered independent of whether it targets voice shoppers or non-voice shoppers. The data contribute a clearer understanding of differentiating these two groups. Based on this, voice shopping should be easy to understand and undertake so that the customer is empowered to finish the purchase without effort (McLean et al., 2020). This can be achieved by the ease of download and registration, recuperating errors, suitable recommendations or alternatives offered by the VA.

Furthermore, the findings of this research highlight the importance of usefulness through the indirect effect of ease of use on voice shopping acceptance. There is a clear significance especially for non-users. Due to the perception of voice shopping as an easy to use technology, persons consider it more useful and become more willing to use it. This is consistent with the findings of Venkatesh and Bala (2008) that perceived ease of use contributes through usefulness.

The analysis indicates that subjective social norms are not directly related to the acceptance of VAs. Contradicting the claims of J. Wirtz et al. (2018) however, it shows that social pressure is not aimed at forcing people to adopt this technology directly. Even though the results are not congruent with the original sRAM, they confirm the findings of Fernandes and Oliveira (2021). Additionally, as the use of VAs is voluntary, the findings are in accordance with Venkatesh and Davis (2000) stating direct impact of subjective social norms on acceptance only occurs in the case of a mandatory technology.

The analysis supports the theory that subjective social norms have an indirect effect through perceived usefulness. This means that social pressure has rather a positive impact by showing consumers how useful a technology may be. These outcomes build on existing evidence from Blut et al. (2016). Accordingly, in Germany, voice commerce can be increased by word of mouth or by important persons touting its usefulness.

The results point out that social-emotional elements, such as perceived humanness, perceived social interactivity, and perceived social presence, have no effect on customer acceptance, while hedonic motivation stands out with a significant effect explicitly on non-users. For people living in Germany, emotional aspects such as humanlike behavior, the way of social interacting, or the perception of being in company of somebody are not of relevance and they don't have the need for a social-emotional relation in order to accept a technology or to actually use it. Even though these findings are in contrast to the associated hypotheses, they are coherent with the previous research by Guzman (2019) indicating that people are unlikely to perceive a VA as a natural, humanlike, or lifelike creature. Sheehan et al. (2020) assume that the preferences for social interaction differ among users. Furthermore, no social is needed if the focus is on utilitarian needs (Fernandes & Oliveira, 2021). But also Chattaraman et al. (2019) consider social presence only if the user wants to build a relation with the VA. These findings should be taken into account when considering how to design the voice shopping process.

While previous research has focused on humanness, social interactivity, and social presence, the findings of this research demonstrate that only hedonic motivation is of relevance. Showing the significance of providing entertaining features rather than human or social features for the customers. By focusing on non-users, the positive impact of this social-emotional element is congruent with the results of Rzepka et al. (2020). These results should be considered when it comes to attracting new voice shoppers. Nevertheless, it is vital to differentiate between the two groups, as data indicate actual users clearly prioritize the functional elements, whereas for persons who have not experienced voice shopping yet, it could be worth adopting out of fun. Consequently, after consumers tried voice shopping, the functional advantages are more important than entertainment, hereby confirming the findings of McLean and Osei-Frimpong (2019). Therefore, businesses should promote the fun aspect of communicating with VAs, especially for those who have not yet engaged in voice shopping, as well as market the enjoyable and agreeable shopping procedure to increase adoption and later use (Zaharia & Würfel, 2021).

Coming to the relational elements, while the study demonstrates that rapport does not matter for either sample, trust in the technology is a prerequisite for customer acceptance. The results meet the expectations considering the need for customers' trust; however, when it comes to rapport, the creation of a theoretical bond between the customer and the VA is not relevant for having the intention to adopt. Even though this is not in line with previous literature (Cerekovic et al., 2017), based on the findings, a plausible explanation is that some persons just do not want to build a relation with a VA. A further explanation is that the respondents considered it rather a complex cognitive/analytical and simple emotional/social task and therefore did not have a high desire for rapport (J. Wirtz et al., 2018). Moreover, by comparing the results of rapport and the social-emotional elements, the findings reveal consistency and underline that in Germany, the functional aspects of the technology are in the foreground. While former investigations stressed the importance of exploring the impact of rapport (Fernandes & Oliveira, 2021), these results prove that for the adoption in this context, it is not substantial that the VA offers a pleasant conversation.

The data demonstrate that perceived control and personalization boost trust and confirm that perceived risk decreases it. The impact of control on trust supports the hypotheses and previous literature (Q. Yang et al., 2015) as the more a person perceives to be in control over the VA and the use of voice shopping, the more they trust in it. Consequently, voice shopping should be of low task complexity.

Congruent with the findings of other studies, the more a VA is offering products and services according to the customers' preferences, sending personalized messages, or being personalized for usage, the more the customers trust the technology and build a relation with it. This is consistent with the studies of Rhee and Choi (2020) and Irfan et al. (2019). Therefore, businesses should take advantage of VAs' capabilities for personalization.

In line with the hypotheses are the risks of giving a voice command, the disclosure of financial information as well as personal information, and their impact on trust. It noticeably shows that the less risk is perceived, the higher the trust of the customer in the VA. This is congruent with the literature (Blut et al., 2016; Kowalczuk, 2018; Zaharia & Würfel, 2020). Furthermore, it shows the importance for businesses to constantly consider the reduction of risk, especially in the data privacy and security sectors. Referring to the three antecedents control, personalization, and risk, the study provides a clearer understanding of their impact on trust in VA acceptance.

This analysis supports the theory that acceptance has a strong and substantial effect on the actual use of voice shopping. The results suggest that if a customer accepts a VA, this will have an impact on the actual use of voice shopping, comprising the frequency of purchases and the wish for continuous use in the future. Thus, these findings are consistent with the conceptual sRAM model (J. Wirtz et al., 2018). Although prior studies investigated the acceptance of voice assistants via the sRAM, to our knowledge, a comparison of users and non-users combined with the consideration of the actual use of voice shopping has not been explored yet. Hence, our results provide new information on the actual use.

However, it is beyond the scope of this study to consider other cultures or countries, such as Spain, in order to examine if other cultures might have a higher need for social-emotional elements. Accordingly, the results may not be generalizable to other markets on an international scale. Future studies should take cultural differences into account, as these might provide different results, especially regarding the influence of social-emotional and relational elements. Consequently, this might lead to different approaches to business. Furthermore, this survey only addressed Amazon Alexa users; thus, the results cannot be confirmed for all types of VAs. Although it can be assumed that the findings cover different types of VAs, future research could investigate other VAs, such as Google Assistant. Therefore, further research is needed to establish an understanding of the general VA adoption and whether there exists a difference in adoption among the VAs. The generalizability of the results is limited by the sample size of 499 persons, which presents a rather small sample for the whole of Germany. Consequently, with more resources, future research should consider a larger sample. Moreover, the survey did not distinguish between low involvement products and high involvement products. A promising avenue for future research includes the consideration of product categories. Besides this, the investigation did not consider the education and income of the respondents, which might offer further helpful insights for the voice commerce process in general and for specific products in particular. Hence, future research could analyze the moderating effect of these variables on VA adoption and its actual use.

Nonetheless, the results are valid for the purpose of determining the antecedents influencing voice shopping in Germany, as they clearly showed that in Germany, the functional elements as well as trust and its antecedents are preeminent and should be considered, as well as the differentiation of users and non-users, especially when it comes to ease of use and hedonic motivation.

# CHAPTER 7: CONCLUSION

## 7. CONCLUSION

This study aimed to investigate the antecedents of innovation adoption of voice shopping. It focused on the virtual assistant Alexa and consumers in Germany. The research project concentrated on the traits of the VA and the user, including functional elements, social-emotional elements, and relational elements. Based on a quantitative analysis of VA adoption and actual use of voice shopping, it can be summarized that one main contribution lies in the superiority of the functional attributes as well as trust, including its antecedents control, risk, and personalization, over the social-emotional elements. Although prior research called for examining the influence of social-emotional elements due to the characteristics of VAs (J. Wirtz et al., 2018), it is outstanding that even within this new AI-based technology context, the impact of functionality is significant and there is no need for social interaction or bonding.

Customers progressively use AI-based technologies in their daily lives, and among the available services after online and mobile shopping, voice shopping became the most important development (Bawack et al., 2021b). As 31% out of possible 85% of Germans use a VA (ARD/ZDF-Onlinestudie, 2020) and 21% out of possible 51% order products with the VA Alexa (Tas et al., 2019), there is a need to know what triggers Germans to accept this new technology and engage in voice shopping in order to leverage the potential of further adoption.

The particularity of this research was to examine whether different or additional variables have to be considered for AI-driven technology in comparison to former technologies without AI. Based on the conceptual framework of the sRAM, this study anticipated the influence of social-emotional and relational elements on VA acceptance and actual use, in addition to the impact of functional elements.

Accordingly, a total of 16 hypotheses were formulated, including the sRAM dimensions, in order to analyze the relations between the constructs of the proposed theoretical model, where the majority was proven and the significance confirmed.

As this study differentiated between users and non-users, the findings delivered additional insights. The main difference between these two groups is that the direct impact of ease of use is only for users in accordance with former findings (Davis, 1989), while the indirect impact is more significant for non-users (Venkatesh & Bala, 2008).

An unexpected insight is that hedonic motivation is only relevant for non-users. Thus, customers without voice shopping experience confirm that fun and entertainment have an impact (K. Lee et al., 2019).

Contrary to the assumption of J. Wirtz et al. (2018) subjective social norms do solely matter indirectly through perceived usefulness for both groups. Moreover, perceived humanness, perceived social interactivity, and perceived social presence do not show evidence of a positive impact on VA acceptance, which differs from the previous work of Moussawi et al. (2021), Amelia et al. (2021), and Fuentes-Moraleda et al. (2020), while the irrelevance of perceived humanness corresponds to the latest results of Fernandes and Oliveira (2021). Contrary to the literature, rapport does not play any role in VA acceptance (Cerekovic et al., 2017).

In line with earlier findings, VA acceptance is considerably influenced by perceived usefulness (Davis, 1989; Fernandes & Oliveira, 2021). An important insight is the confirmation that the antecedents control (Poushneh, 2021b), risk (Zaharia & Würfel, 2021), and personalization (Irfan et al., 2019) play an important role in trust. Confirming trust has an impact on the adoption of VAs and, consequently, on the actual use (B. Lu et al., 2016). The impact of VA acceptance on actual use is, as expected, significantly high (Bawack et al., 2021a).

Consequently, this study complements previous knowledge on VA adoption. It also presents the sRAM in a novel way and empirically verifies its relevance for examining the actual use of voice shopping. Thus, our work presents significant implications not only for theory but also for practice.

## 7.1. Theoretical implications

This paper is among the earliest to investigate the influences on the adoption and actual use of voice shopping by applying the sRAM. After outlining the secondary research and conducting the primary research, it was examined how the factors impact innovation adoption. This study provides recommendations for the progress of VAs in Germany, considering the impelling determinants and contributes to the literature in four ways.

First, besides affirming the preeminent role of the functional element perceived usefulness, the results show that perceived ease of use has a direct influence only if voice shopping has been applied. However, if the perceived usefulness of the VA is given, perceived ease of use and subjective social norms demonstrate their indirect impact.

Second, this study adds to the original social-emotional elements of the sRAM hedonic motivation and shows that by focusing on the German market that solely this variable has a significance on the adoption and only for non-voice shoppers. Thus, in this research, the social-emotional elements and their need for the adoption of VAs are defined solely on the basis of the entertainment factor.

Third, our research reflects, as one of the first, the impact of the antecedents of the relational elements trust and rapport. Hence, this study extends the knowledge of previous ones on the sRAM by considering control, risk, and personalization. Despite the irrelevance of rapport, our results reveal the high importance of trust.

Last but not least, we provide new evidence on the impact of the actual use of voice shopping in Germany. By responding to prior calls for empirical research on the actual use of VAs (Fernandes & Oliveira, 2021) the originality of this research is evident, as previous sRAM investigation has focused mainly on acceptance rather than actual use.

### 7.2. Practical implications

Voice shopping is able to unleash businesses not only to advance their goods and services but also to develop new ones (Simms, 2019). However, many businesses face the problem of not having adequate knowledge of how VAs and voice shopping work in order to create an additional revenue stream (Mari et al., 2020). Therefore, this study identified guidelines for how managers could increase adoption and use. From this research, recommendations can be drawn as well as specific suggestions for businesses in order to design a VA or the voice shopping process.

Businesses should be aware that voice shopping brings new opportunities to sell products and incorporate them into their marketing strategy (Moriuchi, 2019). Firstly, it enables faster and more convenient reordering of products (Klaus & Zaichkowsky, 2020). Secondly, it targets customer needs more effectively, as the data communicated leads to better personalization (Irfan et al., 2019). Thirdly, it provides the opportunity to increase consumer engagement, as it offers new space for customer presence, for example, while driving or cooking (Tuzovic & Paluch, 2018). However, in order to take advantage of these opportunities, it is important that managers consider the key factors that lead to the adoption and ultimately the use of voice shopping according to the given market.

Due to the boost in importance of voice shopping as an additional selling option for many companies, consumer reactions to this new technology should influence the decision making processes of managers. Businesses looking to apply voice shopping should think about the different consumer preferences of their target markets; as for instance, consumers in one market may have different preferences for a particular product or service than consumers in other markets (Belanche et al., 2019).

Results show that in Germany, customers are mainly driven by usefulness. Consequently, managers should concentrate on providing a convenient shopping experience (Klaus & Zaichkowsky, 2020). The outcome has a lasting effect on the consumer's quality of life, as a higher willingness to accept leads to more voice shopping, which subsequently enhances the user experience due to the continuous learning of the VA (McLean & Osei-Frimpong, 2019). Additionally, managers should promote the ease of use of the VA as well as of voice shopping and consider it when designing the process.

However, based on the findings, to address the German market, it is not necessary for the VA to offer a humanlike conversation with the customer. But managers have to bear in mind that they should market the fun factor of voice shopping, especially when reaching out to potential voice shoppers, as the research shows that this antecedent mainly plays a role if the user is not experienced in voice shopping.

From the findings, it can be retrieved that control has an impact on customers' trust; managers should therefore seek to keep the complexity of the purchase process low (Amelia et al., 2021). Consequently, businesses can integrate these factors into their planning and selling processes in order to increase adoption and actual use.

Successful VA adoption can also be achieved by reducing risk. Businesses can increase transparency by providing explanations and information on data privacy and security (Rzepka et al., 2020).

Furthermore, voice shopping provides an efficient way of approaching consumers for various product segments with the aid of personalization (Rhee & Choi, 2020).

Although the study suggests that it is not necessary to build a bond with the consumer, the shopping experience should still be personalized to build trust in the VA. Therefore, businesses should elaborate personalized processes for goods and services to increase consumers' trust and hence, the engagement (B. Lu et al., 2016).

The results imply that managers should have a fair knowledge of the influencing determinants held by their target market to increase VA acceptance and actual use. For being successful, the acceptance of a new technology is the main prerequisite.

### 7.3. Limitations

Despite the implications of VA adoption, the current research is not without limitations that should be considered when interpreting the results of this study and may open avenues for future research.

First, the research was limited to the country of Germany. An expansion of this study examining the cultural influence, especially on the social-emotional elements, would help to round up these findings.

Second, based on the fact that in Germany at the beginning of voice commerce, just one VA offered voice shopping, the results are only applicable to the Alexa shopping experience. A VA comparison might support and confirm these findings.

Third, the current percentage of voice shoppers is still very low, and therefore, with the increasing number of consumers, an additional survey with more respondents should be conducted to attain a meaningful result. Nevertheless, an appropriate sample size was achieved.

This study was built on sRAM and its determinants, while also including hedonic motivation and antecedents of trust. However, the fourth limitation is the selection of influencing variables. Enhancing this paper with additional variables, such as culture, education, or income, could complement the holistic approach. Therefore, researchers may wish to pursue these suggestions.

Nevertheless, the outcome of this investigation delivers vital information for companies and brands and enhances the AI innovation adoption literature by identifying the success-bringing determinants leading to VA acceptance and the actual use of voice shopping in Germany.

### 7.4. Future lines of research

Although the outcome of this study offers new evidence for companies and brands selling their products via VAs, more research should be undertaken, as this specific field of study only scratches the surface of the drivers of AI-based innovation adoption.

The market for research is concentrated in one country. Additional investigations should be examined, considering other countries. Further possibilities for research relate to variations by country. Thereby, the research could focus on a comparison of one other country, only German speaking countries, or culturally different countries. For instance, Spain or the USA could provide more insights due to their cultural differences. Thus, VA adoption and actual use should be investigated more based on international comparisons.

Comparing different VAs at the given time might be a promising avenue for future exploration. Further research should be conducted that investigates different VAs and compares their results regarding the impact of the different elements. Other VAs, as for instance, Google Assistant, could supply different findings.

Further research is essential to investigate whether different product categories, such as health and beauty or household supplies, differ in their results, and to make a comparison between low and high involvement products. Considering this, it might be supportive in predicting VA acceptance and the actual use of voice shopping.

Another factor that has to be considered is that not all respondents who participated in the survey were experienced with or interested in voice shopping. Thus, future studies could focus on experienced users in order to examine this specific sample of consumers as well as the changing behavior of customers over time.

Moreover, for businesses, it would be helpful to know if the effects that were detected generalize to all age groups and genders. Therefore, further studies with different target groups should be conducted. Since it is necessary to find out whether these general results are applicable for all generations and genders. Besides, there might be differences concerning education or income. Additional research is needed to determine the effects of education and income on acceptance and actual use.

Future research should concentrate on developing additional antecedents and a better understanding of the relation between these antecedents, for instance, the indirect effect of hedonic motivation on adoption. Further studies are vital to provide more AI adoption literature concerning determinants of social-emotional and relational elements. As this study concentrated mainly on the positive effects, more research should be undertaken regarding inhibitors and negative effects on adoption and actual use to gain more insights.

The evolution of technology acceptance theories is continuously adapting and extending. Conclusively, more empirical work by applying the sRAM model is essential to gain a comprehensive understanding of the elements and their antecedents.

# CHAPTER 8: BIBLIOGRAPHY

# 8. BIBLIOGRAPHY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# APPENDIX A

# QUESTIONNAIRE ENGLISH

Gender *

Choose one of the following answers
Please choose **only one** of the following:

- ◯ Female
- ◯ Male
- ◯ Diverse

Age *

Choose one of the following answers
Please choose **only one** of the following:

- ◯ Under 24
- ◯ 25 - 40
- ◯ 41- 56
- ◯ Over 57

Please rate the following statements: *

Please choose the appropriate response for each item:

| | 1 strongly disagree | 2 | 3 | 4 neutral | 5 | 6 | 7 strongly agree |
|---|---|---|---|---|---|---|---|
| **People who are important to me think that I should use Alexa for voice shopping.** | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ |
| **People who influence my behavior think that I should use Alexa for voice shopping.** | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ |
| **People whose opinions I value prefer that I use Alexa for voice shopping.** | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ |

Please indicate your agreement or disagreement with the following statements (1 = strongly disagree, 4 = neutral, 7 = strongly agree).

*

Please choose the appropriate response for each item:

| | 1 strongly disagree | 2 | 3 | 4 neutral | 5 | 6 | 7 strongly agree |
|---|---|---|---|---|---|---|---|
| **I personally feel Alexa is natural.** | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ |
| **I personally feel Alexa is human-like.** | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ |
| **I personally feel Alexa is life-like.** | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ |

*

Please choose the appropriate response for each item:

| | 1 strongly disagree | 2 | 3 | 4 neutral | 5 | 6 | 7 strongly agree |
|---|---|---|---|---|---|---|---|
| **I find Alexa pleasant to interact with.** | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| **I think Alexa is nice.** | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| **Alexa makes me feel like she wants to listen to me.** | ○ | ○ | ○ | ○ | ○ | ○ | ○ |

*

Please choose the appropriate response for each item:

| | 1 strongly disagree | 2 | 3 | 4 neutral | 5 | 6 | 7 strongly agree |
|---|---|---|---|---|---|---|---|
| **When interacting with Alexa, I felt like talking to a real person.** | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| **Sometimes Alexa seems to have real feelings.** | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| **I often think Alexa is a real person.** | ○ | ○ | ○ | ○ | ○ | ○ | ○ |

*

Please choose the appropriate response for each item:

| | 1 strongly disagree | 2 | 3 | 4 neutral | 5 | 6 | 7 strongly agree |
|---|---|---|---|---|---|---|---|
| **Using Alexa is fun.** | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| **Using Alexa is enjoyable.** | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| **Using Alexa is very entertaining.** | ○ | ○ | ○ | ○ | ○ | ○ | ○ |

*

Please choose the appropriate response for each item:

| | 1 strongly disagree | 2 | 3 | 4 neutral | 5 | 6 | 7 strongly agree |
|---|---|---|---|---|---|---|---|
| **I believe that Alexa is trustworthy.** | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| **I believe voice shopping is as secure as online shopping.** | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| **I believe that Alexa is reliable.** | ○ | ○ | ○ | ○ | ○ | ○ | ○ |

*

Please choose the appropriate response for each item:

| | 1 strongly disagree | 2 | 3 | 4 neutral | 5 | 6 | 7 strongly agree |
|---|---|---|---|---|---|---|---|
| **I consider Alexa a pleasant conversational partner.** | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| **Alexa makes me feel like she wants to listen to me.** | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| **I relate well to Alexa.** | ○ | ○ | ○ | ○ | ○ | ○ | ○ |

*

Please choose the appropriate response for each item:

| | 1 very low risk | 2 | 3 | 4 medium risk | 5 | 6 | 7 very high risk |
|---|---|---|---|---|---|---|---|
| **How would you characterize the decision to give a voice command to Alexa?** | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| **How would you characterize the decision to disclose financial information to Alexa?** | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| **How would you characterize the decision to disclose personal information to Alexa?** | ○ | ○ | ○ | ○ | ○ | ○ | ○ |

*

Please choose the appropriate response for each item:

| | 1 strongly disagree | 2 | 3 | 4 neutral | 5 | 6 | 7 strongly agree |
|---|---|---|---|---|---|---|---|
| **Alexa offers me products and services according to my preferences.** | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| **I feel that Alexa sends personalized messages to me.** | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| **I feel that Alexa is personalized for my usage.** | ○ | ○ | ○ | ○ | ○ | ○ | ○ |

I already did voice shopping. *

❶ Choose one of the following answers
Please choose **only one** of the following:

○ Yes
○ No

## Voice Shoppers

This section is only for users who already did voice shopping.

*

Only answer this question if the following conditions are met:
((EXP.NAOK == 'V'))

Please choose the appropriate response for each item:

| | 1 strongly disagree | 2 | 3 | 4 neutral | 5 | 6 | 7 strongly agree |
|---|---|---|---|---|---|---|---|
| **Using Alexa for voice shopping is entirely within my control.** | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| **I am able to use Alexa for voice shopping.** | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| **I have the control to make use of Alexa for voice shopping.** | ○ | ○ | ○ | ○ | ○ | ○ | ○ |

*

Only answer this question if the following conditions are met:
((EXP.NAOK == 'V'))

Please choose the appropriate response for each item:

| | 1 strongly disagree | 2 | 3 | 4 neutral | 5 | 6 | 7 strongly agree |
|---|---|---|---|---|---|---|---|
| **Using Alexa for voice shopping is more convenient than online shopping.** | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| **Using Alexa for voice shopping allows me to multitask.** | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| **Overall, I find Alexa for voice shopping useful.** | ○ | ○ | ○ | ○ | ○ | ○ | ○ |

*

Only answer this question if the following conditions are met:
((EXP.NAOK == 'V'))

Please choose the appropriate response for each item:

| | 1 strongly disagree | 2 | 3 | 4 neutral | 5 | 6 | 7 strongly agree |
|---|---|---|---|---|---|---|---|
| **Learning to operate Alexa for voice shopping is easy for me.** | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| **I find it easy to get Alexa to do what I want her to do.** | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| **Overall, I find Alexa for voice shopping easy to use.** | ○ | ○ | ○ | ○ | ○ | ○ | ○ |

*

Only answer this question if the following conditions are met:
((EXP.NAOK == 'V'))

Please choose the appropriate response for each item:

| | 1 strongly disagree | 2 | 3 | 4 neutral | 5 | 6 | 7 strongly agree |
|---|---|---|---|---|---|---|---|
| **Using Alexa for voice shopping is a good idea.** | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| **Using Alexa for voice shopping is pleasant.** | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| **I like the idea of using Alexa for voice shopping.** | ○ | ○ | ○ | ○ | ○ | ○ | ○ |

*

Only answer this question if the following conditions are met:
((EXP.NAOK == 'V'))

Please choose the appropriate response for each item:

| | 1 strongly disagree | 2 | 3 | 4 neutral | 5 | 6 | 7 strongly agree |
|---|---|---|---|---|---|---|---|
| **I will continue using Alexa for voice shopping in the future.** | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| **I am always using Alexa for voice shopping whenever I want to buy something.** | ○ | ○ | ○ | ○ | ○ | ○ | ○ |

*

Only answer this question if the following conditions are met:
((EXP.NAOK == 'V'))

Please choose the appropriate response for each item:

| | yearly | more than once a year | monthly | more than once a month | weekly | more than once a week | more than once a day |
|---|---|---|---|---|---|---|---|
| **How frequently are you using Alexa for voice shopping?** | ○ | ○ | ○ | ○ | ○ | ○ | ○ |

## Non-Voice Shoppers

This section is only for users who did not voice shopping yet.

*

Only answer this question if the following conditions are met:
((EXP.NAOK == 'N'))

Please choose the appropriate response for each item:

| | 1 strongly disagree | 2 | 3 | 4 neutral | 5 | 6 | 7 strongly agree |
|---|---|---|---|---|---|---|---|
| **Using Alexa for voice shopping would be entirely within my control.** | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| **I would be able to use Alexa for voice shopping.** | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| **I would have the control to make use of Alexa for voice shopping.** | ○ | ○ | ○ | ○ | ○ | ○ | ○ |

Even if you have not used Alexa for voice shopping, you might know someone who shared with you his impressions, or you heard about it in the media. Based on this, rate in which measure you believe that Alexa for voice shopping could be within your control.

*

Only answer this question if the following conditions are met:
((EXP.NAOK == 'N'))

Please choose the appropriate response for each item:

| | 1 strongly disagree | 2 | 3 | 4 neutral | 5 | 6 | 7 strongly agree |
|---|---|---|---|---|---|---|---|
| **Using Alexa for voice shopping would be more convenient than online shopping.** | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| **Using Alexa for voice shopping would allow me to multitask.** | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| **Overall, I would find Alexa for voice shopping useful.** | ○ | ○ | ○ | ○ | ○ | ○ | ○ |

Even if you have not used Alexa for voice shopping, you might know someone who shared with you his impressions, or you heard about it in the media. Based on this, rate in which measure you believe that Alexa for voice shopping could be useful.

*

Only answer this question if the following conditions are met:
((EXP.NAOK == 'N'))

Please choose the appropriate response for each item:

| | 1 strongly disagree | 2 | 3 | 4 neutral | 5 | 6 | 7 strongly agree |
|---|---|---|---|---|---|---|---|
| **Learning to operate Alexa for voice shopping is easy for me.** | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| **I would find it easy to get Alexa to do what I want her to do.** | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| **Overall, I would find Alexa for voice shopping easy to use.** | ○ | ○ | ○ | ○ | ○ | ○ | ○ |

Even if you have not used Alexa for voice shopping, you might know someone who shared with you his impressions, or you heard about it in the media. Based on this, rate in which measure you believe that Alexa for voice shopping could be easy to use.

*

Only answer this question if the following conditions are met:
((EXP.NAOK == 'N'))

Please choose the appropriate response for each item:

| | 1 strongly disagree | 2 | 3 | 4 neutral | 5 | 6 | 7 strongly agree |
|---|---|---|---|---|---|---|---|
| **Using Alexa for voice shopping is a good idea.** | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| **Using Alexa for voice shopping would be pleasant.** | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| **I like the idea of using Alexa for voice shopping.** | ○ | ○ | ○ | ○ | ○ | ○ | ○ |

# APPENDIX B

# QUESTIONNAIRE GERMAN

### Geschlecht *

Bitte wählen Sie nur eine der folgenden Antworten aus:

- ◯ Weiblich
- ◯ Männlich
- ◯ Divers

### Alter *

Bitte wählen Sie nur eine der folgenden Antworten aus:

- ◯ Unter 24
- ◯ 25 - 40
- ◯ 41- 56
- ◯ Über 57

### Bitte bewerten Sie folgende Aussagen:

*

Bitte wählen Sie die zutreffende Antwort für jeden Punkt aus:

| | 1 stimme überhaupt nicht zu | 2 | 3 | 4 neutral | 5 | 6 | 7 stimme voll und ganz zu |
|---|---|---|---|---|---|---|---|
| **Menschen, die mir wichtig sind, sind der Meinung, dass ich Alexa für Voice-Shopping nutzen sollte.** | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ |
| **Menschen, die Einfluss auf mein Verhalten haben, sind der Meinung, dass ich Alexa für Voice-Shopping nutzen sollte.** | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ |
| **Menschen, deren Meinung ich schätze, ziehen es vor, dass ich Alexa für Voice-Shopping verwende.** | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ |

Bitte geben Sie an, ob Sie den folgenden Aussagen zustimmen oder nicht (1 = stimme überhaupt nicht zu, 4 = neutral, 7 = stimme voll und ganz zu).

*

Bitte wählen Sie die zutreffende Antwort für jeden Punkt aus:

| | 1 stimme überhaupt nicht zu | 2 | 3 | 4 neutral | 5 | 6 | 7 stimme voll und ganz zu |
|---|---|---|---|---|---|---|---|
| **Ich persönlich finde, Alexa ist natürlich.** | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ |
| **Ich persönlich finde, Alexa ist menschenähnlich.** | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ |
| **Ich persönlich finde, Alexa ist lebensecht.** | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ |

*

Bitte wählen Sie die zutreffende Antwort für jeden Punkt aus:

| | 1 stimme überhaupt nicht zu | 2 | 3 | 4 neutral | 5 | 6 | 7 stimme voll und ganz zu |
|---|---|---|---|---|---|---|---|
| **Ich finde es angenehm, mit Alexa zu kommunizieren.** | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| **Ich finde Alexa freundlich.** | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| **Alexa gibt mir das Gefühl, dass sie mir zuhören möchte.** | ○ | ○ | ○ | ○ | ○ | ○ | ○ |

*

Bitte wählen Sie die zutreffende Antwort für jeden Punkt aus:

| | 1 stimme überhaupt nicht zu | 2 | 3 | 4 neutral | 5 | 6 | 7 stimme voll und ganz zu |
|---|---|---|---|---|---|---|---|
| **Wenn ich mit Alexa interagiere, habe ich das Gefühl, mit einer echten Person zu sprechen.** | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| **Manchmal scheint Alexa echte Gefühle zu haben.** | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| **Ich denke oft, dass Alexa ein echter Mensch ist.** | ○ | ○ | ○ | ○ | ○ | ○ | ○ |

*

Bitte wählen Sie die zutreffende Antwort für jeden Punkt aus:

| | 1 stimme überhaupt nicht zu | 2 | 3 | 4 neutral | 5 | 6 | 7 stimme voll und ganz zu |
|---|---|---|---|---|---|---|---|
| **Alexa zu benutzen macht Spaß.** | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| **Die Nutzung von Alexa ist sehr angenehm.** | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| **Die Nutzung von Alexa ist sehr unterhaltsam.** | ○ | ○ | ○ | ○ | ○ | ○ | ○ |

*

Bitte wählen Sie die zutreffende Antwort für jeden Punkt aus:

| | 1 stimme überhaupt nicht zu | 2 | 3 | 4 neutral | 5 | 6 | 7 stimme voll und ganz zu |
|---|---|---|---|---|---|---|---|
| **Ich glaube, dass Alexa vertrauenswürdig ist.** | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| **Ich glaube, dass Voice-Shopping mit Alexa genauso sicher ist wie Online-Shopping mit Amazon.** | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| **Ich glaube, dass Alexa zuverlässig ist.** | ○ | ○ | ○ | ○ | ○ | ○ | ○ |

*

Bitte wählen Sie die zutreffende Antwort für jeden Punkt aus:

| | 1 stimme überhaupt nicht zu | 2 | 3 | 4 neutral | 5 | 6 | 7 stimme voll und ganz zu |
|---|---|---|---|---|---|---|---|
| **Ich halte Alexa für eine angenehme Gesprächspartnerin.** | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| **Ich glaube, es gibt eine Verbindung zwischen Alexa und mir.** | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| **Ich verstehe mich gut mit Alexa.** | ○ | ○ | ○ | ○ | ○ | ○ | ○ |

*

Bitte wählen Sie die zutreffende Antwort für jeden Punkt aus:

| | 1 sehr geringes Risiko | 2 | 3 | 4 mittleres Risiko | 5 | 6 | 7 sehr hohes Risiko |
|---|---|---|---|---|---|---|---|
| **Wie würden Sie die Entscheidung charakterisieren, Alexa einen Sprachbefehl zu geben?** | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| **Wie würden Sie die Entscheidung charakterisieren, finanzielle Informationen an Alexa weiterzugeben?** | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| **Wie würden Sie die Entscheidung charakterisieren, persönliche Informationen an Alexa weiterzugeben?** | ○ | ○ | ○ | ○ | ○ | ○ | ○ |

*

Bitte wählen Sie die zutreffende Antwort für jeden Punkt aus:

| | 1 stimme überhaupt nicht zu | 2 | 3 | 4 neutral | 5 | 6 | 7 stimme voll und ganz zu |
|---|---|---|---|---|---|---|---|
| **Alexa bietet mir Produkte und Dienstleistungen an, die meinen Vorlieben entsprechen.** | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| **Ich habe das Gefühl, dass Alexa mir personalisierte Nachrichten sendet.** | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| **Ich habe das Gefühl, dass Alexa für meinen Gebrauch personalisiert ist.** | ○ | ○ | ○ | ○ | ○ | ○ | ○ |

Ich habe bereits Voice-Shopping betrieben. *

Bitte wählen Sie nur eine der folgenden Antworten aus:

○ Ja

○ Nein

## Voice-Shoppers

Dieser Abschnitt ist nur für Benutzer gedacht, die bereits Voice-Shopping betrieben haben.

*

Beantworten Sie diese Frage nur, wenn folgende Bedingungen erfüllt sind:
((EXP.NAOK == 'V'))

Bitte wählen Sie die zutreffende Antwort für jeden Punkt aus:

| | 1 stimme überhaupt nicht zu | 2 | 3 | 4 neutral | 5 | 6 | 7 stimme voll und ganz zu |
|---|---|---|---|---|---|---|---|
| **Die Verwendung von Alexa für Voice-Shopping liegt ganz in meiner Hand.** | | | | | | | |
| **Ich bin fähig, Alexa für Voice-Shopping zu nutzen.** | | | | | | | |
| **Ich habe die Kontrolle, Alexa für Voice-Shopping zu nutzen.** | | | | | | | |

*

Beantworten Sie diese Frage nur, wenn folgende Bedingungen erfüllt sind:
((EXP.NAOK == 'V'))

Bitte wählen Sie die zutreffende Antwort für jeden Punkt aus:

| | 1 stimme überhaupt nicht zu | 2 | 3 | 4 neutral | 5 | 6 | 7 stimme voll und ganz zu |
|---|---|---|---|---|---|---|---|
| **Die Nutzung von Alexa für Voice-Shopping ist bequemer als Online-Shopping.** | | | | | | | |
| **Die Nutzung von Alexa für Voice-Shopping ermöglicht mir Multitasking.** | | | | | | | |
| **Insgesamt finde ich Alexa für Voice-Shopping nützlich.** | | | | | | | |

*

Beantworten Sie diese Frage nur, wenn folgende Bedingungen erfüllt sind:
((EXP.NAOK == 'V'))

Bitte wählen Sie die zutreffende Antwort für jeden Punkt aus:

| | 1 stimme überhaupt nicht zu | 2 | 3 | 4 neutral | 5 | 6 | 7 stimme voll und ganz zu |
|---|---|---|---|---|---|---|---|
| **Die Bedienung von Alexa für Voice-Shopping ist für mich einfach zu erlernen.** | | | | | | | |
| **Ich finde es einfach, Alexa dazu zu bringen, das zu tun, was ich von ihr möchte.** | | | | | | | |
| **Insgesamt finde ich Alexa für Voice-Shopping einfach zu bedienen.** | | | | | | | |

*

Beantworten Sie diese Frage nur, wenn folgende Bedingungen erfüllt sind:
((EXP.NAOK == 'V'))

Bitte wählen Sie die zutreffende Antwort für jeden Punkt aus:

| | 1 stimme überhaupt nicht zu | 2 | 3 | 4 neutral | 5 | 6 | 7 stimme voll und ganz zu |
|---|---|---|---|---|---|---|---|
| **Alexa für Voice-Shopping zu nutzen, ist eine gute Idee.** | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| **Alexa für Voice-Shopping zu nutzen, ist angenehm.** | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| **Mir gefällt die Idee, Alexa für Voice-Shopping zu verwenden.** | ○ | ○ | ○ | ○ | ○ | ○ | ○ |

*

Beantworten Sie diese Frage nur, wenn folgende Bedingungen erfüllt sind:
((EXP.NAOK == 'V'))

Bitte wählen Sie die zutreffende Antwort für jeden Punkt aus:

| | 1 stimme überhaupt nicht zu | 2 | 3 | 4 neutral | 5 | 6 | 7 stimme voll und ganz zu |
|---|---|---|---|---|---|---|---|
| **Ich werde Alexa auch in Zukunft für Voice-Shopping nutzen.** | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| **Ich verwende Alexa immer für Voice-Shopping, wenn ich etwas kaufen möchte.** | ○ | ○ | ○ | ○ | ○ | ○ | ○ |

*

Beantworten Sie diese Frage nur, wenn folgende Bedingungen erfüllt sind:
((EXP.NAOK == 'V'))

Bitte wählen Sie die zutreffende Antwort für jeden Punkt aus:

| | Jährlich | Mehr als einmal im Jahr | Monatlich | Mehr als einmal im Monat | Wöchentlich | Mehr als einmal in der Woche | Mehr als einmal am Tag |
|---|---|---|---|---|---|---|---|
| **Wie häufig nutzen Sie Alexa für Voice-Shopping?** | ○ | ○ | ○ | ○ | ○ | ○ | ○ |

## Nicht-Voice-Shoppers

Dieser Abschnitt ist nur für Benutzer gedacht, die noch nicht Voice-Shopping betrieben haben.

*

Beantworten Sie diese Frage nur, wenn folgende Bedingungen erfüllt sind:
((EXP.NAOK == 'N'))

Bitte wählen Sie die zutreffende Antwort für jeden Punkt aus:

| | 1 stimme überhaupt nicht zu | 2 | 3 | 4 neutral | 5 | 6 | 7 stimme voll und ganz zu |
|---|---|---|---|---|---|---|---|
| **Die Verwendung von Alexa für Voice Shopping würde ganz in meiner Hand liegen.** | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| **Ich wäre fähig, Alexa für Voice-Shopping zu nutzen.** | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| **Ich hätte die Kontrolle, Alexa für Voice-Shopping zu nutzen.** | ○ | ○ | ○ | ○ | ○ | ○ | ○ |

Selbst wenn Sie Alexa noch nicht für Voice-Shopping genutzt haben, kennen Sie vielleicht jemanden, der Ihnen seine Eindrücke mitgeteilt hat, oder Sie haben in den Medien davon gehört. Bewerten Sie auf dieser Grundlage, inwieweit Sie glauben, dass Alexa für Voice-Shopping in Ihrer Kontrolle liegen könnte.

*

Beantworten Sie diese Frage nur, wenn folgende Bedingungen erfüllt sind:
((EXP.NAOK == 'N'))

Bitte wählen Sie die zutreffende Antwort für jeden Punkt aus:

| | 1 stimme überhaupt nicht zu | 2 | 3 | 4 neutral | 5 | 6 | 7 stimme voll und ganz zu |
|---|---|---|---|---|---|---|---|
| **Die Nutzung von Alexa für Voice-Shopping wäre bequemer als Online-Shopping.** | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| **Die Nutzung von Alexa für Voice-Shopping würde mir Multitasking ermöglichen.** | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| **Insgesamt würde ich Alexa für Voice-Shopping nützlich finden.** | ○ | ○ | ○ | ○ | ○ | ○ | ○ |

Selbst wenn Sie Alexa noch nicht für Voice-Shopping genutzt haben, kennen Sie vielleicht jemanden, der Ihnen seine Eindrücke mitgeteilt hat, oder Sie haben in den Medien davon gehört. Bewerten Sie auf dieser Grundlage, inwieweit Sie glauben, dass Alexa für Voice-Shopping nützlich sein könnte.

*

Beantworten Sie diese Frage nur, wenn folgende Bedingungen erfüllt sind:
((EXP.NAOK == 'N'))

Bitte wählen Sie die zutreffende Antwort für jeden Punkt aus:

| | 1 stimme überhaupt nicht zu | 2 | 3 | 4 neutral | 5 | 6 | 7 stimme voll und ganz zu |
|---|---|---|---|---|---|---|---|
| **Die Bedienung von Alexa für Voice-Shopping ist für mich einfach zu erlernen.** | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| **Ich fände es einfach, Alexa dazu zu bringen, das zu tun, was ich von ihr möchte.** | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| **Insgesamt würde ich Alexa für Voice-Shopping einfach zu bedienen empfinden.** | ○ | ○ | ○ | ○ | ○ | ○ | ○ |

Selbst wenn Sie Alexa noch nicht für Voice-Shopping genutzt haben, kennen Sie vielleicht jemanden, der Ihnen seine Eindrücke mitgeteilt hat, oder Sie haben in den Medien davon gehört. Bewerten Sie auf dieser Grundlage, inwieweit Sie glauben, dass Alexa für Voice-Shopping einfach zu bedienen sein könnte.

*

Beantworten Sie diese Frage nur, wenn folgende Bedingungen erfüllt sind:
((EXP.NAOK == 'N'))

Bitte wählen Sie die zutreffende Antwort für jeden Punkt aus:

| | 1 stimme überhaupt nicht zu | 2 | 3 | 4 neutral | 5 | 6 | 7 stimme voll und ganz zu |
|---|---|---|---|---|---|---|---|
| **Alexa für Voice-Shopping zu nutzen, ist eine gute Idee.** | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| **Alexa für Voice-Shopping zu nutzen, wäre angenehm.** | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| **Mir gefällt die Idee, Alexa für Voice-Shopping zu verwenden.** | ○ | ○ | ○ | ○ | ○ | ○ | ○ |