“Voice Marketing: Voice Assistants as Tools for Marketing Communication”

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Abbreviations

AG	Aktiengesellschaft
AI	Artificial intelligence
App	Application
AVE	Average variance extracted
BSC	Business Source Complete
B.C.	Before Christ
B2B	Business-to-business
B2C	Business-to-consumer
CASA	Computers are social actors
CFA	Confirmatory factor analysis
CFI	Comparative fit index
COA	Co-occurrence analysis
CR	Composite reliability
DAX30	Deutscher Aktienindex of the 30 major companies
DBIS	Database Information System
df	Degrees of Freedom
D2C	Direct-to-consumer
Et al.	Et alia (and others)
e-	Electronic (examples are e-learning, e-services)
e.g.	Exempli gratia (for example)
FTSE	Financial Times Stock Exchange
H	Hypothesis
I	Interview
ICB	Industry Classification Benchmark
IoT	Internet of Things
IS	Information system
i.e.	Id est (that is)
MATH	Model of adoption of technology in households
MGCFA	Multi-group confirmatory factor analysis
n	Indicator of sample size
n.d.	No date
n.s.	Not significant
PRISMA	Preferred reporting items for systematic reviews and meta-analyses
p.	Page
pp.	Pages
R	Reverse coded items
RMSEA	Root mean square error of approximation

RQ	Research question
SEO	Search engine optimization
S-O-R	Stimulus-organism-response
TAM	Technology acceptance model
TCCM	Theory, context, characteristics, methodology
TLI	Tucker–Lewis index
TPB	Theory of planned behavior
TPSs	Third-party skills
TRAPD	Translation, review, adjudication, pretest, documentation
TTF	Task-technology fit
USA	United States of America
UTAUT	Unified theory of acceptance and use of technology
U & G	Use and gratification
VAM	Value-based adoption model
VAMEM	Value-based adoption and marketing effects model

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1. Introduction

The marketing phenomenon emerged between the two world wars and has since been a fixed component of the business environment (Lindgreen, Palmer, and Vanhamme 2004). However, the marketing of that time differs significantly from that of today, as the field has constantly changed and evolved (Lindgreen, Palmer, and Vanhamme 2004). The major drivers that influence marketing are technological, socioeconomic, and geopolitical trends (Rust 2020). Technological trends, for example, have resulted in a shift from transactional marketing, which focuses on gaining new customers, to relational marketing, with the aim of retaining customers (Lindgreen, Palmer, and Vanhamme 2004; Rust 2020).

Disruptive technologies, such as artificial intelligence (AI) and the Internet of Things (IoT), have further transformed the marketing discipline in an unpredictable way (Rust 2020). AI allows for the analysis of customer data in real time and is therefore an essential tool for improving customer retention (Verma et al. 2021; Wirth 2018). IoT describes a smart environment consisting of connected devices that communicate by transmitting and sharing information with each other (Al-Sarawi et al. 2020). Organizations use IoT to implement digital innovations, such as virtual experts (Bolton et al. 2018). However, the impact of these disruptive technologies is profound. By adopting them, organizations can meet customers' demand for personalized experiences (Sudhakar 2021). Virtual experts, for example, can interact with consumers to consult and provide personalized advice (Bolton et al. 2018). Therefore, the implementation of digital technologies has created promising opportunities for the marketing discipline and facilitated interactive marketing.

Keller (2009, p. 141) introduces interactive marketing as "[o]n-line activities and programs designed to engage customers or prospects and directly or indirectly raise awareness, improve image or elicit sales of products and services." Interactive marketing is one of the major marketing-communication types and actively supports the development of loyal relationships with customers (Keller 2009). According to Wang (2021, p. 1), the peculiarity of this type lies in the "[b]i-directional value creation and mutual-influence marketing process through active customer connection, engagement, participation and interaction." Therefore, interactive marketing is suited to the current era of relational marketing and contributes to retaining customers.

In the 2010s, options to execute interactive marketing communications comprised, for example, websites, online communities, e-mail, and mobile marketing (Keller 2009). Due to technological advancements, these options have been expanded by AI-based tools, such as beacon technology and chatbots (Wang 2021).

Beacon technology enables marketers to execute location-based marketing communications, which has the advantage that services nearby can be promoted in real time to consumers. As the usage of smartphones increases, applications on smartphones serve as a medium for personalized location-based interactive marketing. (Wang 2021)
Along with smartphone applications, which today are familiar tools for creating engaging communications between consumers and companies or brands, chatbots have become one of the most promising communication tools (Torres and Doherty Áine 2022). Chatbots, also called disembodied conversational agents, can be differentiated into text-based conversational agents, such as chatbots, and speech-based ones, such as Google Assistant or Apple Siri (Diederich et al. 2022). A conversational agent can be described as "[a] personal assistant that takes over everyday tasks" (Wege et al. 2018, p. 11), which means that they "[p]erform tasks with or for an individual [...] and own the ability to self-improve their understanding of the interlocutor and context" (Mari, Mandelli, and Algesheimer 2020, p. 406). Additionally, Whang and Im (2021) highlight the social aspect of speech-based conversational agents as possible interlocutors. These agents are also called voice assistants; however, a unified term for them is lacking (Foehr and Germelmann 2020).

The functions and traits of voice assistants, including social ones, form the foundation for the new avenues of marketing communications that are investigated in this dissertation. Moreover, the growing usage of voice assistants by consumers has increased their relevance for companies. Therefore, the era of voice has been invoked.

1.1 The era of voice

Voice interaction is among the top technology trends influencing and shaping the current decade (Marr 2020). In the Monitor Deloitte report "Beyond Touch – Voice Commerce 2030," it was stated that voice assistants, such as Amazon Alexa, Google Assistant, or Apple Siri, are entering into various areas of consumers' lives, including their homes, their cars, and their workplaces (Wege et al. 2018, p. 4). Although some consumers tend to be reluctant to embrace new technologies (Rieger et al. 2021), a shift in the focus of communication from text to voice can be expected for several reasons: Communicating through voice is more intuitive and natural for people (Zoghaib 2022), increases the convenience of consumers' lives (Deloitte 2024), and allows consumers to multitask without being flooded with visual information (Zoghaib 2022). Furthermore, communicating by voice is faster and contains the possibility of personalization (Paluch and Wittkop 2020). Moreover, hearing the voice of a beloved person stimulates brain functions that reduce stress, a reaction that cannot be observed to the same extent when reading a text message (Rizvi 2020).

Recent surveys have already confirmed increasing user numbers of voice assistants (Brocks and Bätjer-Gleitsmann 2021). The number varies slightly between studies, but on average, it has been reported that around 50% of people currently use voice assistants (Brocks and Bätjer-Gleitsmann 2021, p. 4; Klöß and Lange 2022, p. 26; Westwater 2021, p. 6). However, according to the Gartner Hype Cycle for Customer Service and Support Technologies 2022, it will take less than two years until their mainstream adoption (Kraus 2022, p. 4). Consumers usually interact with voice assistants via their smartphones or smart speakers, such as Amazon Echo or Google Home (Rzepka, Berger, and Hess 2020). Voice assistants and smart speakers differ in that voice assistants are AI-based software that enables voice-based interactions, while smart speakers are devices on which the software can be implemented and used (Kilian and Kreutzer 2022b).

Considering the different voice-assistant providers more closely, Amazon Alexa, Google Assistant, and Apple Siri represent the three most adopted voice assistants, of which Amazon Alexa is the market leader (Brocks and Bätjer-Gleitsmann 2021, p. 9; Gaspar and Dieckmann 2019, p. 17; Westwater 2021, pp. 8–10).
Although Amazon Alexa is the market leader, the history of voice assistants was initiated by another company: Apple. In 2011, the company introduced Apple Siri as the first voice assistant on the market. Microsoft then launched a voice assistant called Cortana in 2013, followed by Amazon Alexa in 2014, developed by Amazon. In the same year, Amazon introduced the Amazon Echo as the first smart speaker, which ushered in the next stage of the voice era: devices in consumers' homes that are used solely through voice commands. Google followed the voice trend in 2016 by launching their voice assistant, Google Assistant, as well as their smart speaker, Google Home. (Gollnhofer and Schüller 2018; Voicebot.ai 2021) Huawei launched the most recent voice assistant, Celia, a generative AI-powered voice assistant for smartphones (Voicebot.ai 2023). Generative AI differs from traditional AI because it can also develop new content (McKinsey & Company 2023b), unlike traditional AI, which only responds intelligently to consumer inputs (Marr 2023).

Despite the diverse landscape of voice-assistant and smart-speaker providers, the tasks for which consumers use them are mostly the same. Therefore, the voice-assistant-usage ecosystem can be divided into four application areas: digital assistance, entertainment, shopping, and device control (Wege et al. 2018, p. 12). Amongst these areas, device control is most relevant to consumers because voice assistants are primarily used to control devices in consumers' homes (89%). Entertainment represents the second most important function of voice assistants in the form of, for example, playing music via these devices (84%). The third most used function is digital assistance, as consumers use voice assistants, for example, to start phone calls (77%). (Klöß and Lange 2022, p. 28)

When consumers interact with voice assistants, specific aroused effects can be observed. To understand these effects, it is necessary to explain the fundamentals of voice interactions. Voices transmit linguistic and paralinguistic contents, wherein the linguistic content comprises *what* is said and the paralinguistic content includes *how* something is said (Schuller et al. 2013). Just as the content of a message in terms of *what* is said can be freely designed, the paralinguistic content of voices in terms of *how* something is said can vary, for example, in terms of pitch, timbre, speech rate, and volume (Christenson, Ringler, and Sirianni 2023). An engaging combination of both linguistic and paralinguistic content is advantageous because it allows companies to influence the behaviors and reactions of consumers (Chérif and Lemoine 2019; Christenson, Ringler, and Sirianni 2023). Nonetheless, how exactly can companies benefit from voice-based interactions?

Voice-based interactions in general can arouse emotions (Mehrabian and Wiener 1967), such as pleasant or unpleasant feelings, joy, and sadness (Bliss-Moreau, Barrett, and Owren 2010). The effects that human voices arouse can also be transmitted to technological voices since they cause similar effects (Chérif and Lemoine 2019). Therefore, in the context of technological voices, such as those of the voice assistants Amazon Alexa and Google Assistant, the design of voice interactions is central. The design must be well-considered, as it influences not only the intention of consumers to adopt voice assistants (Christenson, Ringler, and Sirianni 2023) but also their intention to continue use (Poushneh 2021a). Therefore, when consumers interact with voice assistants, the linguistic and paralinguistic contents should be congruent. This is crucial because consumers expect such congruency, and when the spoken words match the voice assistant's personality, it fuels trust in voice assistants (Nass and Lee 2001). Moreover, the combination of *what* and *how* voice assistants communicate can stir social presence (Chérif and Lemoine 2019). In other words, communicating with voice assistants can arouse consumers' feelings about interacting with social human beings. That emphasizes the potential power of voice-based interactions between consumers and companies.

Voice-based interactions offer new opportunities for marketing, which can be summarized under the term voice marketing (Mari, Mandelli, and Algesheimer 2020). Practitioners describe voice marketing as marketing using voice assistants (Chichester 2018; The Wall Street Journal 2019). A definition provided by Paluch and Wittkop (2020) states that voice marketing encompasses the interaction between businesses and customers through voice assistants using human and non-human versions of a voice. Kreutzer and Seyed Vousoghi (2020, p. 13) describe the term more specifically as "[p]lanning, implementation and control […] of business activities by using voice-engines […]." One of the most recent definitions was published by Kilian and Kreutzer (2022a) and describes voice marketing as the use of digital assistants to shape brand presences. However, the effects of voice marketing are extensive. Voice marketing enhances the development of a social connection with consumers (Hu et al. 2023). Therefore, it can be assumed that voice marketing can positively influence brand–consumer relationships (Gollnhofer and Schüller 2018).

The increasing prevalence of voice assistants, combined with the powerful effects of voice marketing, underline the growing strategic relevance of voice marketing. It is therefore important to understand this marketing form and consider its implementation in existing marketing. As such, Section 1.2 discusses how voice marketing can be embedded into the marketing discipline.

1.2 Embedding voice marketing into the marketing discipline

Since the Internet began in the 1990s (CERN 1993), the world has developed into a digitalized environment: 5.30 billion people worldwide, or 65.7% of the world's population, use the Internet (we are social and Meltwater 2023, p. 10). Consequently, technologies such as computers, laptops, and smartphones, which consumers use to access the Internet, have gained importance. Moreover, the use of smartphone continues to increase (Shanahan and Bahia 2023, p. 8).

As the marketing discipline needed to adapt to this changing environment (Zunke 2023), digital marketing evolved (Kotler et al. 2020). The term "digital" refers to technological platforms and channels that facilitate digital communications between companies and consumers (Hanlon and Tuten 2022). Therefore, today's digital marketing involves using digital channels, such as voice assistants (Mari and Algesheimer 2021), social-media platforms, and websites, for marketing communications (Kotler et al. 2020).

For several decades, marketing communications have been focused on text-based communications with consumers (Kilian and Kreutzer 2022b). However, since the launch of Apple Siri in 2011 and the rise of voice assistants, voice-based communications are returning and conquering the marketing discipline (Zoghaib 2022)—this time with the potential to become voice-first in marketing communications (Morrison and Westwater 2023). Consumers choose voice assistants instead of their laptops or smartphones mostly because tasks are completed (or problems are solved) faster, more conveniently, or more simply (Kahle and Meißner 2020). This choice has led to the assumption that communications between companies and consumers will also change and be dominated by voice assistants, emphasizing the power and growing relevance of voice marketing.

To embed voice marketing in the marketing discipline, it is necessary to understand what marketing is supposed to be. A definition of marketing published by the American Marketing Association (2017) states that "[m]arketing is the activity, set of institutions, and processes for creating, communicating, delivering, and exchanging offerings that have value for customers, clients, partners, and society at large." Kotler et al. (2020, p. 6) describe marketing as "[t]he process by which companies engage customers, build strong customer relationships, and create customer value in order to capture value from customers in return."

Both definitions highlight that customers are the focal point of the marketing discipline and that the key role of marketing is to create and provide value for them. Technological innovations, such as voice assistants, can help companies provide value to customers or even increase it (Sudharshan 2020). This is confirmed by several researchers who reported that voice assistants can be implemented in the customer journey, or the path that mirrors consumers' interactions with brands' and companies' touchpoints (Clark 2013), to enhance customer experiences (e.g., Hafner and Henn 2021; Morrison and Westwater 2023; Wolbers and Walter 2021). Therefore, hereafter is illustrated how voice assistants, and thus voice marketing, can provide value to consumers along the customer journey.

Schorer and Hillebrandt (2022) investigated voice marketing in the context of the customer journey in more detail. As a result of their study, they presented the voice customer journey (displayed in Figure 1), which shows when and how voice-marketing activities can be involved along the six phases of the customer journey.

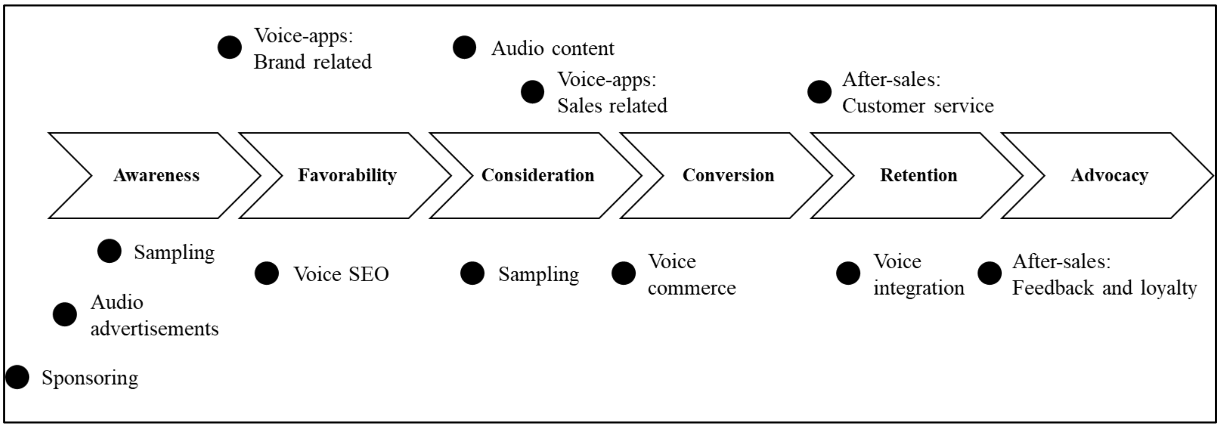


Figure 1. Voice customer journey (own illustration based on Schorer and Hillebrandt 2022, p. 906)

Voice marketing can provide value to consumers in the first phase of the customer journey, the awareness phase, through **audio advertisements**. These advertisements can be implemented on the radio or in podcasts and present information and news about brands and companies (Schorer and Hillebrandt 2022). Voice-assistant applications (abbreviated in Figure 1 as **voice-apps**), otherwise known as Alexa Skills or Google Actions, can also add value in this phase. An example of a voice application is the case of Johnnie Walker. In 2016, the company Diageo developed an Alexa Skill for their brand, Johnnie Walker. The Alexa Skill enabled distinctive whiskey tastings by expanding the physical tasting experience through auditive stories and insider knowledge (Zoghaib 2022). Thereby, the value for consumers consisted of an extension of the physical product (i.e., the whiskey tasting) into the digital environment through additional benefits in the form of digital stories and insider knowledge. According to Amazon, more than 10,000 Alexa Skills exist in Germany (t3n 2021). This number encompasses not only interactively branded Alexa Skills, such as that of Johnnie Walker, but also those that exist for entertainment-only reasons, for example, the Alexa Skill “true or false for family” (Voice Games n.d.). Diageo’s voice application is brand related. However, voice applications can also be sales related and, in that case, are assigned to the conversion phase of the customer journey (Schorer and Hillebrandt 2022). **Sampling**, another voice-marketing activity in the awareness phase, is a combination of audio advertisements and voice applications. The company Bahlsen, for example, took advantage of the “send me a sample” Alexa Skill to send samples of their new product, PickUp chocolate hazelnut, to interested consumers (Daul 2022). This strategy can be used by marketers to strengthen their marketing campaigns (Paluch and Wittkop 2020) and execute promotional activities (Daul 2022). Sampling is not only relevant in the awareness phase but also in the consideration phase. Furthermore, consumers can benefit from **sponsoring** as a voice-marketing activity in the awareness phase. Sponsoring could enrich, for example, podcasts that consumers listen to with interesting information or offers from brands that suit the podcasts’ contents.

A value-adding voice-marketing activity for the second phase of the customer journey, the favorability phase, is **voice SEO**. SEO, or search-engine optimization, involves modifying digital content to achieve higher rankings in Google result lists when consumers use the Google search (Tuten and Solomon 2014). Consumers can take advantage of voice SEO by asking their voice assistants, for example, for Italian restaurant recommendations nearby. In a second step, it is possible that their voice assistants will then navigate them to the recommended restaurant. However, to ensure value for consumers through voice SEO, which requires that they receive sufficient and correct information, companies must optimize their website contents for voice SEO (Hubspot 2022).

To provide value to consumers in the third phase of the customer journey, the consideration phase, companies can offer **audio content** to consumers. Audio content includes information about prices or other details about products or services. The advantage of such content for marketers is that consumers must actively begin communicating with voice assistants to receive certain information. This step improves the acceptance of product-specific information, which consumers would usually receive involuntarily via traditional one-directional advertisement communications.

Voice commerce is the key voice-marketing activity in the fourth phase of the customer journey, or the conversion phase, to bring value to consumers. Voice commerce is comparable to the well-established e-commerce[1] (abbreviation for electronic commerce). E-commerce differs from voice commerce in that the order process occurs via voice assistants (Zoghaib 2022). The value of voice commerce for consumers lies in the advantage that they can purchase products more easily and conveniently (Kilian and Kreutzer 2022b; Mari and Algesheimer

[1] In this dissertation the abbreviation of “e-“ is used in the following as abbreviation for “electronic”.

2021). Additionally, consumers benefit during the voice-commerce process from further opportunities, such as asking for reviews to be read out, shopping lists to be created, or purchased products to be tracked (Mari and Algesheimer 2021). In 2019, 11% of German consumers used voice assistants to order products (PwC 2019). However, most consumers avoid voice-commerce activities due to privacy concerns and insufficient payment solutions (Daul 2022).

In the fifth phase of the customer journey, the retention phase, consumers can benefit from voice marketing through **after-sales services** and **voice integrations**. By including voice assistants in after-sales services (Zoghaib 2022), value for consumers can be guaranteed since their concerns are edited quicker and sometimes even more precisely (SoundHoundAI 2023; Stephens 2021). Furthermore, consumers can use voice assistants to receive more detailed information about payments or reset password for their customer accounts (Stephens 2021). An example of voice integration is the case of the brand Mercedes. The Mercedes-Benz Group AG embedded voice assistants in Mercedes cars (Mercedes-Benz Group AG 2023). Therefore, they integrated AI-based voice-assistant software into their own products (i.e., the cars) instead of interacting with consumers through popular voice assistants like Amazon Alexa or Google Assistant.

To complement the description, value-adding voice-marketing activities for the last phase of the customer journey, the advocacy phase, are pending. However, Schorer and Hillebrandt (2022) did not identify any voice-marketing activities for the last phase of the customer journey.

The voice-marketing activities described in this section illustrate the various possibilities wherein voice marketing can provide value to consumers along the customer journey. These prospects highlight the influence and potential of voice marketing for the marketing discipline. Therefore, the relevance of voice marketing is evident to marketing practitioners as well as academic researchers and is described more in detail in the following section.

1.3 Academic and managerial relevance of voice marketing

Zoghaib (2022, p. 393) states that “[t]he possibilities for consumers and brands to interact vocally are thriving and go beyond advertising […].” This statement highlights the relevance of marketing practitioners and academic researchers increasing their understanding of voice marketing.

Marketing practitioners should address the evaluation and understanding of voice marketing as a priority (Zoghaib 2022) because voice-based interactions are unique in their ability to bring people together (Fennell 2020). Moreover, voice assistants that enable voice-based interactions are implemented in consumers' smartphones (Tuzovic 2022). Therefore, they embody a communication channel for companies that is as close as possible to consumers. Voice-based interactions can also create strong bonds with consumers (Whang and Im 2021). As such, academic researchers recommend marketing practitioners embed voice-marketing activities in their communication mix (Mari and Algesheimer 2021).

Marketing practitioners must thus understand voice marketing and its effects in more detail. Doing so will enable them to evaluate whether such marketing is a promising tool to achieve their marketing goals and, if so, how to leverage it in the most effective way possible. However, sufficient recommendations have been lacking thus far to clarify which forms of voice-marketing activities along the customer journey (see Figure 1) are most suitable to companies' products, services, and values. Zoghaib (2022) developed a voice-marketing framework to provide initial insights that increase the understanding of voice marketing (see Figure 2).

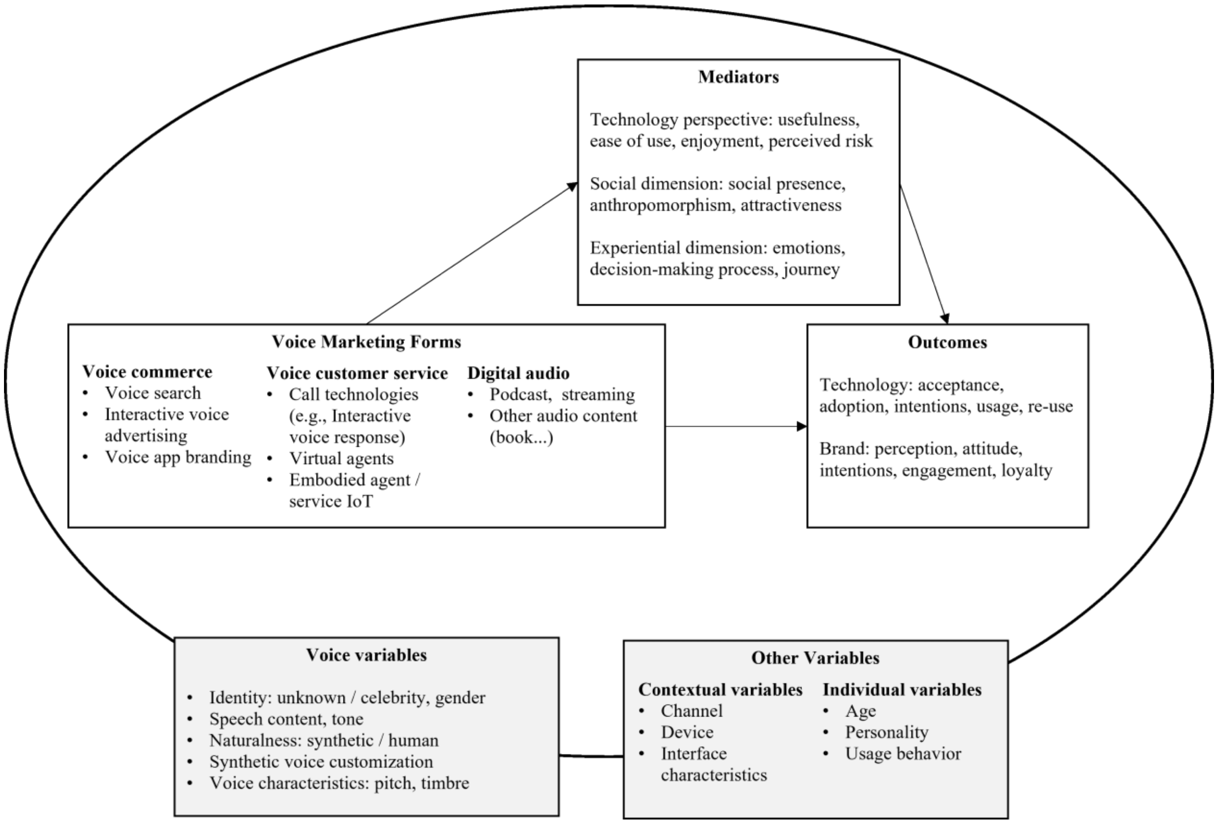


Figure 2. Voice-marketing framework (own illustration based on Zoghaib 2022, p. 402)

According to the framework, it is conceivable that voice-marketing activities shape brand outcomes, such as brand perceptions and consumers' attitudes toward brands. Researchers have confirmed initial positive effects in that voice-marketing activities can strengthen relations between customers and companies (e.g., Gollnhofer and Schüller 2018; Mari and Algesheimer

2021). Furthermore, voice marketing may be an efficient tool to shape both a brand's identity and equity because it enables the creation of fastidious brand experiences (Mari and Algesheimer 2021). However, further possible effects, their extents, and potential differences across industries, countries, and target groups remain unexplored.
Additionally, the voice-marketing framework presented in Figure 2 contains two squares with listings of "voice variables" and "other variables." These variables illustrate that the *way in which* and *what* is communicated through voice-marketing activities is relevant. This is consistent with the findings presented in Section 1.1. Thus, we can assume that companies can benefit from voice-marketing activities by creating engaging interactions with consumers and that this is an opportunity companies should seize. However, what exactly must be done to achieve these benefits has not been fully answered in the literature. Jon Stine, executive director at the Open Voice Network, states, not without reason, that "[v]oice will soon be a primary way consumers connect with the digital world, and a primary way that digital marketers will connect with consumers […]" (Westwater 2021, p. 4). This claim highlights the relevance of gaining further insights about voice marketing and its effects to marketing practitioners.

Furthermore, the authors of the "Beyond Touch – Voice Commerce 2030" report, published by Monitor Deloitte, predicted that future retail will be a closed system where third-party distributors or sellers will no longer play a significant role (Wege et al. 2018, p. 7). Therefore, the direct-to-consumer (D2C) channel, which represents the direct communication and distribution of products and services from companies to consumers, is growing in relevance (Longfield, Baxter, and Habboush 2022). This channel highlights another value-adding facet of voice marketing for marketing practitioners: voice assistants can embody such D2C touchpoints (Sterne 2017). Sales-related voice applications, as explained in Section 1.2, could be especially suitable and highly important D2C touchpoints considering this development in retail. However, companies must be able to implement such applications in the most appropriate way possible. As such, not only voice-application characteristics, such as the tone of voice, interface design, and selected devices, should be determined consciously (Mari, Mandelli, and Algesheimer 2020). It is also required that companies supply voice-assistant applications for the right tasks to provide the greatest possible value to consumers.

Additionally, shopping behavior has been changing significantly due to digital AI-based technologies (Mari and Algesheimer 2021). Therefore, the relevance of voice marketing for companies lies in leveraging voice commerce as a future distribution channel. Thus, it may be possible to increase companies' sales through voice commerce. However, knowledge about the effects of voice commerce on anticipated sales figures is required to evaluate whether investments in its development would be worthwhile.
Increasing costs for human resources also indicate the possible relevance of voice marketing for companies. They may benefit from implementing voice marketing for customer services, resulting in seamless service navigation (Zoghaib 2022). Moreover, such marketing could

result, for example, in a quality-level increase in a company's customer service; release of their employees, especially during holiday seasons and in the case of a high degree of sick leave; and improvement in customer satisfaction due to faster support around the clock. However, comprehensive findings are missing in this area.

Notably, missing insights about voice marketing characterize a diverse, complex, and multifaceted field and indicate that existing knowledge is still in its infancy. However, the presented facets underline the relevance of voice marketing to marketing practitioners today. Nonetheless, the need to increase knowledge about voice marketing is clear, emphasizing the importance of academic researchers exploring this research area, conducting fundamental research, and investigating central questions.

Academic researchers from various disciplines have shown increased interest in voice topics (Tuzovic 2022). Some researchers have even claimed that the topic of voice heralds a new era of marketing (e.g., Poushneh 2021a; Vassinen 2018). However, the literature lacks a common understanding of voice marketing (Zoghaib 2022). A proper definition and tangible criteria of voice marketing as well as a distinct demarcation of other digital voice channels (e.g., podcasts or streaming services) and interactive-marketing channels (e.g., social-media channels) must be developed. One of the challenges in this regard is that voice marketing is as an inter-disciplinary field. Thus, voice marketing affects several disciplines, including marketing, technology, and human–computer interaction. Nevertheless, it is necessary to develop and provide a uniform definition of terms and to delimit voice marketing from other marketing forms, such as social-media marketing.

Section 1.2 describes the influence of voice marketing along the customer journey and the value that such marketing adds at each stage. Additionally, Grewal et al.'s (2022) study provides initial insights about possible effects on the post-purchase stage of this journey. However, expanding the research on the effects of voice marketing along the customer journey is needed to complement the knowledge and, thus, the understanding of voice marketing. This understanding will help to address the problem of insufficient knowledge for marketing practitioners. Moreover, although Zoghaib (2022) presented an initial voice-marketing framework (see Figure 2), the demand for academic researchers to develop and provide a comprehensive and fully tested voice-marketing framework remains.

Academic researchers are expected to grasp and understand new technologies to place innovations in their overall context, evaluate them, and understand their practical uses. However, until now, researchers have not been able to fully explain consumers' usage behavior regarding voice assistants, which are the basis for executing voice marketing. To date, every second person uses voice assistants, but what are the key reasons why almost half of the population choose not to use voice assistants? Barone and Stagno (2023) illuminated this issue and compiled the main drivers (e.g., ease of use, perceived usefulness, trust, and human-likeness) and the main barriers (privacy risks and security risks) of voice-assistant adoption. However, a consumer survey found a contrary result: privacy does pose concerns but is not a barrier to adoption (Westwater 2021, p. 11). Therefore, additional theoretical explanations may extend their findings.

First, prospect theory (Kahneman and Tversky 1979) could explain the voice-assistant adoption rate. This theory describes the phenomenon of humans valuing losses more than gains. Therefore, it is possible that humans do not use voice assistants, although they may provide value (i.e., perceived gains), because they perceive the losses to be too high. As such, even if voice assistants help to perform tasks more easily and conveniently, consumers avoid using them. The perceived value of voice assistants could be a central element in this context (Pal et al. 2020). However, the specific role perceived value plays for voice-assistant adoption in the context of voice marketing remains unclear.

Second, the design of interactions between consumers and voice assistants may explain the voice-assistant adoption rate of about 50%. The uncanny-valley phenomenon is a theoretical frame for this explanation (Mori 1970) and describes how humans prefer human-like voices until they seem too real. Therefore, voice traits that mirror human beings, such as human-likeness, warmth, and competence (Aaker, Vohs, and Mogilner 2010), represent central research objects in voice marketing. Furthermore, several possible mediators may influence the effects of voice marketing on brand- and technology-specific outcomes (see Figure 2). However, there are likely far more relevant mediators that must be considered, such as the influence of conversational agents' expertise (Luria et al. 2019) and brand credibility (Jain et al. 2022). In this regard, the relevance of voice marketing for academic researchers lies in the demand to permeate adoption intention and to provide sufficient and comprehensive explanations.

Voice assistants epitomize technologies that have the potential to arouse promising positive effects through voice marketing. However, other disruptive technological innovations have been, and will be, developed that strongly influence the marketing discipline. For example, text-based conversational agents, called chatbots, are also not to be neglected as technological advancements in this context. Both voice assistants and chatbots are innovative technologies that function through AI. Despite their similar technological basis, both innovations offer unique advantages to the marketing discipline due to their differing forms of communication: text versus voice. This distinction requires that voice assistants and chatbots be clearly distinguished within research. Furthermore, academic researchers must clearly define and differentiate the characteristics and possible effects aroused through marketing communications by using each innovation. However, theory currently lacks separate studies about text-based chatbots and voice-based voice assistants. Moreover, a comparison of both and insights about which benefits they could provide in combination seem to be areas that are worth illuminating (Barone and Stagno 2023).

While highlighting the relevance of voice marketing for marketing practitioners and academic researchers, it becomes clear that additional examinations are necessary to increase the understanding of voice-marketing issues and derive valuable implications. It is therefore required that academic researchers fill these knowledge gaps by comprehensively investigating voice marketing from consumers' and the companies' perspectives. Therefore, this dissertation enriches the marketing literature by contributing to filling this gap. Below, Section 1.4 presents the specific research objectives pursued by this dissertation.

1.4 Research objectives of the dissertation

The era of voice has led to the assumption that marketing communications between companies and consumers will change and be dominated by voice assistants. Therefore, the topic of voice marketing stimulates great interest among academic researchers and marketing practitioners. Thus, the need evolves to better understand voice marketing and its impact on consumers and businesses. However, voice-marketing research is still in its infancy and requires further study. Therefore, this dissertation illuminates three central voice-marketing issues derived from the discussion in the Section 1.3. These issues are summarized in the following paragraphs and serve as the overarching umbrella for this dissertation.

First, the research area of voice marketing is evolving but still in its early stages. There are many unanswered questions from academic researchers and marketing practitioners that must be addressed. However, because of the newness and continuous development of voice marketing, published findings lack a guiding structure. A structure is required to clarify which unanswered questions exist, which questions can be clustered and may be answered jointly, and for which questions sufficiently comprehensive findings already exist. Therefore, the first research objective of this dissertation is to structure the evolving research field of voice marketing and to develop a research agenda. This structure aims not only to guide the course of this dissertation but also to form the framework for future research on voice-marketing issues.

Second, voice marketing can be understood as creating additional customer touchpoints. Therefore, as highlighted in Section 1.2, voice marketing expands customer journeys through voice-first or voice-only touchpoints. These touchpoints disrupt visual and text mediums as the most common forms of marketing communication, which raises the question of how voice marketing touchpoints as "new" communication tools differ from familiar and common ones. Moreover, clarification is needed as to whether—and if yes, to what extent—each of the communication mediums is distinct in their essence and their effects regarding the marketing discipline. These questions reflect a gap in the literature that must be filled and therefore represent the dissertation's second research objective.

Third, the adoption of voice assistants is a prerequisite for voice marketing. Section 1.2, in particular, highlights perceived value as a decisive factor for voice-assistant adoption. However, as previously stated, only around 50% of consumers use voice assistants. Therefore, we aim to investigate the factors that influence perceived value, particularly in the context of voice-marketing activities. Additionally, marketing practitioners claim that there is a lack of suitable methods to measure the marketing effects of digital audio activities (OnlineMarketing.de GmbH 2023). Therefore, this need is addressed as the third research objective of this dissertation.

Altogether, this dissertation pursues three successive research objectives. The structure of this dissertation, to attain the research objectives, is described below in Section 1.5.

1.5 Structure of the dissertation

This dissertation comprises a total of five chapters. An introduction and a summary chapter frame three main chapters of empirical investigations. Chapter 1 introduces the topic of voice marketing and outlines its relevance for academic researchers and marketing practitioners. The described aspects highlight the relevance of investigations in this area. Furthermore, the research objectives of this dissertation are presented. As voice marketing is still evolving, a lack of structure in voice marketing as a research field is stressed. Subsequently, Chapter 2 addresses the first research objective of this dissertation.

In Chapter 2, an empirical approach to structuring voice marketing as a research field is presented. We apply a hybrid review to comprehensively compile and analyze existing literature about voice-marketing issues. To do so, we first conduct a broad analysis from a meta-perspective by quantitatively analyzing 673 papers using a bibliometric analysis. This process reveals the key dimensions of voice marketing as well as under-researched issues. The bibliometric analysis is followed by an in-depth analysis of the existing literature on voice marketing. For this purpose, we use a qualitative semi-systematic literature review. To proceed in a structured manner, we then apply the TCCM (i.e., theory, context, characteristics, methodology) framework. The analysis of 35 papers, to which we have full reading access, provides further insights regarding our research objective. This facilitates a comprehensive and detailed analysis of the literature and existing research results. Therefore, the study presented in Chapter 2 addresses the first research objective of this dissertation by identifying the structure of the voice-marketing research field and formulating a research agenda to comprehensively assess this field.

It is crucial that marketing practitioners be aware of the distinctiveness of each digital-marketing channel. However, as disclosed in Chapter 2, several voice-marketing issues in this context remain unanswered. These issues include findings about the uniqueness of text- and speech-based conversational agents as emerging AI-based digital-marketing channels. Therefore, we address this gap through our investigations presented in Chapter 3.

The significance of conversational agents for the marketing discipline was emphasized by various practitioners in 2016, as it is today. However, there are knowledge gaps, especially in terms of the agents' marketing effects and how the agents can bring value to consumers and businesses. Despite the increasing number of published studies on conversational agents, several knowledge gaps remain. In particular, researchers have recently highlighted the research gap of studies between text-based and speech-based conversational agents. We address this gap in our study presented in Chapter 3, which involves an experimental 1 x 1 between-subject design. We conduct an online survey (n[2] = 557) during which the participants explore a real interaction with either a text-based chatbot or a speech-based voice assistant. We develop a fictional brand and program a new chatbot and voice assistant with a neutral name and voice for the interactions. Altogether, our analysis reveals that the effects of marketing communications using text-based chatbots and speech-based voice assistants differ. As key findings, our work shows that marketing communication through voice assistants has the advantage of a sense of social connection with consumers, while chatbots help brands by being a convenient channel to communicate, provide information, and help customers navigate processes and services.

Understanding the specific effects of speech-based voice-marketing communications in Chapter 3 is the basis for establishing appropriate expectations for voice-marketing applications in practice. Utilizing this knowledge, the study presented in Chapter 4 examines voice-assistant applications developed by companies and brands, which represent another research gap identified in Chapter 2.

Voice-assistant applications developed by brands or companies are called third-party skills (TPSs; Tuzovic 2022). Marketing practitioners aim to use TPSs to help them achieve their marketing goals. However, they need proper theories or tools to measure whether the development and deployment of their TPSs actually contribute to this process. Furthermore, voice marketing continues to evolve, which is why established theories may not reflect the unique characteristics of TPSs. We apply a mixed-methods approach to address the lack of suitable theories and ground our work on the value-based adoption model (VAM) because it most effectively predicts the adoption intention of voice assistants. As part of our mixed-methods approach, we first conduct qualitative expert interviews with marketing practitioners. The interviews help to shape our understanding of the desired TPSs' key marketing effects. Based on the VAM and the insights from the interviews, we develop a conceptual model. The second part of our mixed-methods approach involves testing the conceptual model across industry sectors and countries using quantitative online surveys and analyzing the data with confirmatory factor analyses and multi-group confirmatory factor analyses. These steps reveal

[2] n = Indicator of sample size

that companies can use TPSs to induce positive influences on marketing effects. Therefore, Chapter 4 contributes to theory and practice by successfully developing a marketing measurement tool for TPSs' performances.

Chapter 5 concludes the dissertation by summarizing the research findings. Furthermore, overarching theoretical contributions as well as implications for marketing practitioners are derived. The limitations of this dissertation are also discussed, and possible future research directions are suggested. Finally, a comprehensive outlook on the field of voice marketing is presented.

Altogether, Chapter 1 introduced voice-based interactions and voice marketing and explained their academic and managerial relevance. Furthermore, the research objectives of this dissertation were outlined, and the structure of this dissertation was described accordingly. Following the structure of the dissertation, voice marketing as a research field is now explored scientifically in Chapter 2.

2. Analyzing and structuring voice marketing as a research field [3]

Due to technological advancements, recognizing, transcribing, and interpreting the spoken word in real time is now possible (Rzepka, Berger, and Hess 2020). The combination of automatic speech recognition and AI techniques, such as text-to-speech synthesis and natural-language understanding, has resulted in software that enables conversational interactions between humans and technical devices (Mari 2019). Computerized voice technology is already firmly established in daily life (Dellaert et al. 2020). This software is well-known as, but not limited to, the term voice assistants (Mari 2019). Voice assistants are defined as "[c]onversational agents that perform tasks with or for an individual" (Mari, Mandelli, and Algesheimer 2020, p. 406).

Voice assistants are implemented, for instance, in smartphones or in smart speakers, such as Amazon Alexa (Rzepka, Berger, and Hess 2020). These assistants are often used for providing information about the weather or setting alarms (Mari 2019). Furthermore, voice assistants allow users to play music and start phone calls (Poushneh 2021a). Increasingly, they are also used for shopping activities (Mari, Mandelli, and Algesheimer 2020). Furthermore, voice assistants enable new marketing forms, such as voice advertising or voice recommendation, that can be summarized under the term voice marketing (Hu et al. 2023). A definition provided by Paluch and Wittkop (2020) states that voice marketing encompasses the interaction between businesses and customers through voice assistants using human and non-human versions of a voice.

As sales and popularity of voice assistants grow (McLean, Osei-Frimpong, and Barhorst 2021; Ramadan 2021), in-depth knowledge about voice as a "new advertising medium" (Lee and Cho 2020, p. 2) for marketers and managers is required. Thorough research on the marketing area of voice assistants is scattered and rare (Lee and Cho 2020; Zoghaib 2022). Therefore, we investigated the current research status of voice assistants in the context of voice marketing by conducting a quantitative bibliometric analysis in combination with a qualitative literature review (i.e., a hybrid review).

This chapter is structured as follows. First, the research objectives are described in detail. Next, the quantitative bibliometric analysis is presented, followed by the qualitative literature review. Subsequently, the results of the analyses are summarized and discussed. This chapter finishes by presenting the implications, the limitations, and a conclusion.

[3] Parts of this chapter are taken from Kraemer, Hillebrandt, and Ivens (2022a, 2022b).

2.1 Research objective

The increasing popularity of voice-assistant devices in society in general as well as increasing sales figures in markets of many countries indicate the growing importance of voice marketing as a research field (McLean and Osei-Frimpong 2019; Ramadan 2021). However, the research field of voice marketing is still evolving. Therefore, studies investigating this research field have been scattered (Lim et al. 2022). Extant research has examined different facets of voice assistants, such as user motivations (Lee and Cho 2020), consumer acceptance (Ewers, Baier, and Höhn 2020), consumer attitudes toward voice assistants (Ashfaq, Jiang, and Yu 2021; Poushneh 2021a), and voice shopping (Bawack, Wamba, and Carillo 2021; Whang and Im 2021).

However, Ashfaq, Jiang, and Yu (2021) and Ramadan (2021) state that there is ample need for more detailed studies on the marketing aspects. Moreover, the existing research does not currently include an integrative analysis of published studies to structure voice marketing more formally as a research field. However, practitioners require further knowledge to successfully implement this new marketing form in practice. To provide such implications, academic researchers must expand the research field in a structured manner and investigate the different facets of voice-marketing issues. Since it is not readily apparent which areas of the voice-marketing research field exist that previous studies have examined, the first research question (RQ) is as follows:

RQ 1. Which dimensions does the research field of voice marketing encompass?

Defining the structure of the research field allows existing research streams in the thematically scattered studies to be identified. Therefore, identifying research gaps, revealing the relevance of each, and deriving future research opportunities to close these gaps is possible. As such, the second research question is as follows:

RQ 2. Which research gaps currently exist in the published voice-marketing literature?

Taken together, the research objective is to access voice marketing as an evolving research field and to identify existing research gaps by addressing these two research questions. To do so, we followed the procedure of a hybrid review (Paul and Criado 2020). First, we analyze the research field quantitatively through a bibliometric analysis. Second, we conduct a qualitative literature review to analyze the research field in more detail to identify research streams as well as research gaps. Third, we combine the analysis results to provide answers to the two presented research questions.

2.2 Quantitative bibliometric analysis

The bibliometric analysis in this section follows a four-step process described by Donthu et al. (2021). In the following paragraphs, we outline the four steps and describe how we applied them.

Step 1 includes a definition of the goals and scope of the analysis. To answer the identified research questions, the goal of this analysis was first, to structure voice marketing as a research field, and second, to identify existing research gaps. The Web of Science and Scopus are suitable and popular sources to conduct bibliometric analysis (Donthu et al. 2021) and therefore served as the databases for our study.

Step 2 encompasses the selection of appropriate analysis techniques. For this study, we used co-occurrence analysis (COA) as a technique that allows the disclosure of research fields (Donthu et al. 2021). However, the execution of a COA can have different foci. For instance, COA with a focus on terms has been applied to identify social-media research trends and topic areas (Thaha et al. 2021) and to structure the research field of influencer marketing (Ribeiro, Fernandes, and Fernandes 2020). Alternatively, COA based on authors' keywords is commonly used to identify key research clusters and gaps because authors' keywords reflect the most important thematic areas of their studies and research intent (Comerio and Strozzi 2019; Pesta, Fuerst, and Kirkegaard 2018). COA that focuses on keywords has been applied in the literature, for example, to identify relevant issues regarding the impact of COVID-19 on consumer behavior (Cruz-Cárdenas et al. 2021) or to cluster research issues regarding customer-relationship management (Kevork and Vrechopoulos 2009).
Thus, in this study, we conducted both term and keyword COA. We address the first research question to reveal the voice-marketing research field through the term COA. The keyword COA is then used to complement the findings of the term COA and to answer the second research question regarding the identification of research gaps. The execution of both analysis techniques required a valid and appropriate database, which led to Step 3.

In Step 3, the keyword search string was defined to collect papers from the databases Scopus and the Web of Science. The keywords needed to appear within the abstract, title, or authors' keywords. We did an initial search using the keyword "voice marketing" as the name of the research field. Since the research field is evolving, this keyword was not very popular, which explains the small result lists of one paper on the Web of Science and three papers on Scopus (the one paper on the Web of Science coincided with one of the three papers on Scopus). We therefore extended the search string to include keywords that represent the marketing discipline (e.g., "consumer," "marketing," "brand") accompanied by keywords that represent the voice-assistant field (e.g., "Alexa," "Siri," "smart speaker") to collect a sufficient number of papers. We ensured a high degree of completeness for the keyword search string by querying synonyms via Thesaurus (which is a function used to generate synonyms in the database EBSCOhost) and integrating them into the search string. Finally, the following search string was used to collect papers based on keywords that appeared within their abstracts, titles, or authors' keywords:

> "voice marketing" or (("voice assistant*" or "smart speaker*" or (("intelligent personal assistant*" or "digital assistant*" or "conversational agent*") and voice) or alexa or siri or echo or "google home" or "google assistant*" or "amazon echo") and (consumer* or "brand *" or brand* or marketing or "advertising *" or "advertisement *"))

The result lists were reviewed and revised as follows. First, the selections were limited to papers written in English. Second, since Apple Siri, arguably the first commercially widespread voice assistant, was launched in 2011, truly topic-related research about existing voice assistants could only be published afterwards. Hence, only papers with a publication date of 2011 or later were considered. Last, we limited the document types to scientific publications. These constraints resulted in 673 papers on Scopus and 507 papers on the Web of Science. The revision is visualized using the PRISMA illustration in Figure 3. PRISMA, which was introduced by Moher et al. (2009), stands for preferred reporting items for systematic reviews and meta-analyses.

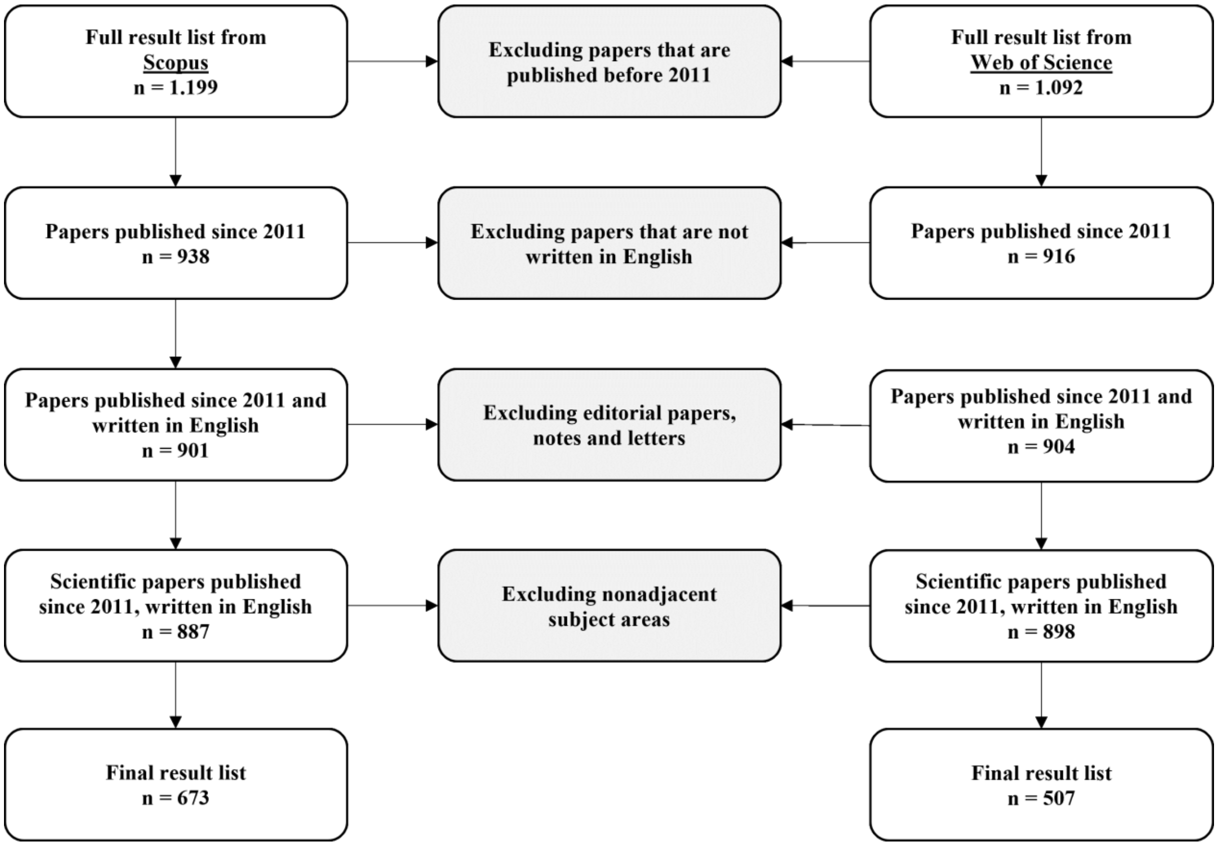


Figure 3. PRISMA illustration for the voice-marketing literature (own illustration based on Moher et al. 2009)

At least 300–500 papers are required to conduct bibliometric analyses (Donthu et al. 2021). The refined list of results from Scopus presented 673 papers, whereas the Web of Science showed 507 papers. According to Donthu et al. (2021), the number of papers collected from both databases was sufficiently large. Although it is possible to combine papers from different databases, Donthu et al. (2021) advise against it. Because Scopus provided a larger number of papers, we decided to use primarily the papers from Scopus as the data for this study. We ensured incisive insights were not dismissed by analyzing and reviewing the papers from the Web of Science as well as comparing them with the results from the Scopus data analysis. Where necessary, we highlighted noticeable deviations and considered them when discussing the results of the analysis.

Step 4 consists of executing the selected analysis techniques. As such, we conducted the two analysis techniques selected for our study, the term and keyword COA, on the papers identified in Step 3. Step 4 is presented below in Section 2.2.1.

2.2.1 Data analysis

The data analysis was conducted by exporting the result lists from Scopus and the Web of Science and analyzing the data using the software VOSviewer. Before discussing the details of the analyses, we first present the descriptive data. The descriptive data, based on the result list from Scopus, revealed that the number of published papers has increased over time with a trend for a further increase (see the blue dotted trend line in Figure 4). In 2011, a small number of 12 papers were published. However, in 2022, the last full calendar year at the time this study was conducted, the number increased to 110 papers (see Figure 4).

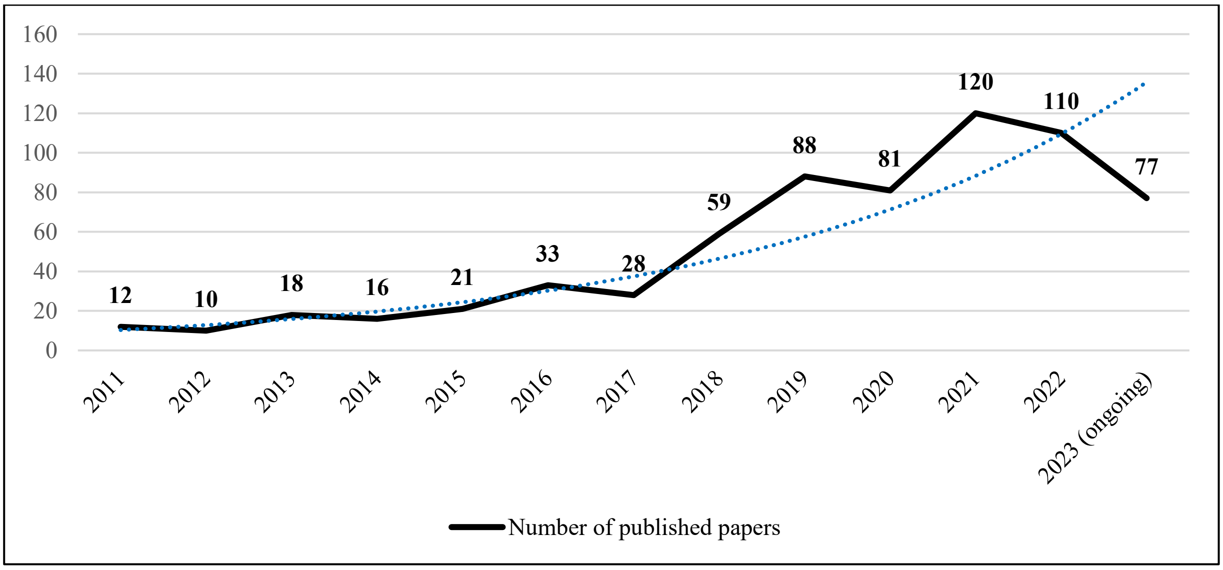


Figure 4. Number of published voice-marketing papers over time with a trend line (blue dotted)

Furthermore, most of the papers were assigned to the subject areas of computer science (27.3%), social sciences (15.8%), or business, management, and accounting (15.1%). These results highlight the interdisciplinarity of the research field. It is also noticeable that most of the papers examining the research field were published in the United States of America (214 papers), followed by the United Kingdom (75 papers), India (54 papers), China (46 papers), and Germany (45 papers). The data was analyzed in more detail by applying the term COA (see Section 2.2.1.1) and the keyword COA (see Section 2.2.1.2).

2.2.1.1 Term co-occurrence analysis

The software VOSviewer was used to create a term co-occurrence visualization based on terms within the abstract and title content of the papers. We used the papers from Scopus as the data and binary counting as an enumeration method to create the visualization. Terms had to appear at least 20 times within the abstract and title contents to be included in the visualization. This threshold was set arbitrarily by the recommendation for conducting bibliometric analysis using VOSviewer (van Eck and Waltman 2018) combined with our practical concerns. These conditions resulted in 111 terms that were allocated to three different clusters, as presented in Figure 5.

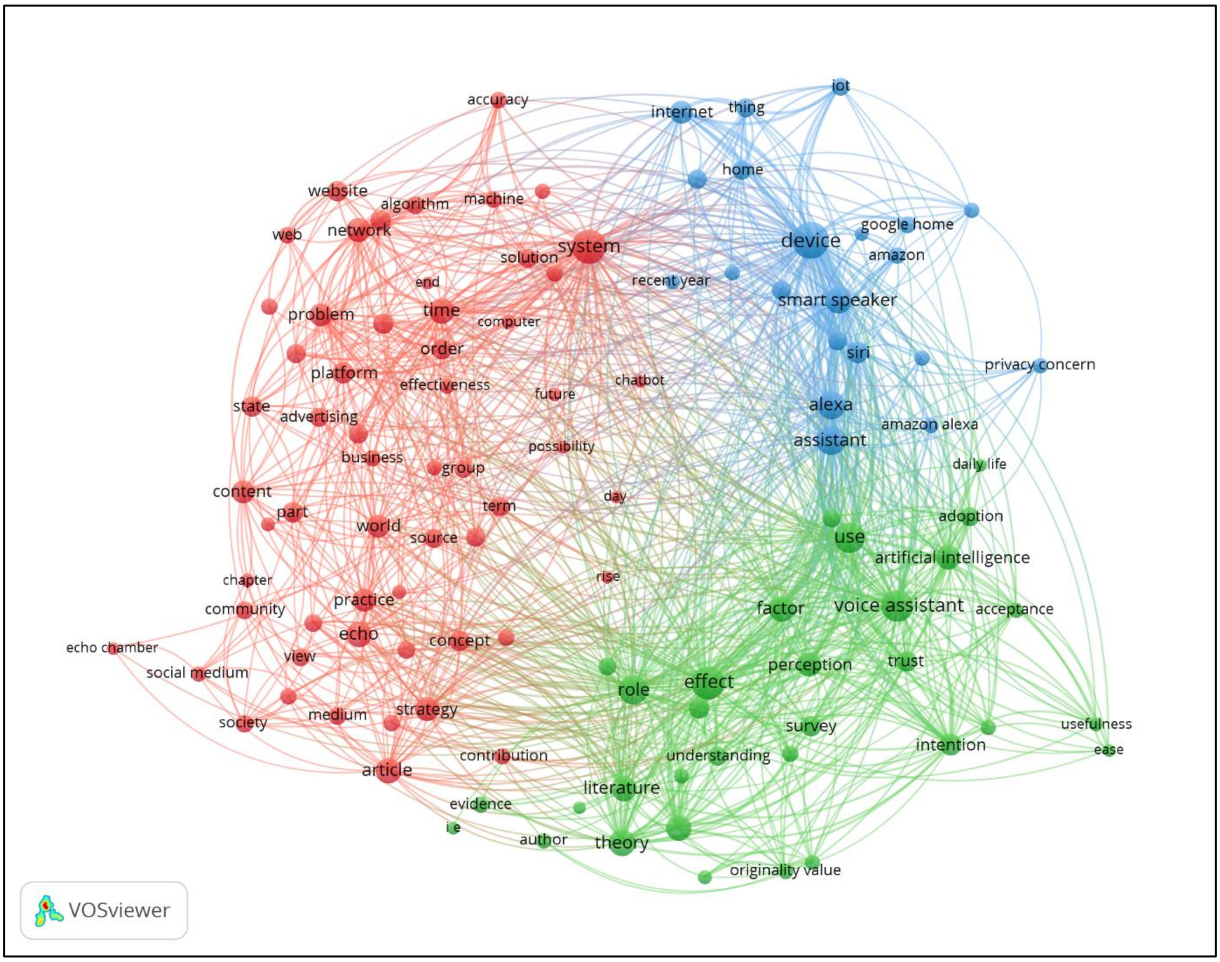


Figure 5. Term co-occurrence cluster visualization (derived from VOSviewer)

Cluster 1, colored red in Figure 5, comprises 58 terms, with *system* being the term with the highest occurrence. The cluster contains terms such as *strategy*, *concept*, *effectiveness*, and *medium*. The multifaceted terms are spread over the whole cluster. *System*, the term with the highest occurrence (151), is followed by nine terms (e.g., *time*, *echo*, *network*, *strategy*, *content*, *practice*) with comparable occurrences (65–87). Based on those terms individually and in combination, the cluster probably encompasses papers that address, for example, voice-marketing issues such as how does voice interaction (for example via the smart speaker amazon *echo*) tangent the existing marketing; which *strategy* via voice assistants should be pursued; which *content* is relevant to executing voice-marketing activities; and what does voice marketing look like in *practice*.

Cluster 2, colored blue in Figure 5, has 32 terms and includes *effect* as its major term, shortly followed by *voice assistant* and *use*. This cluster contains mainly terms that are either related to usage itself, such as *use*, *adoption*, *understanding*, and *daily life*, or the *effect* of the usage (e.g., *perception*, *attitude*, *usefulness*, *trust*, *ease*). Cluster 2 includes the term *marketer*; however, the term has the third-lowest occurrence within the cluster. The term *marketer* is only connected to the term *effect,* which is strongly connected with other terms in Cluster 2 but also with several terms in Cluster 1 and some in Cluster 3. Furthermore, Cluster 2 is located close to Cluster 3. A proximity is especially apparent between the terms *usage*, *daily life*, *adoption*, *artificial intelligence*, *acceptance*, and *voice assistant* of Cluster 2 and the terms *amazon alexa*, *alexa*, *google assistant*, *siri*, *privacy concern*, and *assistant* of Cluster 3.

Cluster 3, colored green in Figure 5, includes 21 terms. *Device*, as the term with the highest occurrence, is surrounded by device-related terms, such as *smart speakers* and *smartphones*, and by terms such as *google* and *amazon* as providers of devices. Additionally, Cluster 3 includes the terms *amazon alexa*, *amazon echo*, and *google assistant* as specific names of voice assistants and smart speakers. Furthermore, terms that describe the smart-home environment, for example, *home*, *security*, *privacy*, and *risk,* are in the middle of Cluster 3. From a meta perspective, Cluster 3 is adjacent to Cluster 2 in that it is particularly close to the term *system* of Cluster 2 and somewhat closer to the term *chatbot*.

Although all three clusters are visually distinguishable, the clusters' terms are all relatively interconnected. However, the cluster boundaries are not blurred. Overall, Cluster 1 contains primarily technological business-strategy terms (e.g., *content*, *performance*, *medium*, and *system*), Cluster 2 comprises terms related to usage issues (e.g., *perception*, *attitude*, *usefulness*, *trust*, and *adoption*), and Cluster 3 encompasses device-related terms (e.g., *smart speaker*, *smartphone*, *amazon alexa*, and *google*). We verified the analysis by running the same analysis based on the data from the Web of Science. The comparison shows three similar clusters (see Appendix 1). Thus, we conclude that the voice-marketing research field can be divided thematically into three different dimensions: **strategy**, **usage**, and **device** (displayed in Figure 6).

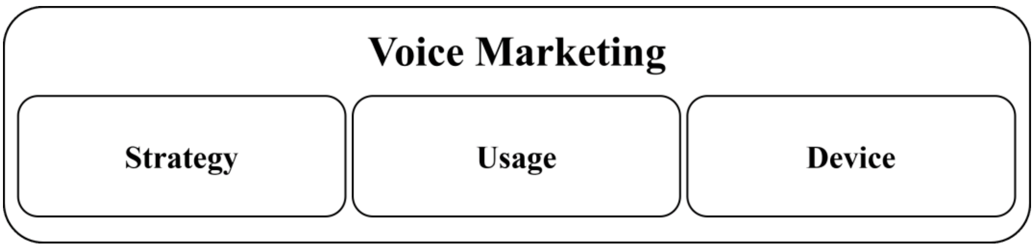


Figure 6. Thematic dimensions of the voice-marketing research field

After revealing the overarching thematic dimensions of the voice-marketing research field through the term COA, Section 2.2.1.2 now presents the keyword COA to specify subtopics and uncover existing research gaps.

2.2.1.2 Keyword co-occurrence analysis

The keyword COA in this study, for which we again used the papers from Scopus as the data, was limited to the article authors' keywords. The keyword COA was visualized in VOSviewer using a full enumeration method. The keywords were displayed only if they occurred at least five times. Since there are no specific recommendations for how often keywords should appear to include them in the analysis (van Eck and Waltman 2018), we oriented ourselves on studies with a similar number of papers (e.g., Emich et al. 2020; Kalibatiene and Miliauskaitė 2021). These conditions resulted in 49 keywords assigned to six clusters delimited by different colors, as displayed in Figure 7.

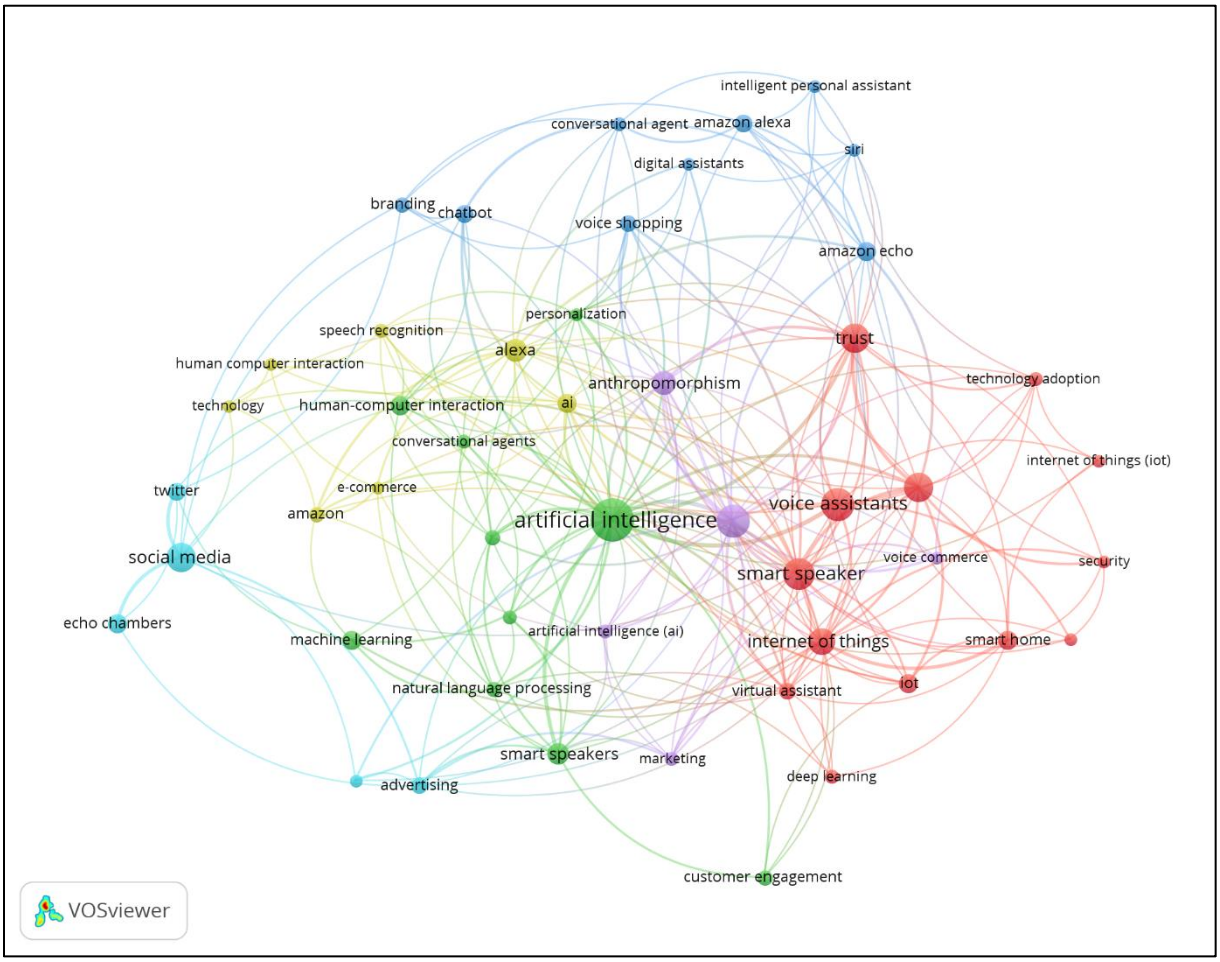


Figure 7. Keyword co-occurrence cluster visualization (derived from VOSviewer)

To address the study's second research question of identifying research gaps, the keywords themselves and their relatedness were examined in more detail. The keywords displayed in Figure 7 differ in terms of their occurrences and co-occurrences. This variation is visibly denoted by their node size (the larger, the more occurrences) and the number of connections (each connection represents one co-occurrence).

The remainder of this section is structured as follows. First, the clusters are described thematically. Second, the occurrences are analyzed in greater detail to identify keywords that are investigated in-depth (i.e., that have high occurrence values) and keywords that are less researched (i.e., that have low occurrence values) and therefore indicate existing research gaps. Third, the co-occurrences are investigated to uncover the scope of the research about specific keywords and identify thematical relations.

Following the described structure, we first delineate the clusters and their thematic focuses by means of Table 1, which presents an overview of the six clusters and their keywords.

Table 1. Clusters and assigned keywords (derived from VOSviewer data)

Cluster	Cluster color	Keywords
Cluster 1	Red	Deep learning, internet of things, internet of things (iot), iot, perceived value, privacy, security, smart home, smart speaker, technology adoption, trust, virtual assistant, **voice assistants**
Cluster 2	Green	**Artificial intelligence**, chatbots, conversational agents, customer engagement, human-computer interaction, machine learning, natural language processing, personalization, smart speakers, virtual assistants
Cluster 3	Blue	Amazon alexa, **amazon echo**, branding, chatbot, conversational agent, digital assistants, intelligent personal assistants, siri, voice shopping
Cluster 4	Yellow	Ai, **alexa**, amazon, e-commerce, human computer interaction, speech recognition, technology
Cluster 5	Purple	Anthropomorphism, artificial intelligence (ai), marketing, **voice assistant**, voice commerce
Cluster 6	Turquoise	Advertising, digital marketing, echo chambers, **social media**, twitter

Note: The keywords in bold represent those with the highest occurrence values in each cluster.

The six clusters are structured by containing keywords that are closely related. Therefore, the keywords indicate the subject of the individual cluster. The **red cluster** describes *voice assistants* in the *smart home* environment, in other words, the use of voice assistants primarily via smart speakers within the users' home. Issues regarding *privacy*, *security*, and *perceived* *value* play a significant role in the *technology adoption*. The **green cluster** comprises different keywords that are used to describe voice assistants and voice assistant devices, such as *virtual assistants*, *conversational agents*, and *smart speakers,* but also a keyword that represents text-based *human-computer interaction*: *chatbots*. The **blue cluster** holds keywords that are related to the *voice shopping* context that can be executed, in particular, through the voice assistant *amazon alexa* and the smart-speaker device *amazon echo* as *intelligent personal assistants*. The cluster also comprises synonyms for voice assistants, such as *digital assistants,* but also presents specific voice-assistant brands (e.g., *siri* and *amazon alexa*). The **yellow cluster** is concentrated on the *technology* of *human-computer interaction* (i.e., *speech recognition*), which often reminds consumers of *alexa* as the most popular voice-assistant software. The **purple cluster** is the only cluster that contains *marketing* as a specific keyword. This cluster combines the keyword *anthropomorphism*, which describes the human-likeness of a *voice assistant*, with the two disciplines of *marketing* and sales in the form of *voice commerce*. The **turquoise cluster** represents the *digital marketing* environment in which *advertising* plays an important role and where consumers have an active voice that is heard on *social media* and *twitter*.

Regarding the thematic dimensions of the voice-marketing research field (i.e., strategy, usage, and device; see Figure 6), it is possible to logically assign the colored clusters from the keyword COA to each dimension. We describe and explain the assignments as follows.

The purple and turquoise clusters can be allocated thematically to the **strategy** dimension of the voice-marketing research field. The purple cluster holds the keyword *marketing* and therefore represents the marketing discipline in particular. Furthermore, the keywords *anthropomorphism* and *voice assistant* next to the keyword *marketing* indicate the strategic note of this cluster. Brands can benefit from anthropomorphistic marketing communications, which also have the power to lead to sales. However, companies must define a strategy and decide whether they will pursue this marketing form and to what degree they will anthropomorphize their brands by communicating through voice assistants. The turquoise cluster describes *digital marketing* as a specific area of marketing. This sphere includes *advertising* activities, which can influence how consumers perceive brands and companies as well as whether they buy and use their products and services. Therefore, these issues represent strategic decisions.

The red and yellow clusters can be assigned to the **usage** dimension of voice marketing. The red cluster encompasses several keywords about usage itself but also about the perception of voice-assistant usage. To use voice assistants, consumers must *trust* them and allow the technology to recognize their voices. Therefore, the technology gains access to the *privacy* of consumers in the form of personal data and background noises (which indicate where consumers are while using voice assistants). Additionally, emotions are transmitted through the tonality of consumers' voices. Furthermore, consumers can also adopt voice assistants through a *smart speaker* that is situated within their homes. To accept the privacy barrier for in-home usage, the use of voice assistants must be *perceived* as providing *value* to consumers to compensate for the fees. Furthermore, the yellow cluster includes the keyword that represents the core of *human-computer interaction,* which works via voice: *speech recognition*. People often associate this functionality with *alexa*. Therefore, the use of, and communicating with, voice assistants is strongly related to and influenced by Amazon Alexa. Considering these results, we allocate the red and yellow clusters to the usage dimension of voice marketing.

The green and blue clusters align thematically with the **device** dimension. Both clusters display several synonymous keywords for voice assistants (e.g., *conversational agents*, *virtual assistants*, *intelligent personal assistant*) or for the devices in which the voice-assistant software is implemented (e.g., *smart speakers*, *amazon echo*). Furthermore, the blue cluster contains keywords such as *branding* and *voice shopping* in relation to voice-based conversational agents (e.g., *amazon alexa* and *amazon echo*) but also with text-based conversational agents, indicated through the *chatbot* keyword. Companies can benefit from branding activities, depending on the device. Examples include the development of third-party skills (TPSs) for *amazon alexa* or optimizing companies' digital contents regarding keywords for voice search on *siri* or *amazon alexa*. Furthermore, *voice shopping* is possible with the help of an *intelligent personal assistant*. However, depending on the promoted product or service, visualizations are beneficial. Therefore, the selection of the most suitable device according to marketing activity is of importance. However, it is noticeable that the keywords of the device dimension are partially blurred into the strategy dimension of the voice-marketing research field. A possible reason for this could be that the decision to cooperate with specific device providers (e.g., Amazon Alexa versus Google Assistant) can also be driven by strategic reasons.

After presenting the first analysis step of this section, which was the thematical description of the clusters, the following paragraphs focus on the second analysis step. This step involves analyzing the occurrences more in detail.

The heart of the visualization in Figure 7 consists of a fusion of the yellow, green, purple, and red clusters. The eye-catching keywords in the core of Figure 7, which have the largest nodes, are *artificial intelligence*, *smart speakers*, *voice assistants*, and *voice assistant*. Overall, 18 keywords have occurrences above 10 and are therefore studied in-depth in the voice-marketing research field (see Figure 8).

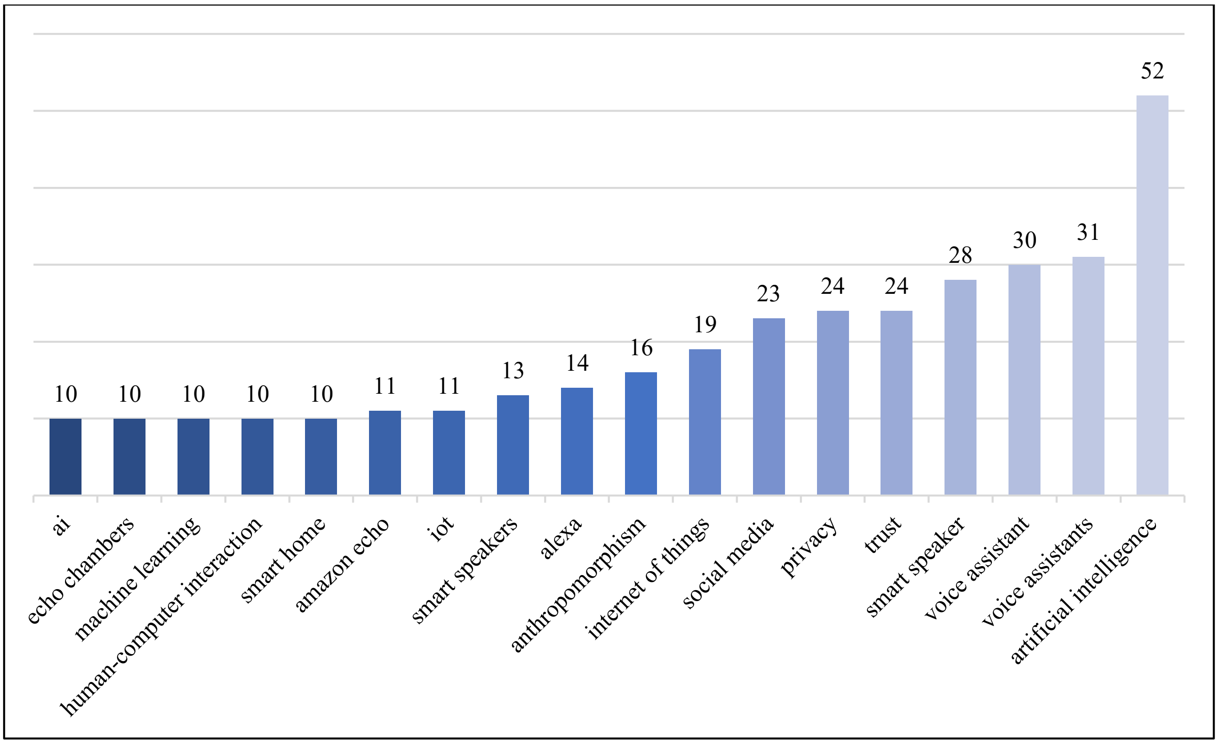


Figure 8. Keywords with occurrences of 10 or above (own illustration)

After considering the occurrences, a third step extends the analysis by including the co-occurrences. Examining the keywords with the highest total co-occurrences of 15 or above reveals a near-complete overlap with the keywords depicted in Figure 8. The only differences in the keyword list with the highest total co-occurrences lay in the additional keywords *virtual assistant(s)* and *human-computer interaction*, *machine learning*, *echo chambers*, and *iot* not appearing.

To identify research gaps, it is necessary to explore the keywords with lower occurrences and co-occurrences, as this indicates limited in-depth or broad research. Therefore, we extracted the keywords with total co-occurrence and occurrence values, both of which were 10 or below. This resulted in 22 keywords from different clusters, as displayed in Figure 9. The keywords are highlighted by the color of their individual clusters.

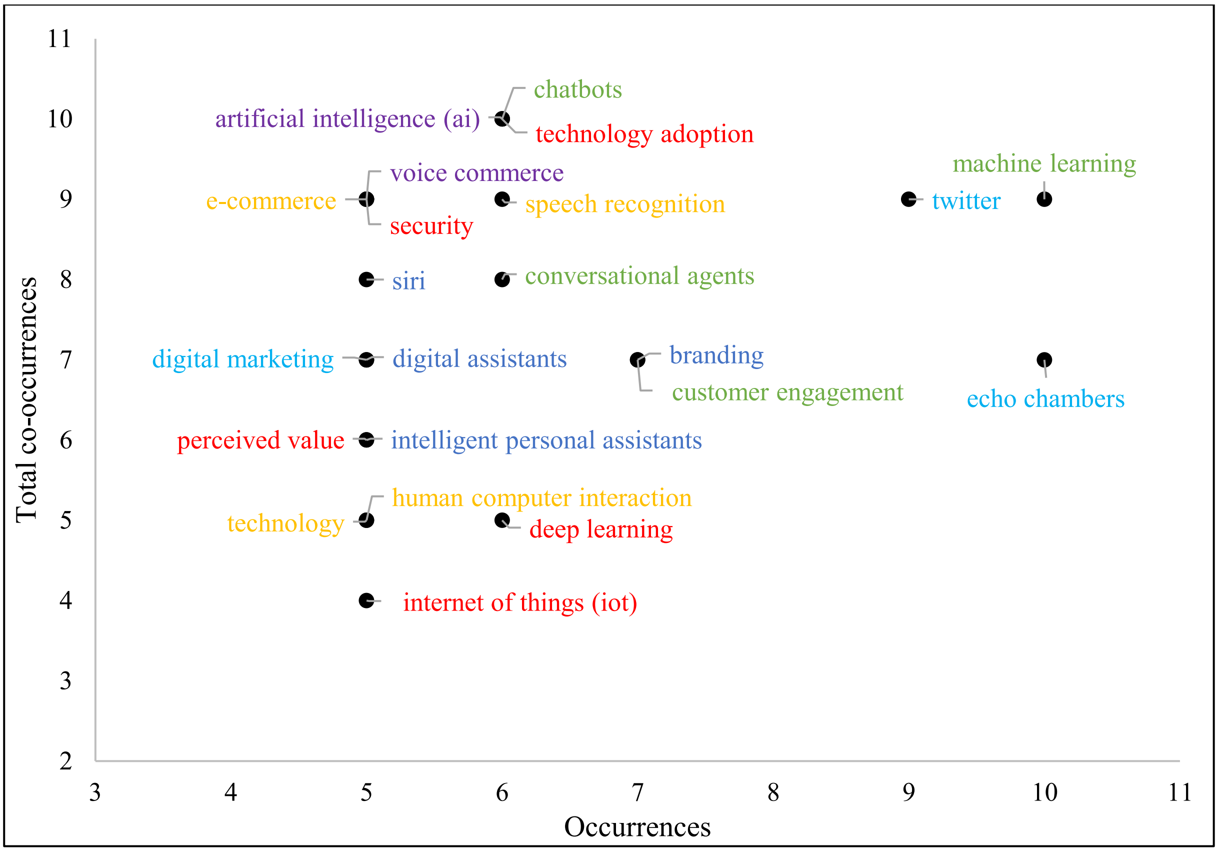


Figure 9. Occurrences and total co-occurrences (links) of less researched keywords

Analyzing the keywords in Figure 9 in more detail reveals three striking aspects. First, the *technology* keywords—*machine learning*, *speech recognition*, and *deep learning*—serve as the basis for the functionalities of voice assistants. Second, the keywords *conversational agents*, *digital assistants*, and *intelligent personal assistants* are synonyms for the widely researched keyword voice assistant. Third, certain keywords in Figure 9 are identical to those displayed in Figure 8 (which depicts more broadly researched keywords), albeit spelled differently. This includes the keywords *artificial intelligence (ai)*, *internet of things (iot)*, *human computer interaction*, and *chatbots* from Figure 9. Furthermore, the keyword *chatbot* appears in both singular and plural in the keyword COA. Examining both keywords separately, the keyword *chatbot* has a total co-occurrence value of 9 and a co-occurrence value of 13, while the keyword *chatbots* has values of 6 (co-occurrence) and 10 (total co-occurrences). However, it can be assumed that combining the keywords and their values delivers a more realistic picture of how broadly and in-depth chatbot(s) are investigated. Doing so results in values for co-occurrence and total co-occurrences above 10, which is why the keyword is excluded in the further analysis of less researched keywords.

Therefore, to present a more realistic picture, Figure 9 needs adjustment to display only valid less researched keywords that require further exploration. To do so, Table 2 provides an overview of the less researched keywords and presents the keywords with which they have co-occurrences.

Table 2. Less researched keywords with their co-occurrence keywords (own illustration)

Keyword	Co-occurrences with
Branding	Amazon alexa, artificial intelligence, chatbot, conversational agent, social media, twitter, voice shopping
Customer engagement	Artificial intelligence, internet of things, iot, smart speaker, smart speakers
Digital marketing	Advertising, artificial intelligence, social media, voice assistant, voice assistants
Echo chambers	Advertising, social media, twitter
E-commerce	Ai, alexa, amazon, artificial intelligence (ai), human computer interaction, smart speakers, voice assistants
Perceived value	Security, smart speaker, virtual assistant, voice assistant, voice assistants
Security	Amazon echo, internet of things, perceived value, privacy, smart home, trust
Siri	Alexa, amazon alexa, amazon echo, digital assistants, intelligent personal assistant, technology adoption, trust, voice assistant
Technology adoption	Artificial intelligence, internet of things, internet of things (iot), privacy, siri, trust, voice assistant, voice assistants, voice commerce
Twitter	Branding, echo chambers, human-computer interaction, machine learning, social media
Voice commerce	Anthropomorphism, artificial intelligence, marketing, smart speaker, technology adoption, voice assistant

In this section, we provided a description and analysis of the six clusters resulting from the keyword COA (see Table 1), offered an overview of broadly researched keywords (Figure 8), and identified less researched keywords (Table 2). The combined and interpreted results of the term and keyword COA are presented below in Section 2.2.2.

2.2.2 Research results

Altogether, we conducted two bibliometric-analysis techniques: the term COA to address the first research question of structuring voice marketing as a research field and the keyword COA to identify existing research gaps.

According to the term COA data-analysis results, all three clusters represent distinctive thematic areas that are described in more depth through their associated terms. In summary, Cluster 1 contains primarily strategic terms, Cluster 2 comprises terms related to usage issues, and Cluster 3 encompasses device-related terms. Thus, voice marketing can be thematically structured into three dimensions: **strategy**, **usage**, and **device**. This structure served as the basis for the subsequent keyword COA.

Regarding the keyword COA, *artificial intelligence*, *smart speaker*, *voice assistant* and *voice assistants* are the keywords in the heart of Figure 7 with the largest nodes. Therefore, they represent the core components of voice marketing, which can be explained as follows. Artificial intelligence is the technology that enables the functionality of voice assistants. Voice assistant is the notion of software as the basis for human–computer interaction via voice. Finally, a smart speaker is a device in which voice-assistant software is predominantly embedded to allow human-like two-way conversations between the device and the user.

We suggest that the issues studied in the voice-marketing research field are therefore linked to at least one of these keywords. Thus, these keywords represent the starting points of research in the field of voice marketing and, accordingly, are researched broadly (since they have high co-occurrences) and in-depth (since they have high occurrences). Nevertheless, several voice-marketing issues require further investigation. The affected issues are displayed as part of the keyword COA in Table 2.

Figure 10 summarizes the results of the bibliometric analysis as follows. First, the three thematic dimensions around which voice-marketing research revolves (identified in Section 2.2.1.1) are displayed. Second, the six clusters' keywords (displayed in Table 1) are allocated to the three main dimensions: The **strategy** dimension comprises the keywords of the purple and turquoise clusters, the **usage** dimension encompasses the keywords of the red and yellow clusters, and the **device** dimension contains the keywords of the green and blue clusters. Third, keywords that require further research (see Table 2) are highlighted in red italics.

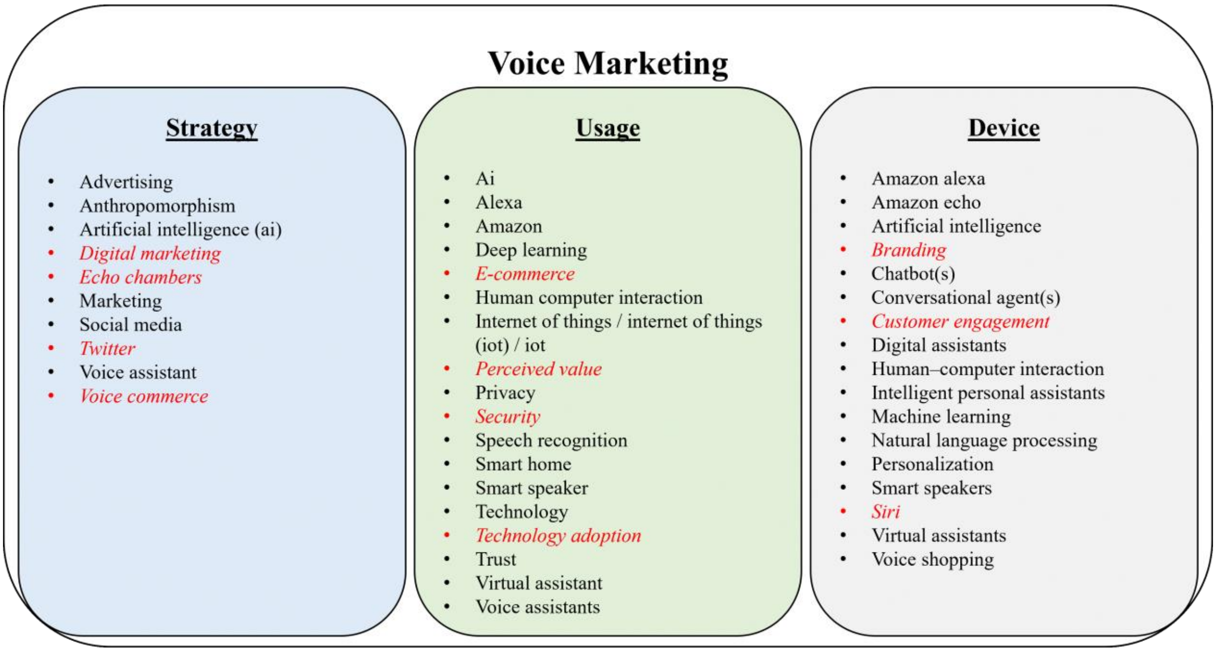


Figure 10. The thematic structure of the voice-marketing research field and research gaps (in red italics)

The presented bibliometric analysis allowed us to identify the keywords that represent topics that have been researched to a lesser degree. Hence, these keywords indicate additional areas for investigation, thereby highlighting research gaps. However, new areas yet to be represented by keywords in the keyword COA signify even larger gaps of a kind that cannot be identified through this type of analysis. Identifying and addressing these gaps is essential, but they fall beyond the scope of this specific research endeavor. Altogether, the bibliometric analysis, as a quantitative research method described in Section 2.2, provided valuable initial findings to answer the research questions of this study. For a more comprehensive consideration of the research field of voice marketing, Section 2.3 proceeds with a qualitative literature review, which facilitates a detailed analysis of the literature. As such, the quantitative results of the bibliometric analysis can be critically scrutinized and supplemented.

2.3 Qualitative semi-systematic literature review

The importance of accurately building research on existing knowledge is emphasized as a priority for academic researchers across disciplines. With the rapid and fragmented nature of knowledge production in business research, staying up-to-date with the state of the research and assessing collective evidence has become challenging. Therefore, literature reviews have gained increased relevance as a research method. Integrating findings from multiple empirical studies, literature reviews have the power to address research questions comprehensively and provide an overview of interdisciplinary areas. They can also synthesize research findings on a meta-level to identify gaps for further investigation and contribute to theoretical frameworks and conceptual models. (Snyder 2019)

We follow the four-step process introduced by Snyder (2019) to execute the literature review presented in this dissertation. The steps include 1) designing and 2) conducting the review, then 3) analyzing the data and 4) writing the review.

2.3.1 Designing the literature review

The execution of literature reviews can focus on different paths depending on a study's research objective. Accordingly, the execution of literature reviews varies. The research objective of this study is to map the research field of voice marketing and provide an overview of the state of the art to identify research gaps. Therefore, conducting a semi-systematic literature review is the most suitable approach to addressing our research objective (Snyder 2019, p. 334). By doing so, we applied the method of qualitative analysis and used the TCCM framework (theory, context, characteristics, methodology) developed by Paul and Rosado-Serrano (2019) to analyze the literature in a structured manner. This approach facilitates the identification of contexts and theory-based research streams, applied methodologies, and investigated characteristics, which include antecedents and outcomes.

As Step 1 of the semi-systematic literature review, we designed the search strategy for collecting literature. We selected the Business Source Complete (BSC), accessible through the database EBSCOhost, as our data source. The reason for this selection was that, according to the Database Information System (DBIS), the BSC is the most relevant database for the research field of economics, which includes marketing. Furthermore, we used the Boolean search operators to develop the keyword search string. We selected the keywords using the keyword "voice marketing" as the name of the investigated research area. Additionally, as the research field is still evolving, we attempted to capture the research area using a combination of keywords that represent the marketing discipline (e.g., consumer, marketing, brand) and keywords that represent the field of voice assistants (e.g., Alexa, Siri, smart speaker). The final keyword search string that we used is similar to that of the quantitative bibliometric analyses:

> "voice marketing" or (("voice assistant*" or "smart speaker*" or (("intelligent personal assistant*" or "digital assistant*" or "conversational agent*") and voice) or alexa or siri or echo or "google home" or "google assistant*" or "amazon echo") and (consumer* or "brand *" or brand* or marketing or "advertising *" or "advertisement *"))

The results list and the process of refining it are described in Step 2 of the semi-systematic literature review in the following section.

2.3.2 Conducting the literature review

The stipulation was that the keywords must be present either in the abstract or the author's keywords. The initial search showed 1,267 results. The publications considered were limited to peer-reviewed journals and works published in English. As voice marketing is a recent research field, conference proceedings were also included to make the overview timelier. As in the bibliometric analysis, we restricted the literature to publications since 2011, coinciding with the launch of Apple Siri as the first voice assistant. After limiting the results to peer-reviewed literature (excluded 1,099 results), works published in English (excluded 17 results), and results published since 2011 (excluded 25 results), the final result list provided 126 papers. These papers were then screened in more detail.

By screening the papers' abstracts, we identified 46 papers as not scientific or not relevant for our study. Two reasons were decisive for this: First, the term "Alexa" appeared in the papers as a representative of the ranking platform and not in the context of the voice assistant Amazon Alexa. Second, the term "echo" was mentioned in relation to echo chambers, which are primarily studied in the social-media environment as a phenomenon of opinion formation but not—as expected for the search-string development—in the context of the smart speaker Amazon Echo.

Furthermore, we excluded 35 papers from which we could not access the full text and 10 papers that were ahead of print. We analyzed the remaining 35 papers, displayed in Table 3, in depth. This analysis is described below in the Section 2.3.3.

Table 3. Overview of selected voice-marketing literature

Author(s) (Year)	Study focus	Source
Acikgoz and Vega (2022)	Examining voice-assistant-usage habits	International Journal of Human–Computer Interaction
Ashfaq, Jiang, and Yu (2021)	Influence of perceived coolness on consumers' attitude toward smart speakers	International Journal of Human–Computer Interaction
Bălan (2023)	Systematic literature review of business research about chatbots and voice assistants	Journal of Theoretical & Applied Electronic Commerce Research
Dellaert et al. (2020)	Influence of voice assistants on purchase decision-making process	Marketing Letters
Ewers, Baier, and Höhn (2020)	Factors affecting the acceptance of digital voice assistants	Journal of Service Management Research
Flavián, Akdim, and Casaló (2022)	Influence of text-based versus voice-based recommendations on credibility, usefulness, and consumer behavior	Psychology & Marketing
Gollnhofer and Schüller (2018)	Distinction of voice touchpoints and implications for management	Marketing Review St. Gallen
Guerreiro and Loureiro (2023)	Experiences with voice assistants and their influences on coolness and consumer–brand relationships	Journal of Business Research
Hamilton, Swart, and Stokes (2021)	Development of policy guidelines to increase consumer privacy	Journal of Strategic Innovation and Sustainability
Hernandez-Ortega and Ferreira (2021)	Feelings of love due to consumer–voice assistant interactions	Psychology & Marketing
Hussein (2022)	Drivers and dangers of voice-assistant usage	American Journal of Management
Jones (2018)	Role of marketing and advertising in the context of voice-controlled homes	Journal of Brand Strategy
La Cruz Lui et al. (2022)	Domain-specific and innate innovativeness as drivers for perceptions of usability with the services of personal assistants	International Journal of Innovation and Technology Management
Lee and Cho (2020)	Users' motives to use smart speaker and their impact on advertising effectiveness	International Journal of Advertising
Liang et al. (2021)	Consumer–voice assistant social relationships and their effects on purchasing	Journal of Electronic Commerce Research
Lucia-Palacios and Pérez-López (2021)	Influence of interactivity on perception of intrusiveness	Journal of Interactive Marketing
Malodia et al. (2022)	Investigation of the decision to avoid using voice assistants	Journal of Business Research
McLean, Osei-Frimpong, and Barhorst (2021)	Motivations to use voice assistants to receive information related to brands	Journal of Business Research
Mendes Ferreira, Correia, and Pereira (2022)	Influence authenticity and attachment on engagement with voice assistants	Journal of Promotion Management
Mittal and Manocha (2023)	Investigation of the factors of awareness levels and usage patterns to understand voice-assistant adoption	International Management Review
Moriuchi (2019)	Investigation of engagement and loyalty between consumer and voice assistants	Psychology & Marketing
Moriuchi (2021)	Influence of anthropomorphism and engagement on re-use intentions	Psychology & Marketing
Park et al. (2022)	Advertising effectiveness through the voice-assistant medium	International Journal of Electronic Commerce
Poushneh (2021a)	Voice assistant traits and their impact on consumer attitudes and behavior	Journal of Retailing and Consumer Services
Poushneh (2021b)	Autonomous behavior of voice assistants to maintain social interactions with consumers	Journal of Retailing and Consumer Services
Ramadan, Farah, and El Essrawi (2021)	Amazon's relationship strategy	Psychology & Marketing
Smith (2020)	Preferred marketing-message design	Journal of Strategic Marketing
Son, Oh, and Im (2023)	Influence of the usage of smart speakers on the search, purchase, and consumption of digital content	MIS Quarterly
Tassiello, Tillotson, and Rome (2021)	Psychological power in the consumer decision-making process for food and beverage purchases	Psychology & Marketing
Uysal, Alavi, and Bezençon (2022)	Beneficial and harmful effects of voice assistants on consumers	Journal of the Academy of Marketing Science
Vernuccio et al. (2023)	Examining strategy pillars to anthropomorphize brands in the context of name-brand voice assistants	Journal of Brand Management
Voorveld and Araujo (2020)	Influence of modality (text versus voice) and name (human-like versus no name) on consumer concerns and persuasion	Cyberpsychology, Behaviors, and Social Networking
Wahida and Mohammad Shah (2022)	Adoption intention as a mediator in the relationship between attitude toward smart speakers and their adoption	Global Business and Management Research
Whang and Im (2021)	Consumers' perception of the human-likeness of voice assistants	Journal of Brand Management
Wolbers and Walter (2021)	Usage of voice assistants within brand's consumer decision journey	Psychology & Marketing

2.3.3 Analyzing the selected literature

The 35 papers were published in different journals and covered various subjects. In this section, we provide a descriptive overview of the literature followed by a detailed analysis using the TCCM framework.

The papers were published between 2018 and 2023. Most of the papers were published in the second half of the publication period (74%/26 papers), which indicates that the voice-marketing research area is growing and holds significance and interest as a research field. Moreover, most of the papers were published in the Psychology and Marketing journal (20%/7 papers) and the Journal of Business Research (9%/3 papers). Two papers also were published in each of the following journals: the Journal of Retailing and Consumer Services, the Journal of Brand Management, and the International Journal of Human–Computer Interaction. The other papers were published in individual journals. Notably, voice-marketing research appears in different journals that address unique thematic subjects, supporting the assumption that voice marketing represents an interdisciplinary research field.

After providing a descriptive overview of the literature, we now present the analysis of the papers in more detail using the TCCM framework. When applying the TCCM framework, its various elements, namely theory, context, characteristics, and methodology, are examined individually.

Theory. An overview of the applied theories is displayed in Table 4. In 54% of the papers, at least one of the total 20 different theories was applied. Most of the papers (13 papers) were based on only one theory (e.g., Vernuccio et al. 2023; Wahida and Mohammad Shah 2022; Wolbers and Walter 2021), while in six papers at least two theories were combined (e.g., Acikgoz and Vega 2022; Ewers, Baier, and Höhn 2020; Uysal, Alavi, and Bezençon 2022). The technology acceptance model (TAM) and the use and gratification (U & G) theory were the only theories applied in the different papers more than once.

Table 4. Applied theories in the voice-marketing literature

Theory	Developed from	Applied by
Attachment theory	Mikulincer and Shaver (2007)	Mendes Ferreira, Correia, and Pereira (2022)
Attachment-aversion theory	Park, Eisingerich, and Park (2013); Schmitt (2013)	Guerreiro and Loureiro (2023)
Concept of privacy cynicism	Choi, Park, and Jung (2018)	Acikgoz and Vega (2022)
Consumer decision journey framework	Edelman and Singer (2015)	Wolbers and Walter (2021)
Decision avoidance theory	Anderson (2003)	Malodia et al. (2022)
Flow theory	Csikszentmihalyi (1997)	Poushneh (2021a)
MAIN model	Sundar (2008)	Voorveld and Araujo (2020)
Media richness theory	Daft and Lengel (1986)	Flavián, Akdim, and Casaló (2022)
Mind perception theory	Gray, Gray, and Wegner (2007)	Uysal, Alavi, and Bezençon (2022)
Parasocial interaction theory	Horton and Wohl (1956)	Lee and Cho (2020); Whang and Im (2021)
Perceived coolness model	Sundar, Tamul, and Wu (2014)	Ashfaq, Jiang, and Yu (2021)
Persuasion knowledge model	Williams (2002)	Voorveld and Araujo (2020)
Social cognition theory	Bandura (1986)	Poushneh (2021b)
Social exchange theory	Homans (1968)	Bălan (2023); Uysal, Alavi, and Bezençon (2022)
Social response theory	Nass and Moon (2000)	Vernuccio et al. (2023)
Stimulus-organism-response framework	Mehrabian and Russell (1974)	Hernandez-Ortega and Ferreira (2021)
Technology acceptance model	Davis (1989)	Acikgoz and Vega (2022); Ewers, Baier, and Höhn (2020); Hussein (2022); Moriuchi (2019); Wahida and Mohammad Shah (2022)
Theory of consumers search	Stigler (1961)	Moriuchi (2019)
Theory of planned behavior	Ajzen (1991)	Moriuchi (2019)
Use & gratification theory	Katz, Blumler, and Gurevitch (1973)	Ewers, Baier, and Höhn (2020); Lee and Cho (2020)

By applying the TAM, the researchers investigated potential dangers encountered by voice-assistant users and reasons driving the demand for the assistants (Hussein 2022); the adoption intention of smart speakers (Wahida and Mohammad Shah 2022); the influence of privacy cynicism on consumer usage habits with voice assistants (Acikgoz and Vega 2022); consumers' acceptance of voice assistants (Ewers, Baier, and Höhn 2020); or influencing factors on adoption, engagement, and loyalty of consumers toward voice assistants (Moriuchi 2019).

Three studies integrated the TAM with at least one other theory: the concept of privacy cynicism (Acikgoz and Vega 2022), the U & G theory (Ewers, Baier, and Höhn 2020), or the theory of consumers search in combination with the theory of planned behavior (TPB; Moriuchi 2019). Thus, only two studies solely applied the TAM.

Furthermore, the studies in which the U & G theory was applied combined it with a second theory, either the TAM (Ewers, Baier, and Höhn 2020) or the parasocial interaction theory (Lee and Cho 2020).

Additionally, it is striking that certain applied theories exhibit partial overlap in the issues they addressed in their respective investigations. For example, the TAM, the TPB, and the U & G theory were used to investigate usage intentions for voice assistants. Furthermore, several theories, such as the parasocial interaction theory or the social exchange theory, served as research bases to examine social interaction with or perception of voice assistants. The described observations about the applications of the theories could indicate two main research streams, namely 1) voice-assistant acceptance and adoption and 2) consumer–voice assistant interaction and perception.

Context. The papers illuminate two different perspectives: devices and domains. Regarding devices, the studies explored either voice assistants or in-home smart speakers. Only a few papers studied a particular voice assistant or smart speaker (e.g., Ramadan, Farah, and El Essrawi 2021).

Besides the focus on a specific device or a comparison of several devices, it is conspicuous that the studies cover different domains, for example, consumers' perception of the devices, consumers' behavior in response to the devices' behavior, or the devices' attributes. A closer examination of the studies' contents reveals that the investigated domains can be clustered into seven groups. The domain groups are illustrated in Figure 11, and the allocation of each paper to its respective domain group is presented in Table 5.

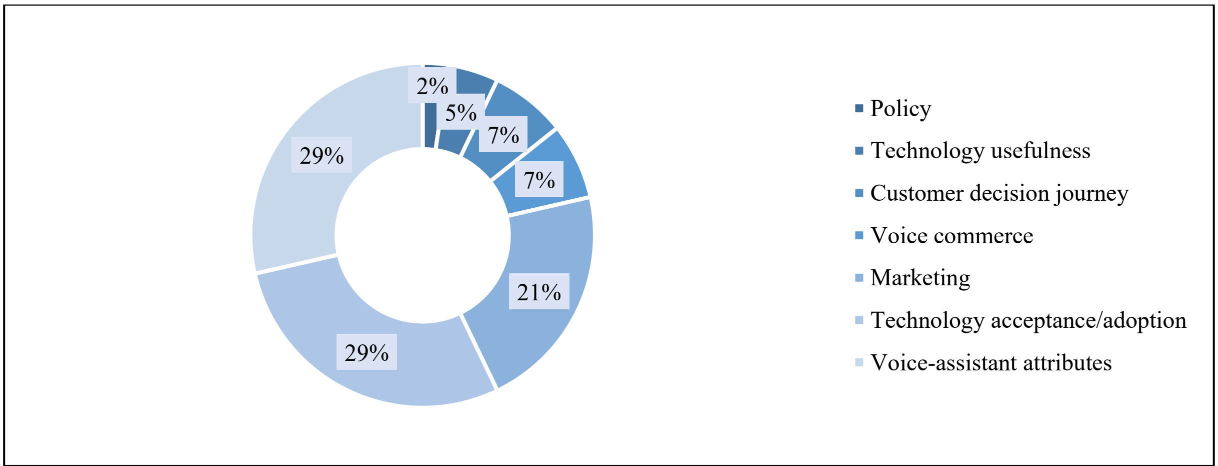


Figure 11. Domains of the voice-marketing research literature

Table 5. Allocation of the voice-marketing studies to the domain groups

Domain group	Number of papers	Studies
Customer decision journey	3	Dellaert et al. 2020; Gollnhofer and Schüller 2018; Wolbers and Walter 2021
Marketing	9	Bălan 2023; Jones 2018; Lee and Cho 2020; McLean, Osei-Frimpong, and Barhorst 2021; Park et al. 2022; Poushneh 2021b; Ramadan, Farah, and El Essrawi 2021; Smith 2020; Vernuccio et al. 2023
Technology acceptance/ adoption	12	Acikgoz and Vega 2022; Ashfaq, Jiang, and Yu 2021; Ewers, Baier, and Höhn 2020; Hernandez-Ortega and Ferreira 2021; Hussein 2022; Malodia et al. 2022; Mendes Ferreira, Correia, and Pereira 2022; Mittal and Manocha 2023; Moriuchi 2019, 2021; Poushneh 2021a; Wahida and Mohammad Shah 2022
Technology usefulness	2	La Cruz Lui et al. 2022; Lucia-Palacios and Pérez-López 2021
Voice-assistant attributes	12	Ashfaq, Jiang, and Yu 2021; Guerreiro and Loureiro 2023; Liang et al. 2021; McLean, Osei-Frimpong, and Barhorst 2021; Mendes Ferreira, Correia, and Pereira 2022; Moriuchi 2021; Poushneh 2021a, 2021b; Uysal, Alavi, and Bezençon 2022; Vernuccio et al. 2023; Voorveld and Araujo 2020; Whang and Im 2021
Voice commerce	3	Flavián, Akdim, and Casaló 2022; Son, Oh, and Im 2023; Tassiello, Tillotson, and Rome 2021
Policy	1	Hamilton, Swart, and Stokes 2021

In seven of the papers, the authors investigated the domain “voice-assistant attributes” either in combination with the domain “technology acceptance/adoption” or the domain “marketing.” Therefore, these papers appear twice in Table 5. In these papers, the focus was on studying, for instance, the impact of the social presence and social attraction of voice assistants on consumer brand-usage intention.

The countries in which the data collection occurred or the investigated age groups are mentioned several times, but the analyses were not conducted with a special focus on these factors. One exception is the study of La Cruz Lui et al. (2022) which executed a gender comparison. Additionally, the detailed investigation of specific categories, such as on-demand video (Son, Oh, and Im 2023) or food and beverages (Tassiello, Tillotson, and Rome 2021), is only partly mentioned.

Characteristics. The papers differ in terms of the investigated antecedents, outcomes, moderators, and mediators. Because we limited the selected literature to papers we had full access to, it was possible to conduct a detailed analysis of the characteristics. To do so, the studies based on quantitative, experimental, and mixed-methods approaches were reviewed (i.e., in total 28 papers), while literature reviews were excluded.

The studies investigated as antecedents mainly voice assistants' attributes (e.g., anthropomorphism, authenticity, attachment, functional intelligence) or usefulness (e.g., perceived ease of use, perceived usefulness). In a few studies, the stimuli were used as antecedents (e.g., Smith 2020; Whang and Im 2021).

The authors investigated three different outcome foci more closely: first, outcomes regarding voice assistants, for example, the intention to use or reuse voice assistants (e.g., Moriuchi 2019; Wahida and Mohammad Shah 2022); second, outcomes related to the brand (McLean, Osei-Frimpong, and Barhorst 2021); third, outcomes with a focus on users, such as their satisfaction with voice assistants (e.g., Poushneh 2021a; Uysal, Alavi, and Bezençon 2022) and their trust in them (e.g., Poushneh 2021b).

The investigated moderators are multidimensional, so they include affective and cognitive aspects (Erevelles 1998). Affective moderators represent mood and feelings or emotions (Erevelles 1998), which are called "feeling state[s]" (Cohen and Areni 1991, p. 298), whereas cognitive moderators describe individuals' evaluations (Erevelles 1998). Examples of affective moderators in the voice-marketing literature are relationship closeness (Uysal, Alavi, and Bezençon 2022) and perceived ease of use (e.g., Hussein 2022). Cognitive moderators that are investigated in the voice-marketing literature include, for example, expertise (Vernuccio et al. 2023) and functional usage (Son, Oh, and Im 2023). Gender as a demographic moderator is also considered (e.g., La Cruz Lui et al. 2022).

Additionally, the mediators explored in existing voice-marketing studies can be divided into affective mediators, such as para-social relationships (Lee and Cho 2020) or procrastination (Malodia et al. 2022), and cognitive mediators, such as credibility (Flavián, Akdim, and Casaló 2022) or AI assistance (Hussein 2022). A comprehensive overview of the investigated antecedents and outcomes, as well as the considered mediators and moderators, is displayed in Figure 12.

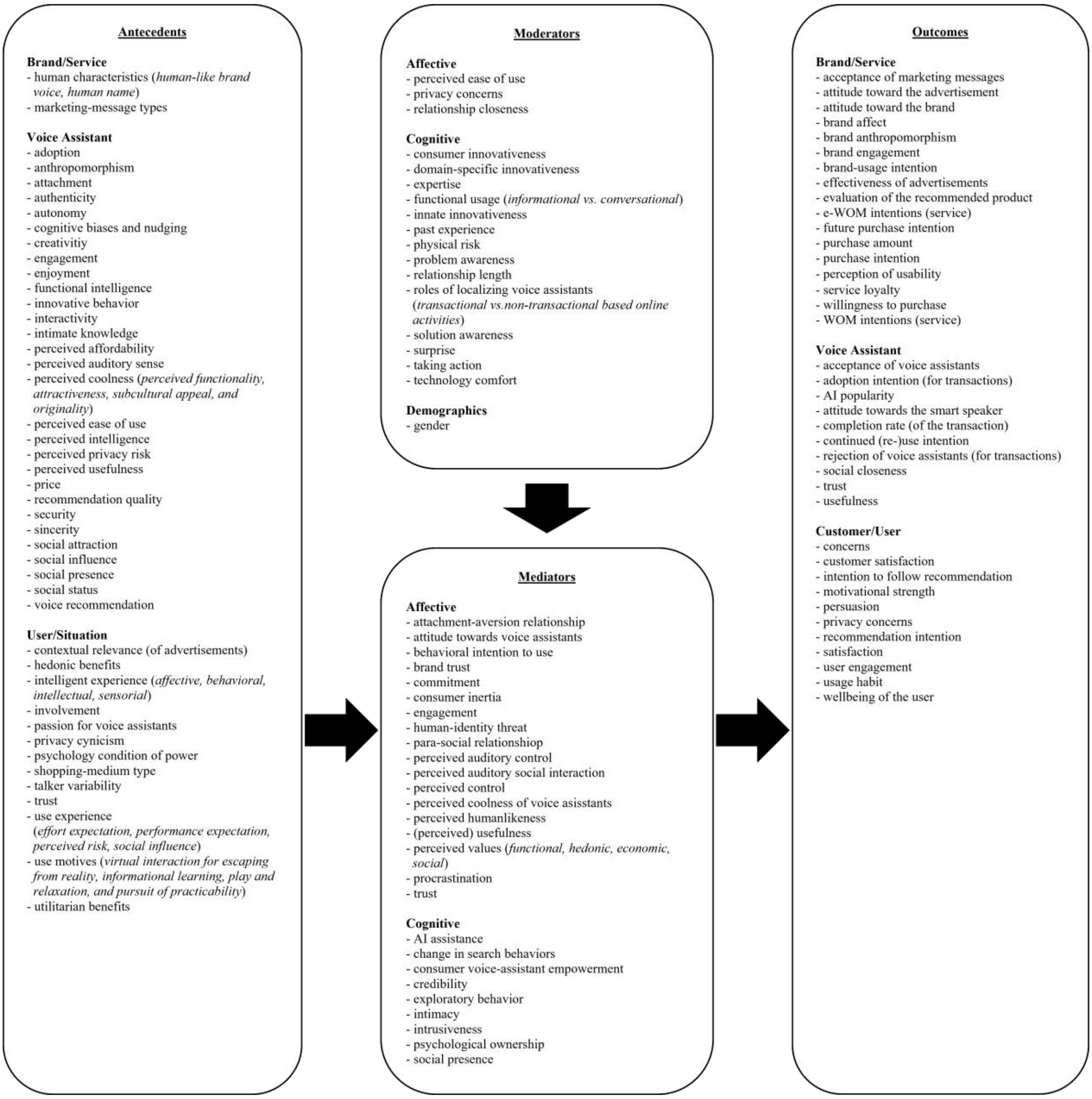


Figure 12. Investigated characteristics in studies from the voice-marketing research field

Methodology. The selected literature presents mainly quantitative studies (51%). Furthermore, 20% of the studies are based on experimental-study designs, 11% are literature reviews, 9% encompass mixed-methods approaches, 6% comprise qualitative studies, and 3% present case studies. In the quantitative studies, the survey method was preferred (e.g., Acikgoz and Vega 2022; Hussein 2022; Vernuccio et al. 2023), while the experimental studies relied mainly on designs such as between-subjects (e.g., Flavián, Akdim, and Casaló 2022; Whang and Im 2021), laboratory experiments (Poushneh 2021b), or online experiments (Voorveld and Araujo 2020). The literature reviews, notably, were primarily not conducted as scientifically systematic literature reviews, with the exception of Bălan’s (2023) study. In the qualitative studies, the method of in-depth interviews was applied (Ramadan, Farah, and El Essrawi 2021; Wolbers and Walter 2021).

2.3.4 Analysis results

After systematically selecting literature from the voice-marketing research field and analyzing it qualitatively using the TCCM framework, this section consolidates the key aspects regarding the identification of research gaps.

Approximately half of the 35 papers analyzed in depth were based on at least one guiding theory. Six papers were based on a combination of at least two different theories. Strikingly, only two theories, TAM and U & G, were applied in more than one paper, with TAM being the model most frequently utilized as a research foundation. The application of various theories to explore the voice-marketing research field, without any single theory being significantly dominant, suggests that a universally accepted and well-suited theory for studying this field has not yet been established. This lack indicates that the research field has been studied extensively with different foci, often spanning across disciplines. However, the depth of the studies is limited, as theories are predominantly applied only once. Nevertheless, the overlap of the investigation issues to which certain theories have been applied is conspicuous. Thus, theories such as the TAM, the TPB, and the U & G theory focus on investigations of voice-assistant usage intentions, while the parasocial interaction theory or the social exchange theory address examinations of social interactions with or perceptions of voice assistants. Therefore, two research streams in the field of voice marketing can be derived:

1) Voice-assistant acceptance & adoption
2) Consumer–voice assistant interaction & perception

Within these two research streams, a total of seven research-stream domains (see Figure 11) are addressed in the literature. These domains can be logically allocated to the two research streams. To do so, we thematically distinguish the domains according to the two research streams into 1) real adoptions of voice assistants and 2) individuals' interactions with and perceptions of them.

For the first research stream, we assume real adoptions of voice assistants to involve using them along the customer journey, which includes the voice-commerce touchpoint (see Figure 1). Furthermore, the usage of voice assistants along the customer journey can be guided by establishing policies. For the second research stream, we assume the existence of domains that represent individuals' perceptions of voice assistants, such as the perceived attributes of assistants (e.g., are voice assistants perceived as useful, cool, or human-like), and the individual interactions of consumers with assistants. Individual interactions are possible through personalized voice-marketing activities (see Section 1.1). Our assumptions result in an allocation of the research-stream domains displayed in Figure 11 to the two research streams as follows:

1) Voice-assistant acceptance & adoption:
   customer decision journey, technology acceptance/adoption, policy, voice commerce
2) Consumer–voice assistant interaction & perception:
   marketing, technology usefulness, voice-assistant attributes

While a quarter of the literature presents studies that explored the research-stream domain "technology acceptance/adoption," investigated issues of the research-stream domains "policy" and "technology usefulness" are rare. Technologies used in the marketing discipline should provide value to consumers to satisfy their needs in the most effective way possible. However, in doing so, ethical aspects should always be considered. Therefore, the voice-marketing literature should be extended by additional studies that address the ethical perspective of the usage of voice assistants for marketing purposes.
Moreover, it seems that the focus thus far has been mainly on investigations of the different cues and attributes of voice assistants. Additional research on the media type of interactions, which is only addressed in the form of a text-versus-speech study from Flavián, Akdim, and Casaló (2022), and on a comparison of different smart-speaker devices and voice-assistant providers is needed. Such research could help, for example, to generate insights about which device (voice assistant versus smart speaker) and which provider (e.g., Amazon Alexa, Google Assistant) is the most suitable for specific contexts and tasks.
Furthermore, comparisons of different countries, specific industries, or product categories; in-depth voice-assistant-provider analyses (e.g., Amazon Alexa, Google Assistant); and target group-specific implications are lacking.

Even though voice marketing belongs to the marketing discipline, over half of the analyzed literature did not exceed the acceptance and adoption of voice assistants and their attributes. Therefore, only a few studies examined the value voice assistants could provide for marketing and branding purposes. This gap is also reflected in the analysis results for the characteristics (see Figure 12). The presented outcome characteristics are often focused on the technology or on voice assistants in general. Therefore, only approximately a quarter of the outcomes are brand- and marketing-specific (e.g., attitude toward a brand or advertisement, brand affect, brand-usage intention). Voice marketing should meaningfully expand marketing strategies. To do so, marketers must know for which industries, contexts, and tasks the implementation of voice assistants is promising. Therefore, future studies should identify marketing outcomes that are highly relevant for marketing practitioners and develop suitable frameworks to investigate and test the outcomes. Additionally, industry-, category-, and country-specific differences can be uncovered, for example, through between-subject experiments. This process would help to establish a foundation for future studies in voice marketing and provide valuable implications for marketing practitioners.

The evolving research field of voice marketing has been mainly studied through quantitative research. However, qualitative research approaches are promising for exploring and understanding a trending research field. Thus far, only a few studies have taken advantage of this research method. It is therefore likely that the foundation for understanding the research field of voice marketing is expandable, which explain the scattered research topics and applied theories.

2.4 Combining the results of the hybrid review

The research objectives in Chapter 2, as outlined in Section 2.1, involve first, identifying the dimensions of voice marketing as a research field and second, uncovering gaps in the published voice-marketing literature. To do so, we formulated the following two research questions (RQ), which we addressed in our study:

RQ 1. Which dimensions does the research field of voice marketing encompass?

RQ 2. Which research gaps currently exist in the published voice-marketing literature?

We integrate the results of the quantitative bibliometric analysis (details in Section 2.2) and the qualitative semi-systematic literature review (details in Section 2.3) below to address both research questions. Section 2.4.1 covers the response to RQ 1, while Section 2.4.2 explores RQ 2.

2.4.1 The structure of the research field of voice marketing

The voice-marketing research field is still evolving, and existing research is scattered. To comprehensively capture and investigate the research field, a guiding overarching structure is required. To derive such a structure, we conducted a bibliometric analysis primarily of literature that we collected from Scopus (n = 673). Through a term COA, we found that the voice-marketing research field revolves around three thematic dimensions: strategy, usage, and device. On the one hand, the dimensions of usage and device can be easily identified through their keywords, so with their clear and distinct delimitation, they seem to be in an advanced stage of development. On the other hand, the strategy dimension appears more scattered, comprising a variety of keywords that partly indicate different thematic focal points.

Since the strategy dimension is still developing distinctiveness, it currently contains several thematic foci. However, at the dimension's heart is the investigation of a voice-marketing strategy, including the development of a concept for how to leverage the voice medium to achieve promising solutions for consumers. The measurement of effectiveness and performance by considering advertising and cost issues, as well as society, also plays a role. Furthermore, the strategy dimension comprises the terms *medium* and *text,* which are connected with the terms *role* and *chatbot*. Therefore, the roles of voice-based and text-based conversational agents may also be interesting subjects to illuminate when investigating strategic voice-marketing issues.

The usage dimension addresses questions that examine voice-assistant usage and its resulting effects. The term *marketer* is also assigned to this dimension, which highlights the dimension's importance for the marketing discipline. By analyzing the terms allocated to this dimension, the following examples of study queries can be formulated: Which factors lead to the acceptance and adoption of voice assistants? When, how, and why do consumers embed the use of voice assistants in their daily lives? Which roles do usefulness, trust, and value play in the context of voice marketing?

The device dimension includes voice-marketing studies that focus on voice-assistant technology itself, general devices for accessing voice technology (e.g., smart speakers), or specific devices for such access (e.g., Apple Siri, Amazon Alexa). Furthermore, the dimension includes the term *home* as an environment for using voice assistants, which encompasses associated aspects such as privacy and security. Studies of the device dimension can be framed to explore important aspects for consumers considering voice assistants for their homes; to compare suitable applications for smart speakers versus voice assistants; and to examine differences among voice-assistant providers, such as in terms of privacy or security.

After clarifying the three thematic dimensions within the voice-marketing research field and outlining their thematic foci, Section 2.4.2 now identifies research gaps within each dimension and derives future research agendas.

2.4.2 Future research directions for the voice-marketing research field

Research gaps in the form of future research directions are presented according to the three dimensions of strategy, usage, and device. For the development of the research directions, the two research streams ([1] voice-assistant acceptance and adoption and [2] consumer–voice assistant interaction and perception), as well as the seven research-stream domains (customer decision journey, marketing, technology acceptance/adoption, technology usefulness, voice assistant attributes, voice commerce, and policy) are considered.

2.4.2.1 Research directions for the strategy dimension

According to the results of the quantitative bibliometric analysis, less researched keywords in the **strategy** dimension are *digital marketing*, *echo chambers*, *twitter*, and *voice commerce*. We develop several research directions in this section.

One initial research direction pertains to digital-marketing issues. The keyword *digital marketing* is researched together with keywords such as *social media* and *voice assistants*. While social media also comprises interactive communication channels, the interactions are primarily based on text and visuals. However, voice assistants represent interactive communication channels with interactions based on voice. This distinction illustrates that, for digital marketing and digital-marketing strategies, awareness of and comparisons between possible communication channels and interaction mediums are relevant. Another interaction medium that is part of the strategy dimension and appears in the keyword COA is *chatbots*. Despite the comprehensive research on this keyword (see Section 2.2.1.2), there is a gap in the literature regarding investigations that compare chatbots and voice assistants, which is worth addressing to offer insights enabling the development of an optimal digital-media strategy.
Additionally, as stated in the analysis using the TCCM framework in Section 2.3.3, analyses regarding different countries, industries, and target groups require further attention, because digital-marketing strategies can vary depending on a company's industry and the country in which it operates. Therefore, future studies could provide valuable insights into identifying target groups for voice-marketing activities and understanding the factors to consider for each target group. Additionally, determining the adjustments required for executing country-targeted voice-marketing approaches and assessing the industries where voice-marketing activities are either mandatory or of lesser importance could be of interest.
Furthermore, the consumer decision journey as a research-stream domain is worth mentioning at this point. As part of digital marketing, it is recommended to link digital-marketing channels with each other, which allows a seamless customer-experience journey. While voice touchpoints (Gollnhofer and Schüller 2018) and the consumer decision-making process by means of voice assistants (Dellaert et al. 2020) have received attention in the research thus far, some aspects remain unanswered. For example, which specific effects arise from the addition of voice touchpoints to the digital customer experience? Furthermore, what adjustments must companies and brands undertake to seamlessly embed voice marketing into the customer journey?

A second research direction addresses echo chambers. The keyword *echo chamber* is displayed in the bibliometric analysis and appears in the semi-systematic literature review. A definition of this keyword states that it is "A situation in which people only hear opinions of one type, or opinions that are similar to their own" (Cambridge Dictionary n.d.). This phenomenon is popular for the social media surrounding but not yet for the voice-assistant environment. It would be interesting to investigate this issue in the context of voice marketing as a digital channel with a degree of social presence. Therefore, studies could assess, for example, the key drivers of echo chambers in general and the factors that can contribute to echo chambers within communications with voice assistants. Alternatively, studies could consider how consumer–voice assistant communications may be advantageous in influencing echo chambers and shaping opinions. Such studies could deliver interesting insights, not only for the marketing discipline but also for psychology, sociology, and politics. Investigations could be based on research about how the platform Twitter works and apply social-theory models that have already been validated for voice-marketing research (see Table 4, e.g., the social cognition theory).

A third research direction focuses on voice commerce. Although sales generated through voice commerce are not the key objective of marketing activities, such revenue supports the survival of brands and companies. Tassiello, Tillotson, and Rome's (2021) study examined consumer–voice assistant interaction in the context of food and beverage purchase choices. Their study could serve as a basis for further research working toward a generalization of the study results. Therefore, consumer–voice assistant interactions in the context of other low-involvement products, such as everyday household products (e.g., toilet paper, toothpaste) or in the context of service offers (instead of products), could be addressed.
Furthermore, Flavián, Akdim, and Casaló (2022) investigated the effects of voice-assistant recommendations on consumer behavior by applying the media richness theory. This study could provide the groundwork to extend research about the "customer decision journey" research-stream domain (see Figure 11). Additionally, investigations regarding cross-medium product and service consultations could be of interest. An example would be to provide recommendations to consumers via voice assistants and to extend the recommendations with visual information that is sent to the consumers' smartphones. Outcomes such as purchase intentions and attitudes toward the product and services may be relevant in this context.

Twitter as a possible fourth research direction is not further considered because in-depth investigations about Twitter in the context of voice marketing seem not to be expedient for two reasons. First, interactions on Twitter are not human–computer based. Second, the interactions do not represent immediate two-way communications. Therefore, the modes of interaction and communication on Twitter compared to voice assistants are not similar, so it is recommended to prioritize future studies on the other issues described in this section.

2.4.2.2 Research directions for the usage dimension

The quantitative bibliometric analysis reveals that research gaps exist for the **usage** dimension regarding e-commerce, perceived value, security, and technology-adoption issues. Combining these results with those of the qualitative semi-systematic literature review, a research agenda for the dimension can be developed.

A first research direction addresses issues related to technology adoption. Based on the qualitative semi-systematic literature review, we observed that “technology acceptance and adoption,” constituting one of the seven research-stream domains, is extensively examined in over a quarter of the existing literature. Therefore, issues concerning the topic itself do not represent urgent research gaps. However, thus far, the topic has not been sufficiently studied in combination with marketing. This conclusion is described in Section 2.3.3 and becomes apparent when examining the keywords associated with technology adoption as presented as the co-occurrences in Table 2. As such, there is a research gap in terms of voice-assistant applications developed by brands or companies. Brands and companies can benefit from investing less time and money in developing applications for popular voice assistants, such as Amazon Alexa or Google Assistant, instead of developing their own voice assistants (SoundHoundAI 2021). Therefore, it is less imperative in the context of voice marketing to investigate the technology adoption of voice assistants, but it is mandatory to investigate the acceptance and adoption intentions of voice-assistant applications developed by brands or companies. Nonetheless, the financial and human resources of brands and companies are limited. Therefore, they must determine whether the development of voice-assistant applications is worth their resources. However, suitable models for measuring the marketing effects of voice-assistant applications developed by brands or companies are lacking. This highlights a substantial research gap within the field of voice marketing.

A second research direction addresses perceived value. The bibliometric analysis reveals that perceived value is studied mainly in the context of voice-assistant software and smart speakers in general (see Table 2). However, it remains unclear what kind of perceived value consumers associate with voice marketing (activities). Additionally, the qualitative semi-systematic literature review reveals that “technology usefulness” as a research-stream domain, to which perceived value can be designated, appears in only 6% of the voice-marketing literature and is therefore under-researched. Moreover, the analysis conducted through the TCCM framework as part of the qualitative semi-systematic literature review confirms that existing studies do not apply theories or frameworks that consider perceived value. Therefore, understanding the value of voice marketing and how it compares to other (digital) marketing activities is a research gap worth addressing. Furthermore, Brocks and Bätjer-Gleitsmann’s (2021, p. 10) study shows that consumers prefer different voice assistants depending on the situation (e.g., walking, on the bus, in the car). Therefore, it remains unclear which specific and distinct value consumers perceive for each voice assistant. Closing this knowledge gap could help to determine why and for which situations consumers need and want specific voice assistants and voice-assistant applications and which functions these applications should therefore provide in each situation. This understanding could help companies develop suitable applications.

A third research direction affects security issues. Wahida and Mohammad Shah (2022) examined security as an antecedent for the adoption intention of smart speakers through a quantitative study. However, consumers often confound security and privacy, which is why the authors combined them into one construct. This observation highlights that security can be understood differently and take different forms. Nevertheless, as the study of Wahida and Mohammad Shah (2022) illustrates, security is an important factor in the voice-assistant context. Therefore, it is necessary to understand the factors that lead to consumers' sense of security. A promising approach to generating this knowledge could be to conduct interviews with consumers. Simultaneously, it would be possible to generate insights about which security factors consumers consider most important when using voice technologies. Decision avoidance theory, which was applied in Malodia et al.'s (2022) study, can serve as the basis for such investigations. Furthermore, the qualitative semi-systematic literature review reveals that the research-stream domain "policy" was only addressed in one paper. Regarding security issues, it would be advantageous to develop policy guidelines for voice-assistant providers and application developers. Such guidelines could help improve the security of voice assistants and smart speakers for consumers and ensure that consumers are educated transparently about relevant details. In this context, the ethical perspective should also be considered.

A fourth research direction could fuel studies about e-commerce. Existing studies have only investigated e-commerce in combination with Amazon Alexa and Amazon but not voice commerce in particular (see Table 2). There is an opportunity to seamlessly transition users of the Amazon Alexa voice assistant to the Amazon e-commerce platform. This shift would be especially beneficial for companies and brands seeking opportunities to convert their voice-marketing activities into sales. However, there is a notable absence of studies in the literature that specifically address this issue. Therefore, research questions about which voice-marketing activities are the most suitable for converting consumers to e-commerce activities could be examined. Investigations in this research area could also help destroy marketing silos and enhance the connection between different marketing platforms and channels to achieve the best possible marketing outcomes.

2.4.2.3 Research directions for the device dimension

For the **device** dimension, the bibliometric analysis uncovers research gaps for issues concerning branding, customer engagement, and the voice assistant Apple Siri. In the following, the keywords are combined with the analysis results from the qualitative semi-systematic literature review to derive a research agenda for this dimension.

The first research direction focuses on branding issues. Companies usually use existing voice assistants, such as Amazon Alexa or Google Assistant, for voice-marketing activities. Doing so facilitates an easier start in this marketing form because consumers are already used to those specific voice assistants or associated smart speakers (e.g., Amazon Alexa Echo or Google Home). However, as with every marketing platform, the possibilities for voice-marketing activities companies can conduct and how they must be developed and designed depend strongly on the voice-assistant provider. Therefore, relevant questions include which voice-marketing activities can be executed on which devices, which advantages and disadvantages of the devices should be considered for voice-marketing activities, and which branding activities could appear on the different devices.

Furthermore, the devices possess distinct voice-assistant attributes. However, for voice-marketing activities, the voice assistant itself should align with consumers' brand associations. Therefore, studies should examine which attributes consumers associate with voice-assistant providers and devices and how closely these attributes must align with those of the companies to ensure a congruent image.

Additionally, branding activities often influence marketing outcomes, such as brand perception and brand image. Furthermore, companies can benefit from these effects by improving their relationships with their consumers. It would therefore be interesting to investigate whether branding activities influence brand perception and, if so, which effect (positive or negative) can be observed to what extent for different devices (e.g., smart speakers versus voice assistants on smartphones).

A second research direction concerns customer-engagement issues. Relationships between consumers and brands can mainly be developed through interactions between the two parties. Therefore, customer engagement plays a crucial role, and to leverage voice marketing in the most effective way possible, voice assistants should already be integrated into consumers' daily lives. This integration is possible when consumers already use voice assistants or smart speakers for daily routines, for example, setting a timer or starting to play music. If that is the case, a promising foundation exists for companies to cultivate customer engagement. The study of McLean, Osei-Frimpong, and Barhorst (2021) investigated which voice-assistant attributes of Alexa Skills lead to brand engagement. Thereby, they developed the foundation for research about customer engagement through voice-assistant applications developed by brands or companies. This study should be repeated across brand categories and countries and consider different target groups (gender, age, and interest-based) to allow generalization of the study results.

Additionally, attributes that reduce customer engagement should be revealed to provide comprehensive implications. Moreover, not only the attributes but also the functions within each of the described contexts could be a relevant factor in sparking or reducing customer engagement, so examining the influence of voice assistants' functions could also be fruitful.

Furthermore, customer engagement along the customer decision journey would be an interesting research issue. When consumers stop in the customer decision journey, voice assistants might stimulate consumer engagement and, in doing so, help consumers resume their individual journey. Studies exploring this issue could provide valuable insights, for example, to improve consumer experiences.

According to the bibliometric analysis results, a possible third research direction could focus on the voice assistant Apple Siri. However, we do not describe this research option further for two reasons. First, the voice assistant belongs to the company Apple and currently provides only voice search (i.e., asking Apple Siri for more information about a specific topic, restaurant, brand, or others). As such, avenues for companies other than Apple to communicate with consumers via Apple Siri seem to be extremely limited. Second, we recommend that Apple Siri, among all other voice assistants, be included in research concerning voice-marketing issues with a focus on devices. In other words, all devices and voice-assistant providers should be investigated and compared. Consequently, from our standpoint, developing a comprehensive research agenda solely for Apple Siri is not advisable.

2.4.3 Summary of the research results

After presenting the results for both the quantitative bibliometric analysis in Section 2.2.2 and for the qualitative semi-systematic literature review in Section 2.3.4, we combined these results in Sections 2.4.1 and 2.4.2. The research results are now briefly summarized in Figure 13:

- the three thematic dimensions as the structure around which the voice-marketing research field revolves in the three colored squares;
- the research streams displayed in the form of bars across the three dimensions, including the research-stream domains; and
- the research agendas based on the outlined research directions formulated as lists for each dimension below the bars.

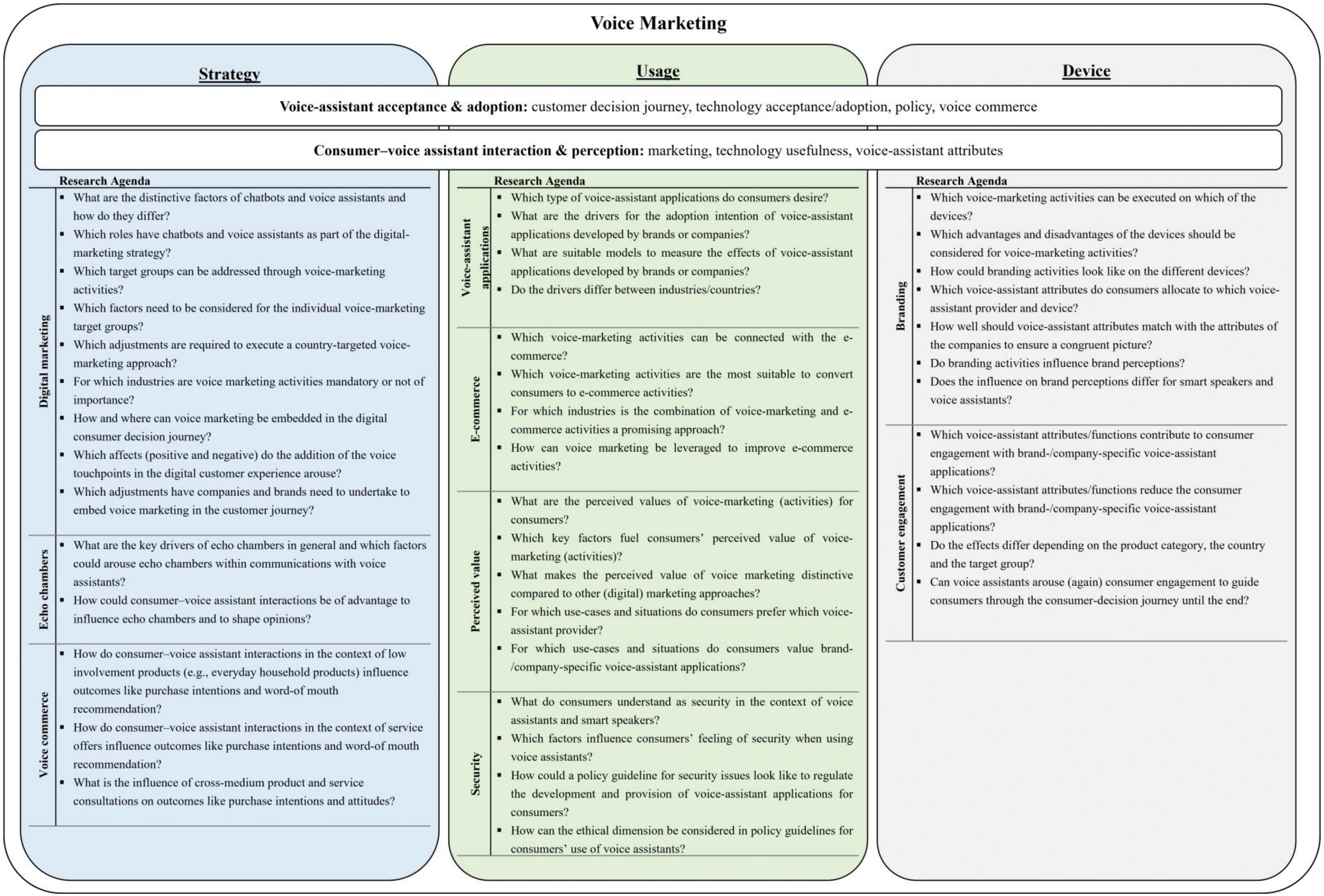


Figure 13. The thematic structure of the voice-marketing research field, research streams, and future research agendas

2.5 Discussion

With our study, we successfully answered the two research questions and therefore contributed to interdisciplinary research areas. Interdisciplinarity is evident in the results of our analysis, which reveal strategy, usage, and device as the three thematic dimensions of voice marketing. These dimensions signify that voice marketing encompasses aspects of management (strategy), consumer psychology (usage), and technology (device).

To answer the research questions, we structured the voice-marketing research field by executing a quantitative bibliometric analysis and expanded the findings through a qualitative semi-systematic literature review drawing on the TCCM framework. This hybrid review enabled a more comprehensive analysis, thereby enhancing the robustness of the research results. Consequently, our study provides valuable implications for academic researchers and marketing practitioners, which are presented below in Sections 2.5.1 and 2.5.2.

2.5.1 Theoretical contributions

With our study, we structured the research field of voice marketing into the three dimensions of strategy, usage, and device. This allowed us to differentiate existing findings about voice marketing and deduce connections between them. Moving forward, future studies can be assigned to the three dimensions of voice marketing, helping to investigate the research field in a more structured manner.

Additionally, the terms analyzed through the bibliometric analysis provide an orientation for voice marketing research in which purposeful authors' keywords can be selected for new studies. Therefore, we hope to establish keywords that are commonly used to investigate and tag voice-marketing studies more uniformly in the future. Doing so has the potential to improve future literature reviews because it would allow researchers to collect findings about a specific voice-marketing topic more easily and comprehensively.

We recommend that academic researchers studying the field of voice marketing and searching for literature include the core keywords (as presented in the center of Figure 7) in their keyword search strings. This recommendation stems from the fact that the research field is still evolving and there is a lack of common terminology for voice-marketing issues. Therefore, a broad keyword search string that encompasses possible synonyms and adjacent keywords is required. Future studies could address this issue by conducting literature reviews that focus on the definitions and terms of the voice-marketing research field. The results of such studies could offer recommendations for commonly used voice-marketing terms in the future. This approach could aid both academic researchers and marketing practitioners in finding relevant studies more easily and reduce the risk of researchers duplicating studies.

Furthermore, we identified several research gaps for each of the three voice-marketing dimensions that call for future research. By presenting them in the form of a clear overview (see Figure 13), we aim to encourage researchers to use this finding as a basis for determining subsequent voice-marketing studies. Through the development of research agendas for each dimension, we contribute to expanding the research field in a well-structured manner. Additionally, we hope that the research agendas inspire and motivate further interesting research studies in this increasingly important field of marketing.

As the analysis of the applied theories reveals, there is currently no established theory specifically designed to investigate voice-marketing issues. However, through the analysis conducted following the TCCM framework, we identified which variables (i.e., antecedents, outcomes, mediators, and moderators) have been investigated in relation to voice-marketing issues thus far. Therefore, we established a basis to develop a conceptual framework for investigations on voice-marketing issues, which could also serve as the foundation for creating a promising fundamental theory for the interdisciplinary voice-marketing research field. Our study results confirm several aspects of the initial voice-marketing framework presented by Zoghaib (2022; see Figure 2), for example, that the investigated outcomes in voice-marketing research comprise the foci “voice assistant” and “brand.” Our study revealed that these two foci can be extended to include “customer/user” (see Figure 12). Combining both frameworks can stimulate researchers to undertake exciting empirical studies, which may involve investigations of variables such as consumers’ perceptions of authenticity and social presence for different voice-marketing activities, including the variables’ influence on brands and voice assistants. Additionally, the frameworks provide initial ideas of possible control variables that should be considered (e.g., speech content, voice characteristics) when designing exploratory voice-marketing studies. Notably, the qualitative semi-systematic literature review in our study focused solely on the TCCM framework. However, employing additional analytical approaches, such as applying the antecedents, decisions, and outcomes framework developed by Paul and Benito (2018), could potentially enhance and expand upon our findings.

Finally, in the keyword COA, conducted as part of the quantitative bibliometric analysis, the keyword *echo chamber* was striking. This keyword represents the process of opinion-building through social media. Interestingly, *echo chamber* appears in our study in the context of voice marketing, which leads to the question of whether it could be an evolving facet of such marketing, a point that warrants further detailed discussion.

Having presented the study’s theoretical contributions, its implications for marketing practitioners are now presented in the following section.

2.5.2 Managerial implications

For marketing practitioners, this study highlights the growing importance of voice marketing and improves their knowledge about the topic. Additionally, this study encourages marketing practitioners to consider this emerging marketing form in strategic decisions for brands and companies. Both marketers and decision-makers stand to gain valuable insights from the findings, enhancing their understanding of voice marketing and its effective implementation, as summarized below.

The study results provide a relevant overview of existing dimensions of voice marketing and the findings within these areas. In particular, the findings from the quantitative bibliometric analysis draw attention to the facets of (a) strategy, (b) usage, and (c) device as the key dimensions of voice marketing:
(a) In the context of the strategy dimension, companies should be aware of voice marketing as a new marketing form. When companies implement voice marketing as part of their marketing strategy, they can benefit from anthropomorphistic communication through voice assistants and from an anthropomorphized perception of themselves and the brands or services they offer. Additionally, companies can execute advertising activities through voice assistants to enrich the customer journey or offer voice commerce to consumers. However, detailed implications about company-specific advertisements and suitable models to measure advertising successes are lacking. Nonetheless, once future studies address these gaps, crucial findings will be delivered and offer valuable insights to companies for their marketing strategies.
(b) The usage dimension of voice marketing emphasizes that, as a prerequisite for voice marketing, consumers must use voice assistants or smart speakers. In this context, companies should prioritize issues such as privacy and trust, as they play crucial roles in ensuring that consumers feel comfortable during usage. These factors can depend on the selected voice-assistant provider, such as Amazon Alexa or Google Assistant, which is why the specific terms and conditions for usage should be kept in mind. Moreover, it is recommended that companies ensure that consumers experience added value when they use voice assistants and, therefore, are recipients of voice marketing. As voice marketing occurs through human–computer interactions, perceived value becomes a central element for consumers choosing to adopt voice technology as the basis for voice marketing. Therefore, companies must ensure that the human–computer interactions between consumers and voice assistants or smart speakers work smoothly and that consumers perceive value when using them.
(c) The device dimension highlights the various options available for companies to execute voice marketing. Companies can use voice assistants, such as Amazon Alexa and Apple Siri, or smart speakers, such as Amazon Echo, for their voice-marketing activities. Accordingly, possible branding and co-branding opportunities differ. For example, companies can develop TPSs for Amazon Alexa and therefore benefit through advertising from Amazon Alexa that highlights the accessibility and functions of TPSs. Nevertheless, this study reveals that chatbots,

which also allow interactive human–computer communications with brands but are based on text, exist as comparable communication channels. Therefore, companies must consider different communication mediums and evaluate which best fit their communication mix.

Additionally, this study highlights research agendas for each voice-marketing dimension that, once researchers address them, will provide relevant insights into emerging trends. Especially in the marketing area, marketing practitioners must remain up to date with the latest market-research insights to incorporate them into their strategic decisions. Doing so also enables marketing practitioners to identify and respond to trends at an early stage. As presented in Figure 13, this study identified possible upcoming questions, such as whether voice marketing is equally relevant for all industries and target groups. Hence, this study clarifies where additional insights can be expected, facilitating more comprehensive knowledge about voice marketing. Nonetheless, companies should address and evaluate these potential future topics from a strategic perspective at an early stage, considering the managerial relevance of the topic to their context.

Furthermore, the qualitative semi-systematic literature review provides special insights concerning voice-marketing effects. On the one hand, the study findings show which marketing outcomes can be addressed through voice-marketing activities. On the other hand, it highlights which variables should be considered during the activities. For example, brand-related outcomes, such as purchase intentions, word-of-mouth intentions, and attitudes toward brands, can be leveraged. However, companies should also pay attention to moderators such as gender, privacy concerns, and expertise as well as mediators such as brand trust, credibility, and engagement. A comprehensive overview of variables that could be of interest to marketing practitioners is displayed in Figure 12.

Overall, this study makes theoretical contributions and provides several implications for marketing practitioners. However, it is not without limitations, which may inspire future research. Therefore, we provide further details in the following section.

2.5.3 Limitations and directions of future research

The approach employed in this study provides a comprehensive and systematic analysis of the current state of the field of voice marketing. Thus, it aims to lay the groundwork for the continued development of broader and deeper knowledge in this important and future-oriented sub-discipline of marketing. Nevertheless, some additional points should be mentioned because, despite the thorough approach taken, our study was not free of limitations.

First, this study benefited from a hybrid review by combining a quantitative bibliometric analysis and a qualitative semi-systematic literature review. However, the selected data sources for both analyses had a direct influence on the analysis results. The use of different data sources had the advantage that a more diverse literature base was used for the study, reducing the risk of obtaining repetitive results. Furthermore, the results of the analyses complement each other. We justified how and why we chose Scopus as a data source and compared the analysis results with VOSviewer figures based on literature from the Web of Science. Nevertheless, an in-depth analysis was conducted only for the literature derived from Scopus. Furthermore, other data sources, such as ScienceDirect or EBSCOhost, are not recommended as the basis for bibliometric analyses, so we did not consider them. Consequently, our study results should be validated through an analytical approach that is comparable to the bibliometric-analysis approach based on the other data sources.

Furthermore, our qualitative semi-systematic literature review was based on the data derived from EBSCOhost as the most relevant data source for business economics, according to DBIS. However, in-depth analyses and comparisons with literature from other data sources were not executed. Additionally, to allow detailed analyses of the existing literature, we excluded papers that were ahead of print or that only provided the abstract. Therefore, extending the selection to include such papers could be of interest to gain further significant information.

Second, it is possible that the chosen analytical techniques influenced the study results. Among the different analysis techniques that exist for conducting bibliometric analyses, we selected the term and keyword COA as proven techniques to structure a research field and derive associated research gaps. Nevertheless, to further validate the study results, it may be beneficial to apply additional bibliometric-analysis techniques, such as co-authorship or co-citation analysis. Additionally, conducting the literature review and determining the developed categories involved a subjective perspective. Merging and verifying the study results with the findings of further structured literature-review approaches, such as an integrative review as introduced by Snyder (2019), may help reduce this subjectivity.

Third, the way we processed the analyses should be considered. At the time of the study, a wide range of synonyms for voice assistants were used in the literature. Hence, it is possible that the breadth and depth of the studied topics were not fully captured and displayed in this study. We attempted to address this issue by considering promising keyword combinations that represent voice-marketing issues. However, a comprehensive keyword search string could not be ensured. Therefore, future studies should strive to adopt consistent definitions and terminology. Additionally, it is recommended that a conceptual delimitation of voice marketing and related marketing fields be developed.

Furthermore, issues that have not been investigated in the literature thus far do not appear as keywords in the visualization of the bibliometric analysis, although they may represent existing research gaps. Thus, the results of the quantitative bibliometric analysis will not have uncovered all existing research gaps. This limitation has been counterbalanced by combining the analysis results with the findings from the qualitative semi-systematic literature review. However, this review did not include literature derived from a backward paper search and was confined to publications in English; these limitations suggest options for further research.

Fourth, there exists the possibility that the study results are biased due to the countries in which voice-marketing studies are predominantly published. We found that research is mainly published in the United States of America, the United Kingdom, India, China, and Germany, which can all be classified as well-developed countries. This presents several questions: How does the voice-marketing research field appear in less developed countries? Does voice marketing even play a role in those countries? Our study results provide a basis to validate and expand the structure of the voice-marketing research field through further investigations across countries.

Finally, we recommend repeating this study on a regular basis because of the increasing number of published papers in this research field. Therefore, new knowledge is shared occasionally, which highlights the need to remain up-to-date about existing research gaps and identify new topics that are emerging with relevance to the research field. Additionally, the recent launch of generative AI has the power to reshape the field of marketing (Chui et al. 2023). Thus, further developments in voice marketing driven by generative AI should be observed.

2.6 Conclusion

Voice technologies, mainly in the form of voice assistants, accompany consumers in their daily lives. These evolving voice-based human–computer interactions offer companies and brands a new marketing form: voice marketing. Since voice marketing is still in its early stages, the research field and existing findings are scattered. However, marketing practitioners need valid and reliable implications to understand voice marketing and how to implement it successfully. Furthermore, existing studies, research findings, and applied theories for human–computer interaction must be re-confirmed for the voice-marketing context.

This highlights the need to investigate voice marketing as a research field, structure the field, and identify existing research gaps. Accordingly, this chapter addressed two research questions: First, which dimensions does the research field of voice marketing encompass? Second, which research gaps currently exist in the published voice-marketing literature? To answer these questions, a hybrid review was conducted, which included a quantitative bibliometric analysis and a qualitative semi-systematic literature review. The quantitative bibliometric analysis revealed that voice marketing revolves around the three thematic dimensions of strategy, usage, and device. Subordinate thematic issues as well as under-researched issues (i.e., research gaps) were identified. The research gaps were complemented by conducting a qualitative semi-systematic literature review.

Consequently, the study results present several existing research gaps for all three dimensions of strategy, usage, and device that should be addressed in the future. Regarding the strategy dimension, it is necessary to conduct research, for example, on digital marketing, echo chambers, and voice commerce. We recommend using the strategy dimension to address research questions about, for example, the distinctive factors of chatbots and voice assistants, including significant differences between the two forms. The usage dimension requires investigations concerning the issues of voice-assistant applications developed by brands or companies, e-commerce, perceived value, and security. Therefore, this dimension shows research gaps, for example, on drivers for the adoption intention of voice-assistant applications developed by brands or companies or on suitable models to measure possible effects of the applications. The device dimension demands research about branding and customer-engagement issues. Unanswered research questions include, for example, how branding activities could appear on different devices or how branding activities influence brand perceptions.

The study results presented in this chapter provide an overarching picture of the voice-marketing research field and contribute to the existing literature by providing a structural foundation. Furthermore, the findings highlight some central issues that are crucial to understanding voice marketing from a meta perspective. One of these central issues is to understand the distinctiveness of the interactive voice medium, which has gained growing importance compared to text, which is the most familiar medium for human–computer interactions thus far. We explore this issue in the following chapter based on the following reasoning: The strategy dimension, which contains issues regarding voice-marketing strategies, is still in its infancy. Therefore, further research is in demand to generate knowledge that guides the development of suitable voice-marketing strategies distinguished from, but still embedded in, overall marketing strategies. As a foundation, understanding how text-based human–computer interactions compare to voice-based ones is crucial. Because this issue is identified in this study as a highly relevant research gap (see Figure 13), this gap must be closed. Consequently, the study presented in Chapter 3 addresses this need.

3. Capturing the distinctiveness of voice-marketing communication[4]

Ashfaq, Jiang, and Yu (2021) and Ramadan (2021) state that existing literature about voice assistants lacks in-depth research on topics with specific relevance to the field of marketing. This assertion is confirmed by the study findings presented in Chapter 2. Thus, in our study presented here in Chapter 3, we address one specific research gap identified for the strategy voice-marketing dimension. By doing so, we aim to increase the understanding of text compared to voice-based human–computer interactions as the foundation for voice marketing. This consideration contributes to research on voice assistants as interactive marketing-communication channels and the differentiation of the voice-marketing communication medium.

Since marketing communication has changed over time (Kotler et al. 2020), brands can now communicate with consumers in a more interactive way: through conversational agents as communication channels (Diederich et al. 2022; Smith 2020; Tsai, Liu, and Chuan 2021). Conversational agents can be differentiated into text-based, such as chatbots, and voice-based, such as Google Assistant (Diederich et al. 2022). These communication channels evoke interactions and, along with them, enable engaging communication between consumers and brands (e.g., Smith 2020; Tsai, Liu, and Chuan 2021).

Conversational agents, listed as one of the 10 breakthrough technologies in 2016 (MIT Technology Review 2016), have already been identified as a new disruptive technology that will change the way people interact with websites and applications (Dale 2016). This assumption was also highlighted in 2016 by Chief Executive Officer Satya Nadella of Microsoft (Business Insider 2016). The relevance of conversational agents is just as important today as it was in 2016, as reports, for example, in the Harvard Business Review (Kannan and Bernoff 2019) and Forbes (Sudhakar 2021) illustrate. That conversational agents will continue to be of great importance in the future is demonstrated by the Gartner Hype Cycle (Kraus 2022, p. 4), which states that mass consumption of the agents will be reached within the next two years. Additionally, the development of generative AI suggests a strong future for the advancement and improvement of conversational agents. Furthermore, every communication medium not only transmits messages but also has the power to change human society (McLuhan 1964). This power implies an even greater relevance of conversational agents for academic researchers and marketing practitioners moving forward.
However, existing research investigates conversational agents without considering the brands or companies that use them as marketing-communication channels (Diederich et al. 2022). Hence, there is a need to improve knowledge about the effects that the agents arouse and how

[4] Parts of this chapter are taken from Kraemer, Hillebrandt, and Ivens (2023a).

the agents can be used in a way that is beneficial to both human society and businesses. Therefore, we investigate these issues in our study presented here in Chapter 3.

This chapter is structured as follows. In Section 3.1, the research objective is outlined, followed by reviewing the literature as the theoretical background in Section 3.2. Section 3.3 presents the derived conceptual model and formulated hypotheses based on the reviewed literature. To test the hypotheses, an empirical study in the form of an experiment with a 1 x 1 between-subject design is executed in Section 3.4. The discussion of the research results and the presentation of the limitations with future research opportunities then occurs in Section 3.5. This chapter finishes by presenting a conclusion in Section 3.6.

3.1 Research objective

Because of the relevance of conversational agents, as indicated in the introduction of this chapter, they have attracted the interest of marketing practitioners and academic researchers alike. Moreover, there is a need to increase knowledge about them. Multiple studies have expanded findings about the effects of interacting with chatbots and voice assistants on outcome dimensions such as consumer trust (Saffarizadeh, Boodraj, and Alashoor 2017), consumer experience (Lee and Choi 2017), and consumer satisfaction (Lee and Choi 2017; Otoo and Salam 2018). However, despite the increasing number of published studies concerning conversational agents (Mariani, Hashemi, and Wirtz 2023), some knowledge gaps remain open. An example is the comprehensive findings about the implementation of conversational agents as marketing-communication channels (Diederich et al. 2022).

The reviews conducted by Diederich et al. (2022) and Schwede et al. (2022) stress the lack of research on text- and speech-based conversational agents in direct comparison. Drawing on the elements of the expressive-perceptual dimensions,[5] speech is considered the most important element because of its naturalness. As such, speech-based communications require a lower level of cognitive effort compared to text-based communications. (Kock 2004) Additionally, McLean and Osei-Frimpong (2019) state that social presence and social attractions, which means that consumers think, for example, that Amazon Alexa could be their friend (Lee et al. 2006; McLean and Osei-Frimpong 2019), represent unique social advantages of speech-based communications through voice assistants. Thereby, they define social presence in the form of a newly developed scale, which includes items such as “When I interact with the voice assistant it feels like someone is present in the room” or “My interactions with the voice assistant are similar to those with a human” (McLean and Osei-Frimpong 2019, p. 32). Taken together this highlights the distinctiveness of speech-based communications and therefore the importance of

[5] The expressive-perceptual dimensions include the elements that make communications appear natural, such as language and facial expressions (Kock 2004).

research on conversational agents being distinguished into text-based chatbots and speech-based voice assistants.

Despite initial research directly comparing chatbots and voice assistants (e.g., Flavián, Akdim, and Casaló 2022; Rzepka, Berger, and Hess 2022), existing research is insufficient in two aspects. First, existing studies have investigated the influences on and effects of conversational agents but not with regard to the brands or companies that implement them as communication channels (Diederich et al. 2022). Second, previous studies have shown that marketing-communication channels shape brand positioning and influence how consumers perceive brands (e.g., Chan, Chen, and Tse 2018; Liu et al. 2019). However, it remains unclear to what extent chatbots and voice assistants, as evolving marketing-communication channels, can be leveraged in this regard and whether their effects differ due to their distinctiveness.

Overall, research that considers the brand perspective and the distinctiveness of text-based chatbots and speech-based voice assistants must be expanded. The study presented in this chapter addresses these gaps and directly compares consumers' communications with chatbots and voice assistants and the effects on the brands that use them as marketing-communication channels. To do so, we formulate the following research questions (RQ):

RQ 1. Which effects does marketing communication through conversational agents have on the brands that use them for marketing communications?

RQ 2. Does the distinctiveness of chatbots and voice assistants lead to different effects on the brands?

To address the two research questions, we follow the structure presented in this chapter. Consequently, we describe the theoretical background in Section 3.2 below.

3.2 Literature review

Vlasic and Kesic's (2007) study suggests that consumers prefer interactive marketing communications over the traditional communication approach of one-way interactions. The main reason for this preference is that interactive marketing communication can overcome time–space restrictions (Hoey 1998). Moreover, Vlasic and Kesic (2007) present different definitions and conclude that interactive marketing communications offer benefits such as convenience and intellectual challenges while allowing for control of the communication. They define interactive marketing communication as a dialogue between at least two parties with personalized communication that is adaptable to the individual participants in the conversation.

According to this definition, chatbots and voice assistants as AI-based communication channels enable interactive marketing communication.

The social response theory can be described as a theoretical framework that helps to explain the social reactions of users when they interact with media technologies (Nass et al. 1993). Therefore, before exploring the details of AI-based interactive marketing communications through chatbots and voice assistants, we outline the social response theory in Section 3.2.1 to clarify the theoretical foundation.

3.2.1 Social response theory

Since the 1990, the computers are social actors (CASA) paradigm has served as a foundation to investigate the social interactions of users with computers (Nass, Moon, and Green 1997), television (Nass and Moon 2000), and even websites (Liew and Tan 2018). Based on this paradigm, Nass and Moon (2000) analyzed several experimental studies and derived the social response theory. This theory suggests that humans transfer their expectations and rules from their social environment toward technologies like computers.

The social response theory has been applied since the 2000s to investigate, for example, online stores (Ruijuan, Yixiao, and Dongjin 2022), Facebook fan pages (Perez-Vega et al. 2018), and Twitter as a social actor (Li and Li 2014). Wang and Fodness's (2010) study furthered the discussion by studying avatars on retail websites. Research based on the social response theory has shifted over the several years toward investigations of more human-like study subjects. Hence, researchers draw on this theory to study human-like conversational agents (e.g., Kronemann, Kizgin, and Rana 2022). For example, studies have not only investigated design principles for text-based chatbots (e.g., Gnewuch et al. 2022; Gnewuch, Morana, and Mädche 2017) but also the adoption process of speech-based smart speakers (Hsieh and Lee 2021) and factors that influence that adoption process (Lee et al. 2021).

Xu, Chen, and Huang (2022) reinvestigated the social response theory to strengthen its explanatory power. To do so, they conducted a study with 834 participants to analyze whether mindfulness or mindlessness has a higher power to arouse social reactions toward technologies. Mindlessness is the automatic application of social rules (i.e., the cognitive process begins automatically), while mindfulness represents active cognitive processing to apply them (Langer 1992, 2000). Their study revealed the key finding that mindlessness is more powerful. In other words, social responses to AI-based technologies, such as conversational agents, occur primarily because humans automatically apply social rules and expectations to them.

Considering the social response theory, Section 3.2.2 focuses on communications through AI-based technologies like chatbots and voice assistants. Therefore, the section presents how communication through AI-based technologies works and which factors are relevant to ensuring the best possible conditions for successful interactions with consumers.

3.2.2 Introduction to AI-based communication

Communications operate under the fundamental belief that humans inherently engage in the act of conveying messages (Guzman and Lewis 2020). However, today, it is also possible to convey messages through technologies (Guzman and Lewis 2020). Nevertheless, humans still prefer human–human communications to human–computer communications (Araujo 2018). One reason for this is that in human–computer communications, responses often do not meet consumers' expectations (e.g., Ashktorab et al. 2019; Luger and Sellen 2016), and consumers are concerned about their data and privacy (Genpact 2017). These reasons could be decisive in determining why human–human versus human–computer communications arouse different effects. For instance, Mou and Xu (2017) found that humans show different personality traits when they interact with humans as opposed to AI-based technologies. Consequently, humans show greater openness, agreeableness, extroversion, conscientiousness, and willingness to disclose personal information when interacting with other humans (Mou and Xu 2017).

However, in the beginning of conversational-agent development, Massaro et al. (1999) claimed that human–human communications can be improved when they are mediated through conversational agents. Initial research suggests that a higher level of human-likeness in conversational agents leads to a greater acceptance of the communication medium not only for speech-based interaction (Schreibelmayr and Mara 2022) but also for text-based interaction (Adam, Wessel, and Benlian 2021). Furthermore, human-designed conversational agents decrease privacy concerns (Ischen et al. 2020).
Since AI-driven communication now has the potential to mimic human-like characteristics to a significant degree (Mariooryad and Busso 2012), the opportunity exists to realize the full potential and advantages of human–computer communications. Therefore, AI has the power to erase the frontiers between humans and machines (Weil 2017). Moreover, humans already value human–computer communications, appreciating that they can evoke feelings of social presence (Chattaraman et al. 2019), that they satisfy the need for (quasi-)human interaction (Sheehan, Jin, and Gottlieb 2020), and that they are entertaining (Brandtzaeg and Følstad 2017). Therefore, research on human–computer communication must determine how to further improve its value.

To contribute to this need, we rely on the findings of Guzman and Lewis (2020), who present two key facets of AI-based communication that guide our study: 1) the relational components representing people's associations with AI technologies and 2) the functional components that clarify the relevance and usefulness of these technologies (Guzman and Lewis 2020). We illuminate both facets in the following two sections.

3.2.3 Relational components of AI-based communication

We refer to the social response theory (Nass and Moon 2000, for details see Section 3.2.1) to outline the relational components of AI-based communication. In summary, this theory states that humans perform social responses when they interact with technologies that show human-like attributes, such as anthropomorphism or social cues (Mariani, Hashemi, and Wirtz 2023). Speaking, the modality of voice assistants, feels more natural and intuitive to humans than text-based communications (Kock 2004). That speech-based communications thus lead to the perception of anthropomorphism or that they arouse social responses is shown, for example, in the study of Schreibelmayr and Mara (2022). Furthermore, text-based chatbots can be anthropomorphized or receive social cues, for instance, through their communication style as well as content, appearance, or response time (Feine et al. 2019, p. 43).
However, the extent to which AI-based conversational agents are humanized is relevant to avoiding the uncanny-valley effect (Mori 1970). This effect is as relevant today as it was when it was first observed, for example, in the context of encounters where humans avoided robots that were too human-like (Strait et al. 2015).

Anthropomorphism and social cues even surpass humanizing communications or objects because they have the power to shape people's associations about the sender of the communication (Wan, Chen, and Jin 2017). Since consumers associate anthropomorphism with warmth and competence in a positive way (El Hedhli et al. 2023), research about AI-based marketing communications can rely on the popular stereotype content model developed by Fiske et al. (2002). The stereotype content model presents the two dimensions of warmth (e.g., friendliness) and competence (e.g., capability) as the key attributes of how humans are perceived. AI-based technologies can adapt human sensations (Liu and Sundar 2018). Therefore, text-based chatbots and speech-based voice assistants can express and convey warmth and competence, which is highlighted, for example, by the study of Li, Song, and Zhou (2022). The authors encouraged brands to integrate digital technologies into their brand communications because they influence a brand's market performance positively. Moreover, they emphasize considering brands' competence and warmth in the integration. Furthermore, warmth and competence are relevant attributes to determine the quality of consumer–brand interactions (Lou, Kang, and Tse 2022) as well as consumers' brand emotions and attitudes (Ivens et al. 2015).

Ultimately, we can suggest the purposeful use of chatbots or voice assistants as marketing-communication channels to create engaging brand communications that shape brand attitudes and improve brands' market performance (e.g., market share). To accomplish the theoretical background for this study, the following section explores functional components as the second key facet of AI-based communication (Guzman and Lewis 2020).

3.2.4 Functional components of AI-based communication

Chatbots and voice assistants differ significantly in one technical aspect: means of communication. When interacting with these technologies, communicating via chatbots is performed by the common and familiar means of writing, while communication with voice assistants is achieved through speech. Therefore, the two modalities allow, but also enable, different functions.

As companies have limited financial and human resources, the question of where to invest is always pressing. Therefore, they need reliable information to make the decision about which communication channels they will leverage. To support marketing practitioners in this regard, the fundamental importance of the task-technology fit for specified tasks, proven by Goodhue and Thompson (1995), can help. Therefore, companies are advised to first evaluate which tasks they plan to transfer to chatbots or voice assistants. This process is considered purposeful, as Rzepka, Berger, and Hess (2022) found that, depending on the task, either the modality of text- or speech-based communications may be more suitable. Their findings show, for example, that consumers perceive more fun and higher satisfaction when they execute an information-searching task through voice assistants (Rzepka, Berger, and Hess 2022). Furthermore, the study of Flavián, Akdim, and Casaló (2022) compared text- and speech-based product recommendations and revealed that the modality "voice" provides higher efficiency in this regard. Additionally, they discovered that efficiency is mediated by consumers' perceptions of the recommendations' usefulness and credibility. Moreover, Rzepka, Berger, and Hess (2022) found that processing the task of an information search by means of voice assistants causes, compared to text-based communications, different levels of perceived efficiency, cognitive effort, enjoyment, and service satisfaction.

The presented studies highlight that consumers' modality preferences depend on the type of task (e.g., Rzepka, Berger, and Hess 2022), which therefore should be controlled when researching conversational-agent issues. Furthermore, it becomes clear that, in addition to modality, another distinctiveness of conversational agents lies in their usage context. In other words, the type of task and the goals of consumers, for which they perceive conversational agents as being beneficial, differ and depend on the context (Rzepka, Berger, and Hess 2022). In sum, the task-technology fit is crucial to determining whether brands could benefit from using chatbots or voice assistants for marketing communications.

We conclude this section by highlighting two key takeaways as the theoretical foundation for our study. First, we ground our study on the key facets of AI-based communication according to Guzman and Lewis (2020), namely relational and functional components. Second, while social presence represents the core relational component in this research, we use task-technology fit on behalf of the functional components (Guzman and Lewis 2020). Both traits serve as initial variables to develop the conceptual model and derive hypotheses in the following section.

3.3 Conceptual-model development

Marketers recognized that brand communications can positively influence brand outcomes, such as customer loyalty (Ball, Coelho, and Machás 2004; Merisavo 2006) or brand image (Bruhn, Schoenmueller, and Schäfer 2012). These communications can contribute to building (long-term) relations with customers (Ball, Coelho, and Machás 2004; Kusa, Zauskova, and Cabyova 2020).

Van Pinxteren, Pluymaekers, and Lemmink (2020) conducted a literature review on human-like communications through conversational agents. In their work, they present a theoretical framework that describes possible determinants to improve the quality of relationships between consumers and conversational agents (see Figure 14).

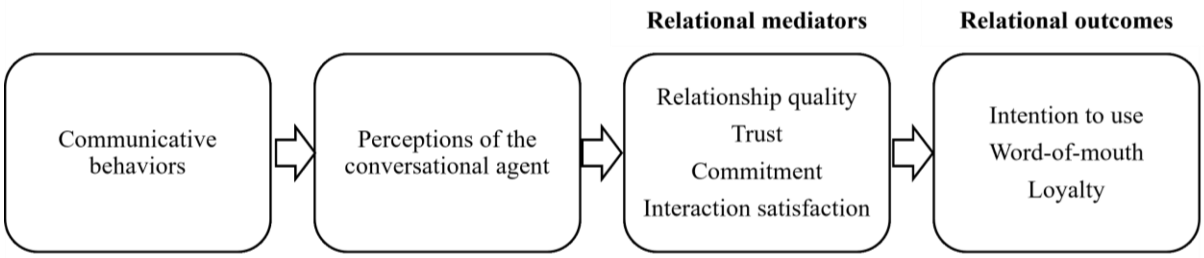


Figure 14. Theoretical framework of consumers–conversational agent relationships (own illustration based on van Pinxteren, Pluymaekers, and Lemmink 2020, p. 205)

The development of the conceptual model for our study, outlined in the following sections, is based on the theoretical model displayed in Figure 14 and adapted to the context of our study. To structure the development of the conceptual model, the following sections follow the four steps of the framework.

3.3.1 Communicative behaviors

According to van Pinxteren, Pluymaekers, and Lemmink (2020), the factor "communicative behaviors" comprises verbal and nonverbal communications with customers. In our study, we apply the key facets of AI-based communication as communicative behaviors, according to Guzman and Lewis (2020). In other words, in our study, the constructs of social presence and task-technology fit mirror communicative behaviors.

Social presence was originally described as the prominence of participants and their interpersonal connection in a mediated dialogue (Short, Williams, and Christie 1976). Since early research investigated social presence in the context of human–human communications, a shift toward "[q]uasi-social relationships with new forms of artificially intelligent beings […]" can be observed (Biocca and Harms 2002, p. 10). Thus, social presence can be understood as designing AI technologies to evoke the feelings of social beings (van Doorn et al. 2017). As explained in Section 3.2, social presence is an important characteristic for successful interactive AI-based marketing communications. Studies that have examined communications through chatbots show that companies benefit from higher social presence when their chatbots' identities are undisclosed (Cicco, Da Costa e Silva, and Palumbo 2020) and when chatbots communicate in an informal style (Liebrecht, Sander, and van Hooijdonk 2020). In both cases, the increased social presence leads to a positive influence on attitudes toward the brand or the company. This effect was also confirmed by Pitardi and Marriott's (2021) study, which demonstrates that existing social presence has a positive influence on attitudes. Furthermore, social presence in communications through voice assistants increases word-of-mouth recommendations (Mishra, Shukla, and Sharma 2022).

As "communicative behaviors" influence "perceptions of the conversational agent" (see Figure 14), we now illuminate which factors have intercorrelations with social presence and task-technology fit in Section 3.3.2.

3.3.2 Perceptions of conversational agents

Although research findings have confirmed the positive influence of communicative behaviors on attitudes (e.g., Pitardi and Marriott 2021), existing studies suggest that the influences are mediated. The basis for this suggestion is the study of Flavián, Akdim, and Casaló (2022), who found that the mediating effect of consumers' perceptions of conversational agents is significant. They emphasize that this effect is particularly relevant for investigations of behavioral intentions, such as word-of-mouth intention in the context of text- and speech-based communications. Thus, Flavián, Akdim, and Casaló's findings support the theoretical framework of van Pinxteren, Pluymaekers, and Lemmink (2020). Therefore, we present now study findings about possible mediating effects that are important for our study.

The study of Li, Song, and Zhou (2022) reveals that perceived brand warmth and competence have mediating effects in the context of digital brand communications. Both brand-perception constructs can have a positive effect on attitudes toward a brand (Roy and Naidoo 2021). Furthermore, Mishra, Shukla, and Sharma (2022) found that social presence shapes utilitarian attitudes, while Bedué's (2020) study revealed the influence of social presence on not only utilitarian attitudes but also hedonic attitudes. Therefore, we consider utilitarian and hedonic attitudes, as well as perceived brand warmth and competence, as mediators in our study and formulate the following hypotheses:

H1. The stimuli's communicative behaviors (i.e., social presence + task-technology fit) positively influence consumers' perceptions of a brand (i.e., perceived brand warmth + competence).

H2. The stimuli's communicative behaviors (i.e., social presence + task-technology fit) positively influence consumers' perceptions of the communication (i.e., hedonic + utilitarian attitudes).

As the theoretical framework shows (see Figure 14), the "perception mediators" influence the "relational mediators," which are derived below in Section 3.3.3.

3.3.3 Relational mediators

Van Pinxteren, Pluymaekers, and Lemmink (2020) listed concrete relational mediators, such as relationship quality, trust, and rapport, in a framework developed from their literature review (see Figure 14). To derive the relational mediators for our study, we refer especially to the studies of Rzepka, Berger, and Hess (2022) and Pitardi and Marriott (2021). Rzepka, Berger, and Hess (2022) revealed that speech- and text-based communications arouse different levels of satisfaction and cognitive decision effort. Furthermore, Pitardi and Marriott (2021) highlighted the correlation between social presence and consumer trust. The Edelman[6] Trust Institute (2023, p. 21) also stated in the Edelman Trust Barometer report that trust is an important factor to fuel consumer relationships. This effect has been confirmed by several studies (e.g., Chen et al. 2022; Foehr and Germelmann 2020). Therefore, we conclude that the factors of cognitive decision effort, trust, and satisfaction are relevant relational mediators to

[6] Edelman Holdings, Inc. is a global company that is specialized on communication strategies. It cooperates with different firms and organizations to develop implications how to promote and develop brands. (Edelman Holdings, Inc. n.d.)

investigate in our study. We complement these relational mediators with the construct brand attitude because of the correlations between perception mediators and brand attitudes (e.g., Pitardi and Marriott 2021), which were described above. Consequently, we formulate the following hypotheses for our study:

H3. Consumers' perceptions of a brand positively influence relational mediators (i.e., attitude toward the brand + trust + cognitive decision effort + customer satisfaction).

H4. Consumers' perceptions of communication positively influence relational mediators (i.e., attitude toward the brand + trust + cognitive decision effort + customer satisfaction).

Last, according to the framework of van Pinxteren, Pluymaekers, and Lemmink (2020), "relational mediators" influence "relational outcomes." Consequently, we determine these outcomes for our study in the following section.

3.3.4 Relational outcomes

In our study, we investigate possible effects on word-of-mouth as a relational outcome. The reason for this selection is twofold. First, word-of-mouth is a key consequence of customer satisfaction (Lang and Hyde 2016), which is one of the defined relational mediators in our study and considered a highly important marketing-performance indicator (Buttle 1998). Furthermore, word-of-mouth can be deemed a construct that is the preliminary stage of usage loyalty (Ladhari 2007). Therefore, it is logical to investigate possible effects on word-of-mouth before empirically testing deeper links, such as loyalty. Hence, by investigating this construct, we ensure the managerial relevance of this study.

Second, possible correlations are observed between word-of-mouth as a relational outcome and the relational mediators in our study, which are satisfaction (Anderson 1998; de Matos and Rossi 2008; Ngoma and Ntale 2019), trust (Ngoma and Ntale 2019; Ranaweera and Prabhu 2003), and brand attitude (Chu and Chen 2019; Foroudi, Palazzo, and Sultana 2021). Proof of a possible correlation between word-of-mouth and cognitive decision effort in the literature is, to the best of our knowledge, lacking. However, cognitive decision effort is an important aspect in the context of conversational-agent research because, according to Rzepka, Berger, and Hess (2022), speech-based interactions require less cognitive decision effort than interactions through text-based chatbots. Therefore, we address this research gap with our study to enrich theoretical contributions.

Furthermore, Mishra, Shukla, and Sharma's (2022) study provides initial indications for correlations between social presence and word-of-mouth. Therefore, we aim to test the possible direct effects of the stimuli's communicative behaviors (i.e., social presence and task-technology fit) on the relational outcome. We formulate the hypotheses accordingly:

H5. The relational mediators positively influence the relational outcome (i.e., word-of-mouth).

H6. The stimuli's communicative behaviors positively influence the relational outcome (i.e., word-of-mouth).

Beyond deriving the hypotheses from the theoretical framework displayed in Figure 14 and study findings from the literature, we illuminate additional variables that are of interest for our study. In Chapter 2, we presented characteristics that have been investigated in the context of conversational agents thus far (for details see Section 2.3.3). The analysis revealed several possible influencing factors. Therefore, we review the study findings in detail to select the influencing factors that will be included in this study as control variables. This process is described in the section below.

3.3.5 Control variables

Popular scientific models help to investigate technology acceptance. One of the most popular models is the UTAUT2 (unified theory of acceptance and use of technology), created by Venkatesh, Thong, and Xu (2012). UTAUT2 is a development of the previous UTAUT, which was based on the TAM (technology acceptance model). The UTAUT2 considers that individual differences, such age, gender, and user experience, can influence the usage intentions of technologies. Their reliable test of two quantitative studies confirmed that individual factors impact behavioral intentions. Therefore, we consider these factors for our study and further examine existing study findings in the context of conversational agents.

Studies about embodied conversational agents in different contexts, such as the e-health sector (ter Stal et al. 2020) or management conversations (Derrick and Ligon 2014), show that the gender of users influences the perception of conversational agents. Furthermore, the studies of Belda-Medina and Calvo-Ferrer (2022) and Terblanche and Kidd (2022) confirm this moderating effect in the context of disembodied text-based chatbots. The possible effect of gender on communications through speech-based conversational agents was investigated in detail by Liu and Yao (2023). They executed a 2 x 3 online experiment and compared different pairs of users' genders (male versus female) and Amazon Alexa's genders (male versus female versus neutral). Their study comprised a representative sample of 250 participants. Analysis results revealed differences for the user–Amazon Alexa gender pairs, for example, in terms of engagement and attraction. This finding highlights the relevance of controlling gender in investigations about conversational agents. Therefore, we included gender as a control variable in our study.

Not only gender but also age play a key role in the current digital era. Study results confirm that the elderly are less likely to adopt, for example, the Internet (Niehaves and Plattfaut 2014), mHealth (i.e., the usage of smartphones for healthcare; Cajita et al. 2017), and mobile-shopping applications (Natarajan, Balasubramanian, and Kasilingam 2018). Considering sociocultural factors, younger generations tend to be early adopters of technology due to their exposure to it from an early age, while older individuals may resist or be slower to adopt these innovations (Wang, Myers, and Sundaram 2013). Therefore, we added age as a control variable in our study.

Wang, Yuan, and Li's (2020) study investigated smart speakers and analyzed the influence of users' previous experience with the speakers and lifestyles. They found that previous experience has effects on the preferred communication style and efficiency. Furthermore, Gnewuch et al. (2022) highlight the influence of previous experiences with text-based chatbots on users' interactions with them. The authors conducted a laboratory experiment with 202 participants and revealed that previous experience is a key moderator when investigating the social responses of users to text-based conversational agents. Since our study is focused on investigating whether the social cues of conversational agents arouse different consumer perceptions, we determined that including previous user experiences as a control variable in our study was relevant.

The studies described above verified the main influences of each of the individual variables. Although initial studies that consider all three variables can be found (e.g., Kasilingam 2020; Palau-Saumell et al. 2019), they present partly contrary results about existing effects. While the effects of gender, age, and user experience are confirmed for the adoption of mobile-banking applications (Owusu Kwateng, Osei Atiemo, and Appiah 2019) and for the usage of chatbots on smartphones for shopping activities (Kasilingam 2020), in the study context of mobile applications for restaurants, only user experience played a significant role (Palau-Saumell et al. 2019). Therefore, it is necessary to re-evaluate existing findings in our study context.

Overall, gender, age, and previous user experience with conversational agents are emphasized in several studies as relevant influencing factors, partly with inconsistent study results. Thus, we controlled the effects and effect strengths of text- and speech-based interactions with conversational agents by including the control variables of gender, age, and previous usage experience in our study, leading to the following hypothesis:

H7. Usage experience, age, and gender influence the variables of conversational-agent communication.

3.3.6 Proof of concept

Although the relationships between the constructs are primarily grounded on the theoretical model of van Pinxteren, Pluymaekers, and Lemmink (2020), possible relations are also supported by study findings in the literature. We found additional support for the suggested relationships by drawing on the popular social cognitive theory (Bandura 1986), which argues that human motivation and human action can be explained from a social-cognitive perspective. The theory focuses on mutual causation through the interplay of cognitive, behavioral, and environmental factors. In this study, the communication channels of chatbots and voice assistants form the environmental factors, consumers' perceptions of the interactions ("perception mediators") represent the cognitive factors, and behavioral factors are captured by measuring "relational mediators" and "relational outcomes." Taken together, the solid derivation and comprehensibility of the assumed relationships in our study is underscored. The process of assessing the constructs is described in Section 3.3.7.

3.3.7 Measurements and scales

We used scientifically developed scales to assess the relationships. We measured the traits of voice assistants and chatbots as marketing-communication channels in our study through the two constructs of "social presence" with five items (Gefen and Straub 2004) and "task-technology fit" with three items (Zhou, Yang, and Hui 2010). Both constructs used 7-point Likert scales.

The mediating constructs "perceived brand warmth" and "perceived brand competence" were each measured with three items according to the stereotype content model (Fiske et al. 2002) on 7-point Likert scales (Aaker, Vohs, and Mogilner 2010). The mediators "hedonic attitudes" and "utilitarian attitudes" were both measured with five items on a 7-point semantic differential (Voss, Spangenberg, and Grohmann 2003).

We assessed the relational mediator consumers' "attitude toward the brand" through five items on a 7-point semantic differential scale (Spears and Singh 2004). Furthermore, we used 7-point Likert scales to assess the constructs "trust" using the 4-item scale of Chaudhuri and Holbrook (2001) and "cognitive decision effort" with the six items of Hong, Thong, and Tam (2004), who adapted the items of Pereira (2000). We measured the 3-item "customer satisfaction" construct of Fornell (1992) using 10-point Likert scales.

We captured the relational outcome of the marketing communications by measuring possible influences on "word-of-mouth" intention on one validated item on a 7-point Likert scale (Chitturi, Raghunathan, and Mahajan 2008). Furthermore, we controlled the influencing factors using the 3-item construct "usage experience" from Moriuchi (2021), who adopted the scale of Shen et al. (2011). Additionally, we asked for the demographics (gender, family status, and employment situation) through single-choice options and for the age through an open text field. An overview of the conceptual model's constructs and their items is displayed in Appendix 2.

Since we executed the study in Germany, we translated all constructs to German using the TRAPD method (Behr, Braun, and Dorer 2015, pp. 7–8). TRAPD is an abbreviation for translation, review, adjudication, pretest, and documentation. This method requires translations of two independent persons that are reviewed, discussed, and adjusted, if needed.

Overall, the conceptual model for our study was developed by drawing on social cognitive theory and correlations according to the theoretical framework presented by van Pinxteren, Pluymaekers, and Lemmink (2020). The final conceptual model for our study is presented in Figure 15. We tested the conceptual model in our empirical study, which is described in Section 3.4 below.

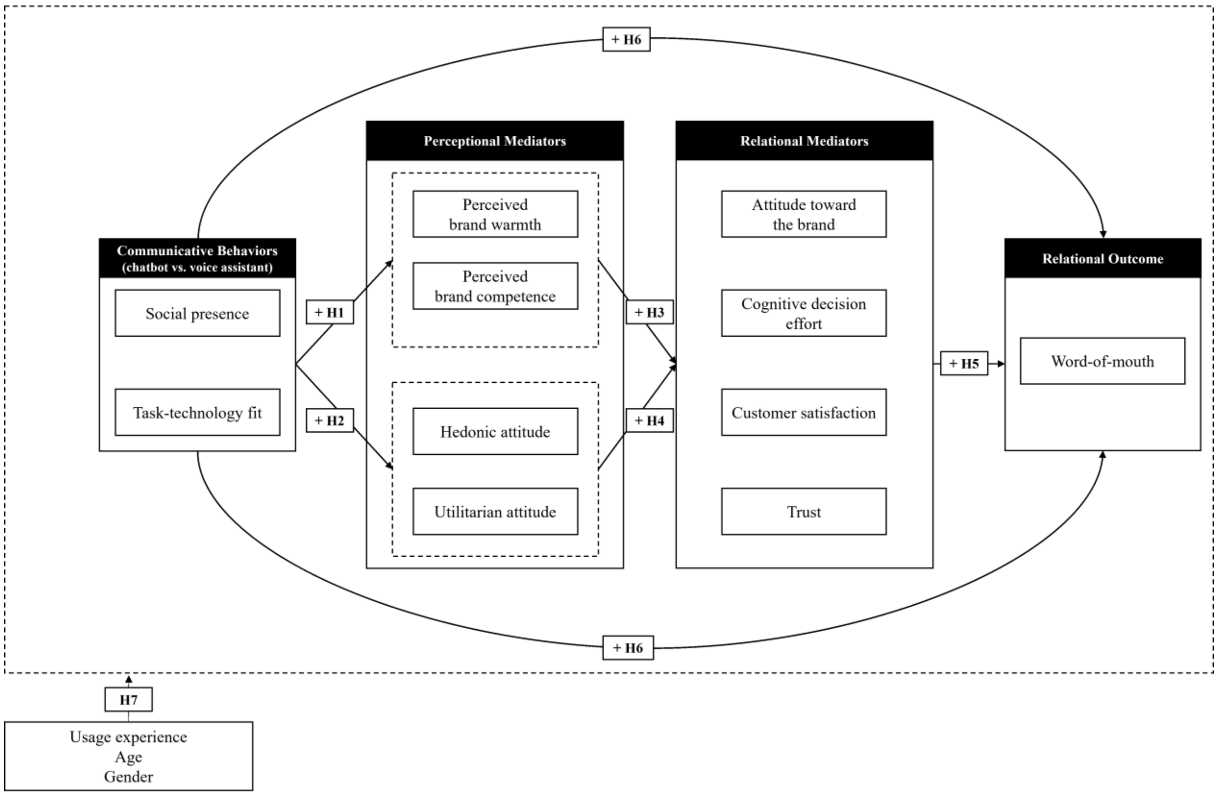


Figure 15. Conceptual model to investigate text- versus speech-based marketing communications

3.4 Empirical study

The hypotheses were tested using data collected through two quantitative online surveys using the survey tool UNIPARK. The reason for selecting quantitative surveys as the method for our study was that they are the most suitable for verifying hypotheses (Martin and Bridgmon 2012). Details about the development and structure of the questionnaire for the survey are described in the Section 3.4.1.

3.4.1 Research design

The research objective for our study was to assess and directly compare consumers' perceptions of marketing communications with a brand through a speech-based voice assistant and a text-based chatbot. To generate perceptions as realistically as possible, we included a real interaction between the participants and the conversational agents in the online questionnaire. Therefore, we conducted an experiment with a 1 x 1 between-subject design. We programmed the online questionnaire in such a way that participants were allocated randomly to the voice assistant or chatbot group. To avoid biases in the responses due to previous experiences with a certain brand, we decided to use a fictional brand in the questionnaire. Details are described hereinafter.

3.4.1.1 Developing the fictional-brand stimulus

We developed several fictional brands by combining two methods: first, using sound symbolism, and second, replacing the last syllable with semantics (Klink 2000, 2001). This resulted in 16 fictional brands, displayed in Table 6. We also added a brief description of the brand.

Table 6. The fictional brands developed for the study

Fictional brand	Description
BeeSoft	Lip balm made from honey for gentle care and a shimmering glow for exceptionally soft lips.
Brotogo	The tasty and healthy breadsticks for on-the-go are your bro-companion for those small cravings in between.
Butterine	Look forward to an unparalleled combination of rich buttery taste and the delicate spreadability of margarine, which can easily be spread on bread and toast even at fridge temperature–for a silky-smooth indulgence.
Delohause	Your event venue, perfect for events with a feel-good factor. For birthdays, weddings, anniversaries, or team events, everyone feels welcome here–just like at home.
EdisonEcar	The next-generation electric car automatically charges its battery from solar panels on the car roof while driving–for long-lasting driving pleasure.
Frizzi	Sparkling, refreshing carbonated water from mineral-rich springs, especially invigorating on hot summer days.
Italiasta	Authentic Italian pasta in various delicious shapes brings the Italian vacation experience to your home.
Kogewelt	The bank of the global future that makes cash withdrawals–no matter where or in which currency–available worldwide for free.
Oschoko	Full-bodied chocolate tablet made from a blend of milk and dark chocolate, guaranteeing a particularly chocolaty delight with round chocolate chunks.
Schokolinis	Small milk chocolate lentils coated with a crunchy glaze–perfect for a little on-the-go treat.
Senjoysoft	The lightweight sunscreen ensures soft skin and worry-free enjoyment of sunny hours.
Veycrunch	Crispy fresh chips with paprika flavor–baked in the oven for a particularly light taste.
Vollnussbar	The nut bar with whole nuts provides enjoyment and energy for the entire day.
Yufunkt	Functional sportswear with individual size variations that perfectly adapt to you and your unique body.
Zikividuell	Your provider for personalized insurance policies tailored perfectly to your needs, with quick advice for secure protection in case of damage.
Ziming	The ultimate laptop for all gamers, guaranteeing fast response times, high-resolution graphics, and unique sound quality.

To ensure the brands' fictiveness, we tested brand recognition of the fictional brands. To do so, we executed a pre-test (n = 28) with a total of 25 brands, of which 9 were real brands and 16 were the developed fictional brands. We added the 9 real brands—Apple, Buitoni, Bresso, Choceur, Hej Riegel, ING, Nivea SUN, Selters, and Smart—to ensure that participants did not detect the goal of the survey at first glance. We took care to include a selection of brands that we assumed to have high (e.g., Apple), medium (e.g., Selters), or low popularity (e.g., Choceur). We showed the participants of the pre-test all 25 brands with a short brand description in a randomized manner and asked them if they knew the brands. The pre-test showed that eight out of the 16 fictional brands were unknown and therefore suitable for our study (see Table 7). Out of the eight suitable brands, we chose one fictional brand that represents an industry and product that everybody, independent of age and gender, can relate to. This resulted in the selection of the fictional sunscreen brand “Senjoysoft” for our study.

Table 7. Results of the pre-test to test the fictiveness of the developed brands

Fictional brand	“Yes, I know the brand”	“No, I do not know the brand”
Apple	28	0
BeeSoft	9	19
Bresso	22	6
Brotogo	0	28
Buitoni	6	22
Butterine	0	28
Choceur	18	10
Delohause	0	28
EdisonEcar	2	26
Frizzi	3	25
Hej Riegel	9	19
ING	22	6
Italiasta	1	27
Kogewelt	1	27
Nivea SUN	27	1
Oschoko	1	27
Schokolinis	2	26
Selters	23	5
Senjoysoft	0	28
Smart	26	2
Veycrunch	0	28
Vollnussbar	2	26
Yufunkt	0	28
Zikividuell	0	28
Ziming	0	28

3.4.1.2 Structure of the questionnaire

After developing the fictional brand for our study, the questionnaire for the online survey was constructed as follows. The first questions of the questionnaire considered a short description of voice assistants or chatbots in general. As such, we ensured a common understanding among the participants about the subject. Furthermore, we asked for the participants' demographics at the beginning of the questionnaire for a specific reason. Since the survey contained a real interaction with a chatbot or voice assistant, we wanted to assess whether possible higher drop-out rates could be justified by demographics such as gender or age. The participants then explored a real interaction with the developed fictional brand "Senjoysoft" through a voice assistant or a chatbot, which is described more in detail below. The questionnaire continued with questions to assess the constructs and finished with the option to provide feedback on the survey.

As mentioned, during the online survey, the participants explored a real interaction with a brand through either a chatbot or a voice assistant. To avoid biases in the responses due to previous experiences with a specific chatbot or voice assistant, we programmed a neutral voice assistant and a neutral chatbot, both called "Sascha," a gender-neutral name. Since consumers use conversational agents mainly to execute individual tasks, such as information-search tasks (Diederich et al. 2022), the goal of the interaction was to receive information about a brand and its products. To ensure comparability, the answers of the chatbot and the voice assistant for consumer–brand interactions were designed similarly in terms of what the voice assistant said and what the chatbot wrote. The conversations began with an introduction of the voice assistant or chatbot, followed by a user's command. The chatbot and voice assistant recognized the spoken and written words of the user and reacted with pre-programmed answers. The users were allowed to interact with the chatbot and voice assistant for as long as they wanted. An overview of the dialogues of the interactions with the fictional brand through the voice assistant is presented in Figure 16 and with the chatbot in Figure 17.

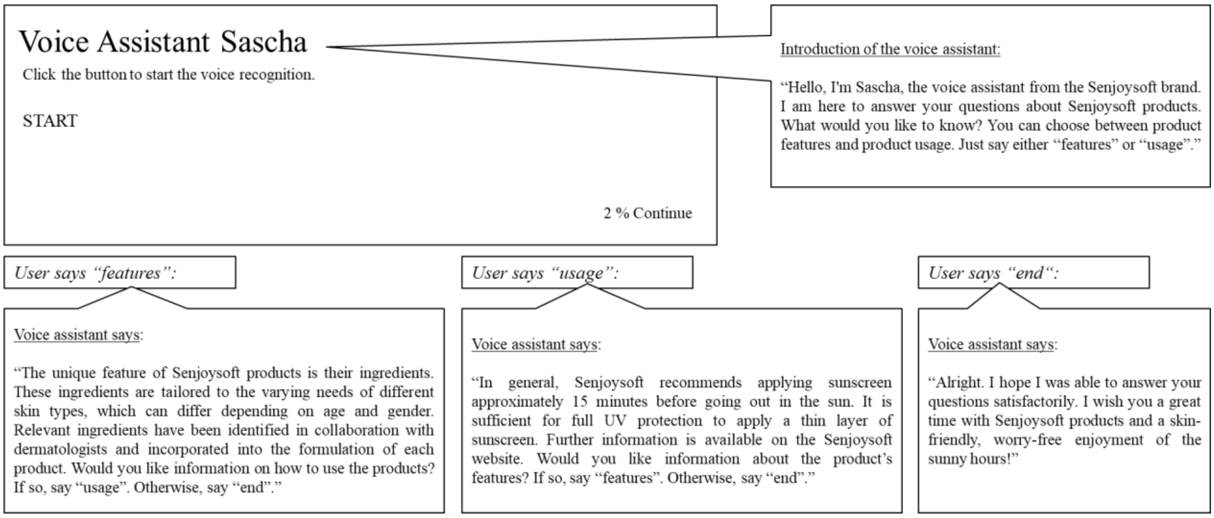


Figure 16. Flow of consumer–brand interaction through the voice assistant

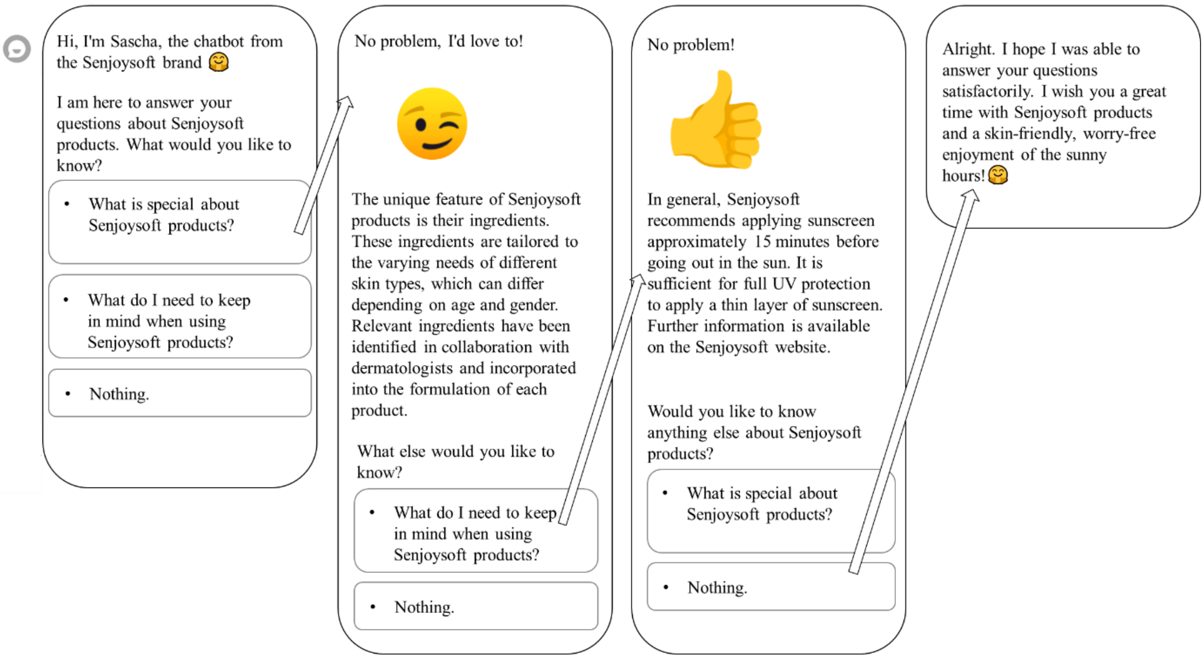


Figure 17. Flow of consumer–brand interaction through the chatbot

We included several control questions within the questionnaire to ensure the quality of the data. The first control question guaranteed that the fictional brand was unfamiliar to the participants, while the second control question asked for a specific detail that the chatbot wrote or the voice assistant said. This control question was included right after the interaction to ensure that the participants had interacted attentively with the chatbot or voice assistant respectively. Doing so was important because we conducted online surveys and, thus, did not observe the participants while they were answering the questions. Thus, we needed a validation check to confirm the participants really explored the interaction to receive representative answers regarding their perceptions of the interaction. A third control question was included toward the end of the questionnaire to ensure that the participants still read the questions carefully.

In the event that participants gave the wrong answer to the control question regarding the interaction or the attention check, the survey finished immediately. In addition to the control questions, we ensured the quality of the data by excluding questionnaires that were answered too quickly.

3.4.1.3 Sample

We conducted a pre-test with a convenience sample, and a comprehensive study was also conducted with a larger sample recruited through a market-research institute. Participants in the pre-test were recruited by snowball sampling and received no incentives to participate, generating a sample of 108 participants. After cleaning the data, the basis for the data analysis consisted of 94 questionnaires, of which 35 were allocated to the voice-assistant group and 59 to the chatbot group.

Most of the participants reported being male (61%). Furthermore, most of the participants stated that their family status was single (89%), they were aged between 25 and 34 years (59%), and they were in an employment situation as a student (53%). An overview of the descriptive data is presented in Table 8.

Table 8. Descriptive data of the pre-test sample

Gender	**Absolute**	**Relative**
Male	37	39%
Female	57	61%
Diverse	0	0%
Total	94	100%
Age	**Absolute**	**Relative**
<18	1	1%
18–24	29	31%
25–34	55	59%
35–44	3	3%
45–54	0	0%
>54	6	6%
Total	94	100%
Family status	**Absolute**	**Relative**
Single	84	89%
Married	10	11%
Registered life partnership	0	0%
Divorced	0	0%
Widowed	0	0%
Total	94	100%
Employment situation	**Absolute**	**Relative**
Pupil	1	1%
Student	50	53%
Apprentice	1	1%
Employee	34	36%
Civil servant	3	3%
Self-employed person	1	1%
Retired	1	1%
Others	2	2%
Currently not employed	1	1%
Total	94	100%

The goal of the comprehensive study was to test the hypotheses using a larger database to increase the study's validity. The participants were acquired through a market-research institute and received incentives for participating in the survey. The control questions and stimuli that required real interactions led to a high drop-out rate. Nevertheless, the refined and final data consisted of a sufficient total sample size of 557, of which 268 participants interacted with the voice-assistant stimulus and 289 with the chatbot stimulus.

While the gender distribution was balanced, most of the participants reported their family status as single (51%) or married (38%). Most of the participants were either older than 54 years (35%) or between 25 and 34 years (24%). The employment situation indicated the most often was employed (48%). The full descriptive data is displayed in Table 9.

Table 9. Descriptive data of the comprehensive study sample

Gender	**Absolute**	**Relative**
Male	285	51%
Female	271	49%
Diverse	1	0%
Total	557	100%
Age	**Absolute**	**Relative**
<18	1	0%
18–24	67	12%
25–34	136	24%
35–44	89	16%
45–54	71	13%
>54	193	35%
Total	557	100%
Family status	**Absolute**	**Relative**
Single	283	51%
Married	210	38%
Registered life partnership	4	1%
Divorced	39	7%
Widowed	21	4%
Total	557	100%
Employment situation	**Absolute**	**Relative**
Pupil	8	1%
Student	80	14%
Apprentice	9	2%
Employee	265	48%
Civil servant	18	3%
Self-employed person	33	6%
Retired	102	18%
Others	5	1%
Currently not employed	37	17%
Total	557	100%

3.4.2 Data analysis

We used the pre-test to examine whether adjustments to the questionnaire were required. To ensure that analyses of the pre-test data for the two sample groups (i.e., voice-assistant versus chatbot stimuli) were possible, we first tested the comparability of the participant demographics. Using the chi-square test, we revealed through a p-value above the threshold of 0.05 that no significant differences existed between the two sample groups in terms of gender ($p = 0.225$). Additionally, we tested whether a normal distribution of our sample was given by applying the Shapiro–Wilk test as a prerequisite to executing the Levene's test. The Levene's test can provide insights about the comparability of the age of participants between two sample groups. The results of the Shapiro–Wilk test revealed that no normal distribution was given since the p-value was below 0.05 ($p < 0.001$). Therefore, we conducted the Mann–Whitney U test, which does not have normal distribution as a prerequisite, to examine the comparability of the two sample groups in terms of age. The Mann–Whitney U test showed a p-value of 0.236. Since the p-value was above the threshold of 0.05, this indicated that the two sample groups were comparable in terms of age. Therefore, further analyses were possible.

We tested the conceptual model's items and constructs to identify any necessary adjustments for the subsequent comprehensive study. All items and constructs showed reliable values for internal consistency and reliability indicated through the average variance extracted (AVE) above 0.5 (Bagozzi and Yi 1988), the composite reliability (CR) above 0.6 (Bagozzi and Yi 1988), and the Cronbach's alpha (α) above 0.7 (Streiner 2003). One exception was the AVE value of cognitive decision effort for the voice-assistant sample group. This value could have resulted from the estimates based on the small sample size. Since the construct's CR and Cronbach's α show good values, we refrain from adjusting the questionnaire for the comprehensive study. The values are presented in Table 10.

Table 10. Scales' reliability values of the pre-test

Construct	**AVE (chatbot / voice assistant)**	**CR (chatbot / voice assistant)**	**Cronbach's α (chatbot / voice assistant)**
Attitude toward the brand	0.790 / 0.716	0.95 / 0.93	0.950 / 0.933
Cognitive decision effort	0.523 / 0.342	0.87 / 0.74	0.855 / 0.768
Customer satisfaction	0.756 / 0.681	0.90 / 0.86	0.895 / 0.848
Hedonic attitude	0.725 / 0.816	0.93 / 0.96	0.929 / 0.955
Perceived brand competence	0.681 / 0.790	0.86 / 0.92	0.869 / 0.914
Perceived brand warmth	0.716 / 0.682	0.88 / 0.86	0.880 / 0.867
Social presence	0.745 / 0.659	0.94 / 0.91	0.936 / 0.909
Trust	0.620 / 0.543	0.88 / 0.80	0.861 / 0.827
Task-technology fit	0.698 / 0.910	0.87 / 0.97	0.888 / 0.964
Utilitarian attitude	0.666 / 0.644	0.90 / 0.91	0.904 / 0.899
Word-of-mouth	./. (one item)	./. (one item)	./. (one item)

Note: AVE = average variance extracted, CR = composite reliability, and α = alpha.

Here, we opt not to present detailed figures for the structural equation modeling of the pre-test sample because of the small sample size. Therefore, the calculated values do not reflect representativeness and robust figures. We will present detailed structural equation modeling figures later as part of the comprehensive study, which is based on a larger sample size.

Based on the successful pre-test, we continued with the comprehensive study. We collected data, as mentioned in Section 3.4.1.3, through a market-research institute. Once again, we ensured the methodological requirements for the comprehensive study through a randomized assignment of the sample groups to the voice-assistant and chatbot stimuli. Furthermore, we controlled possible demographic biases between the two sample groups of the comprehensive study by analyzing the comparability of both groups.

We aimed to assess the comparability of the participants' ages through the Levene's test. Therefore, we tested whether a normal distribution of both sample groups was given using the Shapiro–Wilk test as a prerequisite for the Levene's test. The Shapiro–Wilk test presented a significant p-value of < 0.001. This value indicated that our sample groups lacked a normal distribution. However, the Shapiro–Wilk test sometimes shows misleading results for larger sample sizes of hundreds of participants, which is our case with 557 participants. Nevertheless, we assumed, for safety reasons, a lack of normal distribution and therefore executed the Mann–Whitney U test to analyze the comparability of both sample groups.

The results of the Mann–Whitney U test showed that the two sample groups differed significantly in terms of age ($p = < 0.001$). Furthermore, the difference in the mean values of the age of both groups was striking ($M_{(chatbot)} = 53.73$; $M_{(voice\ assistant)} = 34.80$). Thus, we calculated the r value to assess the effect strengths. The results showed that a medium strength exists ($Z = -13{,}209$; $r = 0.15$). We considered this issue for the upcoming data analysis. Additionally, we tested the comparability of the two sample groups in terms of gender through a chi-square test. The results showed a p-value ($p = 0.338$) above the threshold of 0.05, which indicated that no significant difference exists.

After examining the comparability of the two sample groups, we tested our conceptual model by adopting structural equation modeling. The results are presented in the following two sections along with the two research questions of this study.

3.4.2.1 Data analysis to address research question 1

Through RQ 1, we aim to illuminate which effects marketing communications through conversational agents have on brands. To do so, we tested the derived hypotheses through structural equation modeling. The structural equation modeling was conducted using the software IBM SPSS AMOS. First, we tested scale reliabilities through the AVE (threshold > 0.5; Bagozzi and Yi 1988), the CR (threshold > 0.6; Bagozzi and Yi 1988), and Cronbach's α (threshold > 0.7; Streiner 2003). After excluding two items from the cognitive decision effort construct, all thresholds were met (see Table 11). Second, we tested the Fornell and Larcker (1981) criterion that requires inter-correlations scores lower than the AVE score. All constructs met this criterion. The figures are displayed in Table 12 for the chatbot sample group and in Table 13 for the voice-assistant sample group.

Table 11. Scales' reliability values of the comprehensive study

Construct	**AVE (chatbot / voice assistant)**	**CR (chatbot / voice assistant)**	**Cronbach's α (chatbot / voice assistant)**
Attitude toward the brand	0.848 / 0.743	0.97 / 0.94	0.967 / 0.939
Cognitive decision effort	0.701 / 0.620	0.90 / 0.87	0.895 / 0.861
Customer satisfaction	0.793 / 0.754	0.92 / 0.90	0.918 / 0.906
Hedonic attitude	0.808 / 0.793	0.95 / 0.95	0.952 / 0.949
Perceived brand competence	0.910 / 0.783	0.97 / 0.92	0.968 / 0.916
Perceived brand warmth	0.780 / 0.760	0.91 / 0.90	0.909 / 0.903
Social presence	0.875 / 0.829	0.97 / 0.96	0.972 / 0.961
Trust	0.779 / 0.675	0.93 / 0.89	0.934 / 0.892
Task-technology fit	0.836 / 0.821	0.94 / 0.93	0.940 / 0.929
Utilitarian attitude	0.726 / 0.712	0.92 / 0.92	0.928 / 0.924
Word-of-mouth	./. (one item)	./. (one item)	./. (one item)

Note: AVE = average variance extracted, CR = composite reliability, and α = alpha.

Table 12. Inter-item correlation matrix for the data from the chatbot sample group

	1.	**2.**	**3.**	**4.**	**5.**	**6.**	**7.**	**8.**	**9.**	**10.**	**11.**
1. Attitude toward the brand	**0.848**										
2. Cognitive decision effort	0.127	**0.561**									
3. Customer satisfaction	0.496	0.141	**0.793**								
4. Hedonic attitude	0.555	0.047	0.578	**0.808**							
5. Perceived brand competence	0.587	0.069	0.361	0.377	**0.910**						
6. Perceived brand warmth	0.530	0.038	0.425	0.475	0.539	**0.780**					
7. Social presence	0.404	0.028	0.494	0.623	0.293	0.476	**0.875**				
8. Trust	0.384	0.056	0.537	0.472	0.342	0.407	0.483	**0.779**			
9. Task-technology fit	0.479	0.140	0.618	0.429	0.408	0.403	0.379	0.533	**0.836**		
10. Utilitarian attitude	0.612	0.171	0.707	0.608	0.461	0.407	0.448	0.454	0.604	**0.726**	
11. Word-of-mouth	0.551	0.021	0.341	0.537	0.484	0.480	0.424	0.353	0.348	0.430	./.

Note: The bolded elements are the AVEs.

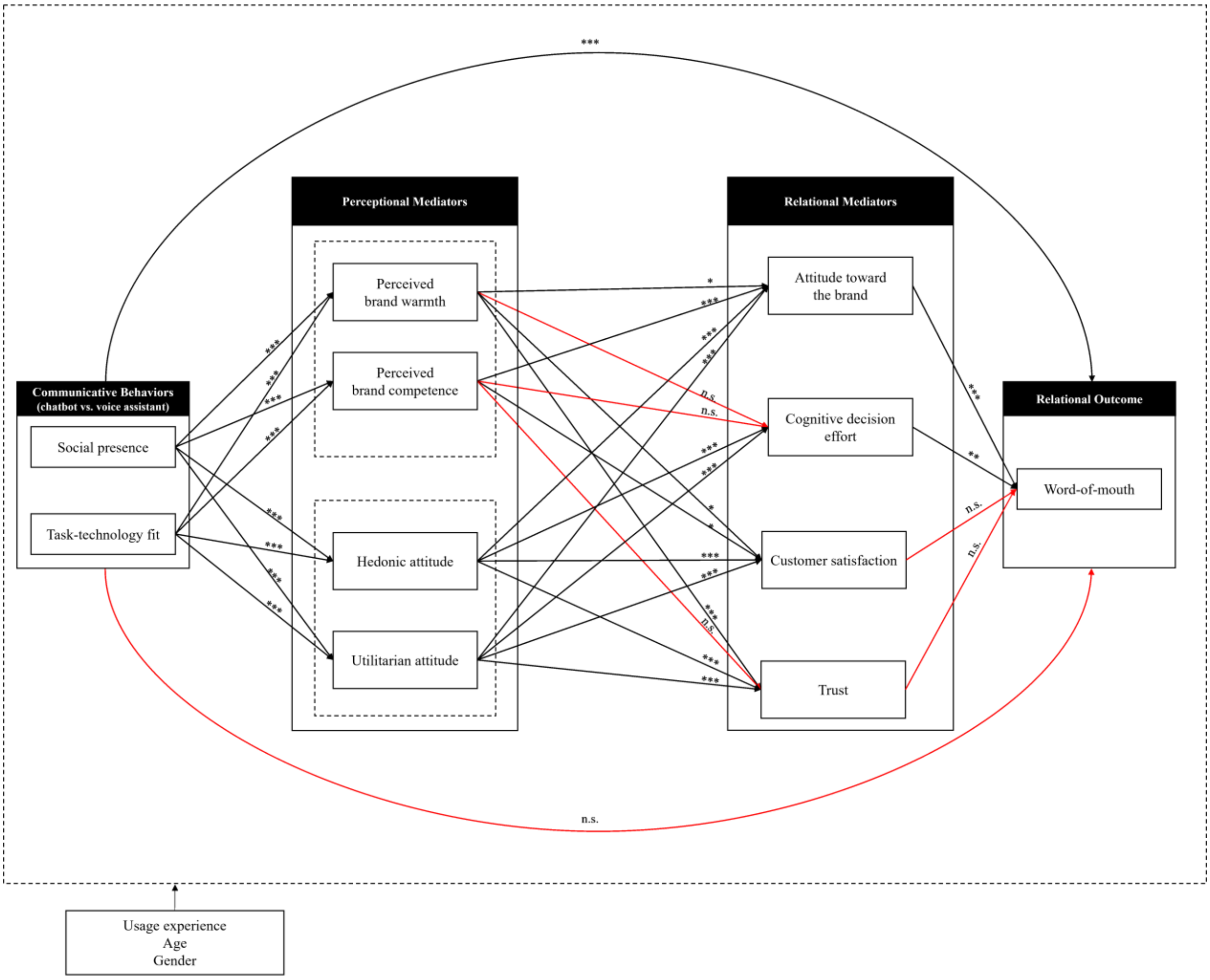
Table 13. Inter-item correlation matrix for the data from the voice assistant sample group

	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.
1. Attitude toward the brand	**0.743**										
2. Cognitive decision effort	0.123	**0.620**									
3. Customer satisfaction	0.529	0.323	**0.754**								
4. Hedonic attitude	0.706	0.173	0.714	**0.793**							
5. Perceived brand competence	0.558	0.071	0.329	0.429	**0.783**						
6. Perceived brand warmth	0.398	0.015	0.213	0.371	0.640	**0.760**					
7. Social presence	0.449	0.077	0.454	0.549	0.398	0.376	**0.829**				
8. Trust	0.377	0.157	0.572	0.588	0.249	0.229	0.469	**0.675**			
9. Task-technology fit	0.271	0.084	0.496	0.465	0.127	0.128	0.346	0.529	**0.821**		
10. Utilitarian attitude	0.610	0.237	0.686	0.741	0.355	0.262	0.402	0.490	0.377	**0.712**	
11. Word-of-mouth	0.561	0.127	0.361	0.536	0.587	0.436	0.540	0.457	0.185	0.526	**./.**

Note: The bolded elements are the AVEs.

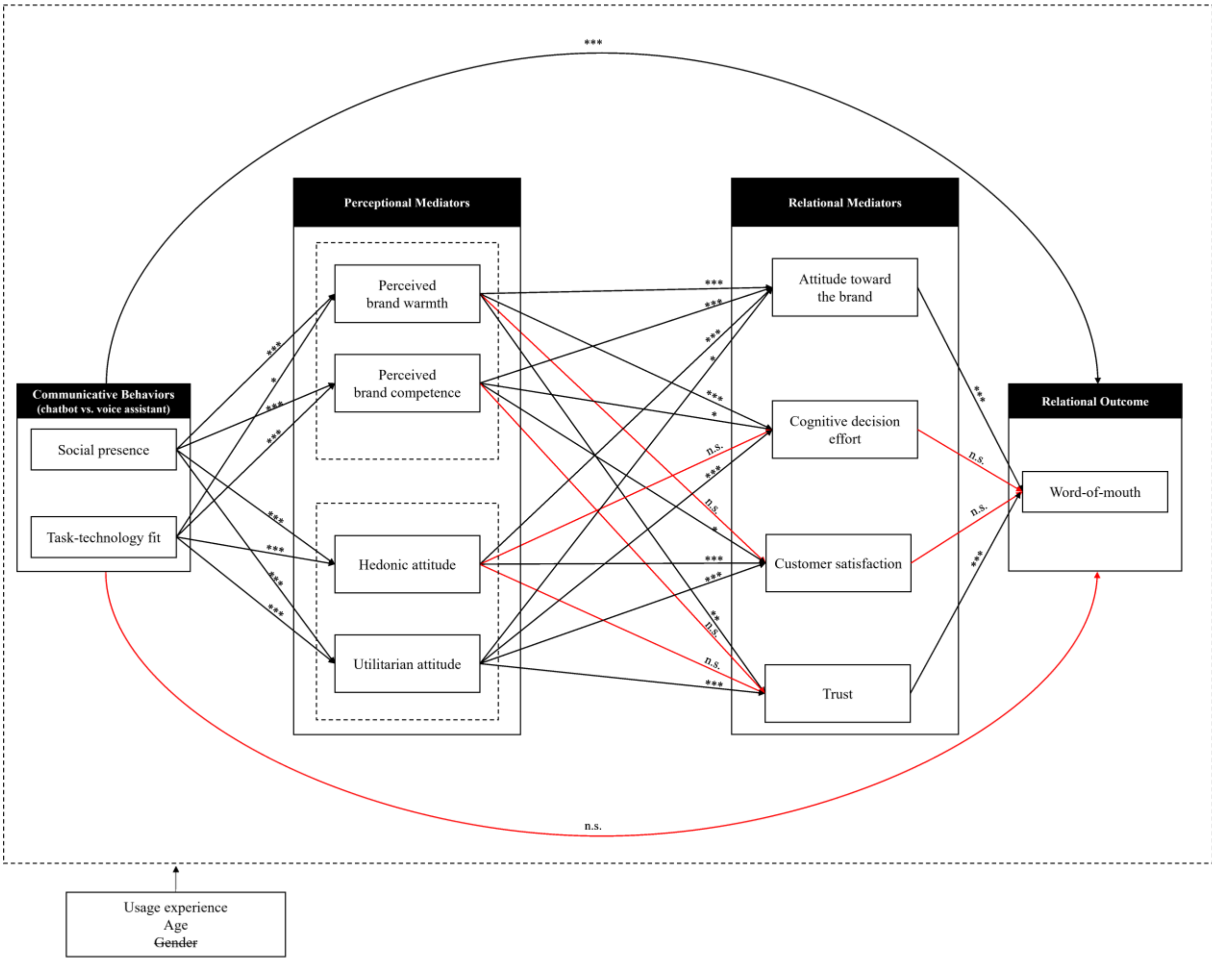
Third, after confirming that all scales show valid and reliable values, the models for both sample groups were tested regarding their model-fit indices. To demonstrate a good model fit, a root-mean-square error of approximation (RMSEA) of <0.08 (Browne and Cudeck 1992) and a Tucker–Lewis index (TLI) of >0.90 (Bentler and Bonett 1980) are recommended.
The analysis of the chatbot sample group showed a good model fit since all the model-fit indices met the thresholds ($\chi 2$ = 1,724.658, df = 749, p-value = 0.000, χ^2/df = 2.303, TLI = 0.929, RMSEA = 0.067). The model-fit indices of the voice assistant sample group also confirmed a good model fit ($\chi 2$ = 1,601.554, df = 749, p-value = 0.000, χ^2/df = 2.138, TLI = 0.916, RMSEA = 0.065).
We tested the robustness of the models by calculating the correlations between the perception mediators. Therefore, we considered possible influences of variables that we did not control in our study, referring to perception theories (e.g., schema theory). The robustness test confirmed good model-fit indices and revealed existing significant correlations between all perception mediators. An exception is the correlation between the mediators perceived brand warmth and utilitarian attitude in the chatbot sample group which is not significant (p = 0.402).

Based on the good model-fit indices, the structural equational modeling results can be reviewed. The results for RQ 1 for the chatbot sample group are displayed in Figure 18 and for the voice assistant sample group in Figure 19. For readability, the effect sizes are excluded from the figures and listed in Table 14 instead.



*Note: * = p < 0.05, ** = p < 0.01, *** p < 0.001, and n.s. = not significant (highlighted in red).*

Figure 18. Results for the conceptual model of the chatbot sample group



*Note: * = p < 0.05, ** = p < 0.01, *** p < 0.001, and n.s. = not significant (highlighted in red).*

Figure 19. Results for the conceptual model of the voice-assistant sample group

Table 14. Effect strengths and significance levels of the conceptual models

Relation		Chatbot effect strength (p-value)		Voice-assistant effect strength (p-value)	
Social presence	→ Perceived brand warmth	0.494	(<0.001)	0.589	(<0.001)
	→ Perceived brand competence	0.212	(<0.001)	0.429	(<0.001)
	→ Hedonic attitudes	0.629	(<0.001)	0.645	(<0.001)
	→ Utilitarian attitude	0.262	(<0.001)	0.382	(<0.001)
Task-technology fit	→ Perceived brand warmth	0.372	(<0.001)	0.154	(0.006)
	→ Perceived brand competence	0.557	(<0.001)	0.327	(<0.001)
	→ Hedonic attitudes	0.306	(<0.001)	0.310	(<0.001)
	→ Utilitarian attitude	0.700	(<0.001)	0.551	(<0.001)
Perceived brand warmth	→ Attitude toward the brand	0.144	(0.003)	0.193	(<0.001)
	→ Cognitive decision effort	0.091	(n.s.)	0.271	(<0.001)
	→ Customer satisfaction	0.131	(0.004)	0.016	(n.s.)
	→ Trust	0.234	(<0.001)	0.217	(0.001)
Perceived brand competence	→ Attitude toward the brand	0.346	(<0.001)	0.335	(<0.001)
	→ Cognitive decision effort	0.020	(n.s.)	-0.177	(0.01)
	→ Customer satisfaction	-0.111	(0.005)	0.097	(0.015)
	→ Trust	0.028	(n.s.)	0.035	(n.s.)
Hedonic attitude	→ Attitude toward the brand	0.211	(<0.001)	0.389	(<0.001)
	→ Cognitive decision effort	0.304	(<0.001)	-0.020	(n.s.)
	→ Customer satisfaction	0.220	(<0.001)	0.409	(<0.001)
	→ Trust	0.283	(<0.001)	0.015	(n.s.)
Utilitarian attitude	→ Attitude toward the brand	0.327	(<0.001)	0.132	(0.012)
	→ Cognitive decision effort	-0.728	(<0.001)	-0.633	(<0.001)
	→ Customer satisfaction	0.734	(<0.001)	0.555	(<0.001)
	→ Trust	0.353	(<0.001)	0.478	(<0.001)
Attitude toward the brand	→ Word-of-mouth	0.570	(<0.001)	0.480	(<0.001)
Cognitive decision effort	→ Word-of-mouth	0.131	(0.001)	-0.012	(n.s.)
Customer satisfaction	→ Word-of-mouth	-0.112	(n.s.)	0.053	(n.s.)
Trust	→ Word-of-mouth	0.066	(n.s.)	0.192	(<0.001)
Social presence	→ Word-of-mouth	0.267	(<0.001)	0.231	(<0.001)
Task-technology fit	→ Word-of-mouth	0.109	(n.s.)	-0.048	(n.s.)

Note: n.s. = not significant.

We examined the hypotheses (see Figure 15) by reviewing the structural equation modeling results. Thus, we further examined the relations in both models with their significance levels and effect strengths, which are discussed below.

H1 predicted that the stimuli's communicative behaviors of social presence and task-technology fit positively influence perceptions of the brand (i.e., perceived brand warmth and competence). This hypothesis can be accepted for marketing communications via chatbots and voice assistants.

H2 anticipated that the stimuli's communicative behaviors of social presence and task-technology fit positively influence perceptions of the communication (i.e., hedonic and utilitarian attitudes). This hypothesis can also be accepted for both marketing-communication channels (i.e., voice assistants and chatbots).

H3 stated that consumers' perceptions of a brand (i.e., perceived brand warmth and competence) positively influence the four relational mediators: attitude toward the brand, cognitive decision effort, customer satisfaction, and trust. This hypothesis can be partly accepted. For both marketing-communication channels, consumers' perceptions of the brand have a significant positive influence on their attitude toward the brand.
Significant effects on the cognitive decision effort exist only for marketing communication through voice assistants and not through chatbots. However, when communicating through voice assistants, the effect of perceived brand warmth on cognitive decision effort is positive, while the effect of perceived brand competence on cognitive decision effort is negative.
For marketing communications through chatbots, both brand perception constructs have a significant influence on customer satisfaction. However, while the effect of perceived brand warmth on customer satisfaction is positive, the influence of perceived brand competence on customer satisfaction is negative, which contradicts our assumptions. For voice-assistant marketing communications, only perceived brand competence (but not perceived brand warmth) has a positive influence on customer satisfaction.
Furthermore, a positive influence of perceived brand warmth on trust is observable, which is not the case for perceived brand competence. These effects are equal for both chatbot and voice-assistant marketing communications.

H4 expected positive influences of consumers' perceptions of marketing communication on relational mediators. This hypothesis can be fully accepted for the hedonic attitudes of marketing communications through the chatbot but only partly accepted for the voice assistant. The hedonic attitudes of voice-assistant marketing communications show significant positive effects on attitude toward the brand and customer satisfaction but not on cognitive decision effort or trust.
Furthermore, the influences of the utilitarian attitudes of chatbot and voice-assistant marketing communications on the relational mediators are all significant and positive, except for the effects on cognitive decision effort which are negative. However, it should be noted that, because of the reversed items, high values for cognitive decision effort mean that the interaction

is frustrating and complex. Therefore, the negative influences of utilitarian attitudes on this construct can be interpreted as positive because they lower the cognitive decision effort.

H5 presumed positive influences of relational mediators on relational outcome (i.e., word-of-mouth). This hypothesis can be partly accepted. Only attitude toward the brand and cognitive decision effort have positive influences on word-of-mouth for marketing communications through chatbots. However, the influences of customer satisfaction and trust on word-of-mouth are not significant. In the context of voice-assistant marketing communications, attitude toward the brand and trust positively influence word-of-mouth, while cognitive decision effort and customer satisfaction show no significant effects.

H6 anticipated a direct positive effect of social presence and task-technology fit on word-of-mouth. This hypothesis can partly be accepted because social presence has a direct positive effect but not task-technology fit. This is the case for both chatbot and voice-assistant marketing communications.

In conclusion, it can be inferred that marketing communications using chatbots and voice assistants have a predominantly positive impact on the marketing constructs of attitude toward the brand, trust, and customer satisfaction. Furthermore, positive effects on word-of-mouth as a relational outcome can be observed, albeit with some indirect effects. However, there are certain influences that contradict our hypotheses or do not align with them, which will be discussed in Section 3.5.

After examining the relationships within the conceptual models from H1 to H6, we will now review H7. This hypothesis assumed that user experience, age, and gender are influential factors in consumers' perceptions of conversational-agent interactions. To test this, we conducted linear regression analyses (for the influence of age and user experience) and ordinal regression analyses (for the influence of gender) to measure the possible effects of these variables on the constructs of the conceptual model.

The results show that user experience and age, but not gender, influence several constructs in the chatbot sample group. More specifically, user experience influences the communicative behaviors of social presence ($p = < 0.001$) and task-technology fit ($p = < 0.001$), consumers' perceptions of the brand (perceived brand warmth with $p = < 0.001$ and competence with $p = 0.012$), and communication (hedonic attitudes with $p < 0.001$ and utilitarian attitudes with $p = 0.004$). Furthermore, user experience positively influences the relational mediators of attitude toward the brand ($p = 0.003$), customer satisfaction ($p = 0.003$), and trust ($p = < 0.001$) as well as the relational outcome word-of-mouth ($p = < 0.001$). In all relationships, we observed that the higher the experience, the more positive the effect.

Additionally, the factor of age plays a role because of its influence on the consumers' perceptions of communication (hedonic attitudes with $p = 0.011$ and utilitarian attitudes with $p = 0.018$) and the relational mediators (attitude toward the brand with $p = 0.047$ and customer satisfaction with $p = 0.021$). For this influencing factor, we also observed that the higher the age, the more positive the effects.

When consumers interact with voice assistants, the influencing factors of user experience and age, but not gender, show significant effects. Thereby, the higher the user experience, the more positive the impact on task-technology fit ($p = 0.038$), trust ($p = < 0.001$), and word-of-mouth ($p = 0.001$).
Furthermore, the factor of age influences consumers' perceptions of brand competence ($p = 0.026$) and communication (utilitarian attitudes $p = < 0.001$ and hedonic attitudes $p = < 0.001$) as well as the two relational mediators of attitudes toward the brand ($p = 0.001$) and customer satisfaction ($p = 0.003$). Interestingly, the analysis results show that the older the participants, the more positive the evaluation of the listed constructs.

In this section, we conducted analyses to address RQ 1 and assessed, thereby, which marketing outcomes conversational agents stimulate. However, we also aimed to investigate the effects of chatbot and voice-assistant marketing communications in direct comparison. We perform corresponding analyses in Section 3.4.2.2 below.

3.4.2.2 Data analysis to address research question 2

To address RQ 2, we investigated whether the communication mediums (text versus voice) stimulate different effects by conducting two analyses. First, we tested whether the chatbot and voice-assistant construct values differ significantly, and second, we tested whether their relationship effects within the conceptual model differ significantly.

To test possible differences in the construct values, we executed a t-test analysis. This analysis showed that the mean values for almost all constructs (except for cognitive decision effort and trust) are higher for the chatbot than for the voice-assistant sample group. Furthermore, the t-test analysis revealed that eight out of 11 construct values of the voice-assistant sample group differ significantly from those of the chatbot sample group. Exceptions are the construct values for task-technology fit ($p = 0.415$), perceived brand competence ($p = 0.063$), and trust ($p = 0.822$). Furthermore, we confirmed the analysis results' robustness by executing a bootstrap analysis. An overview of the mean values and the t-test analysis results is displayed in Table 15.

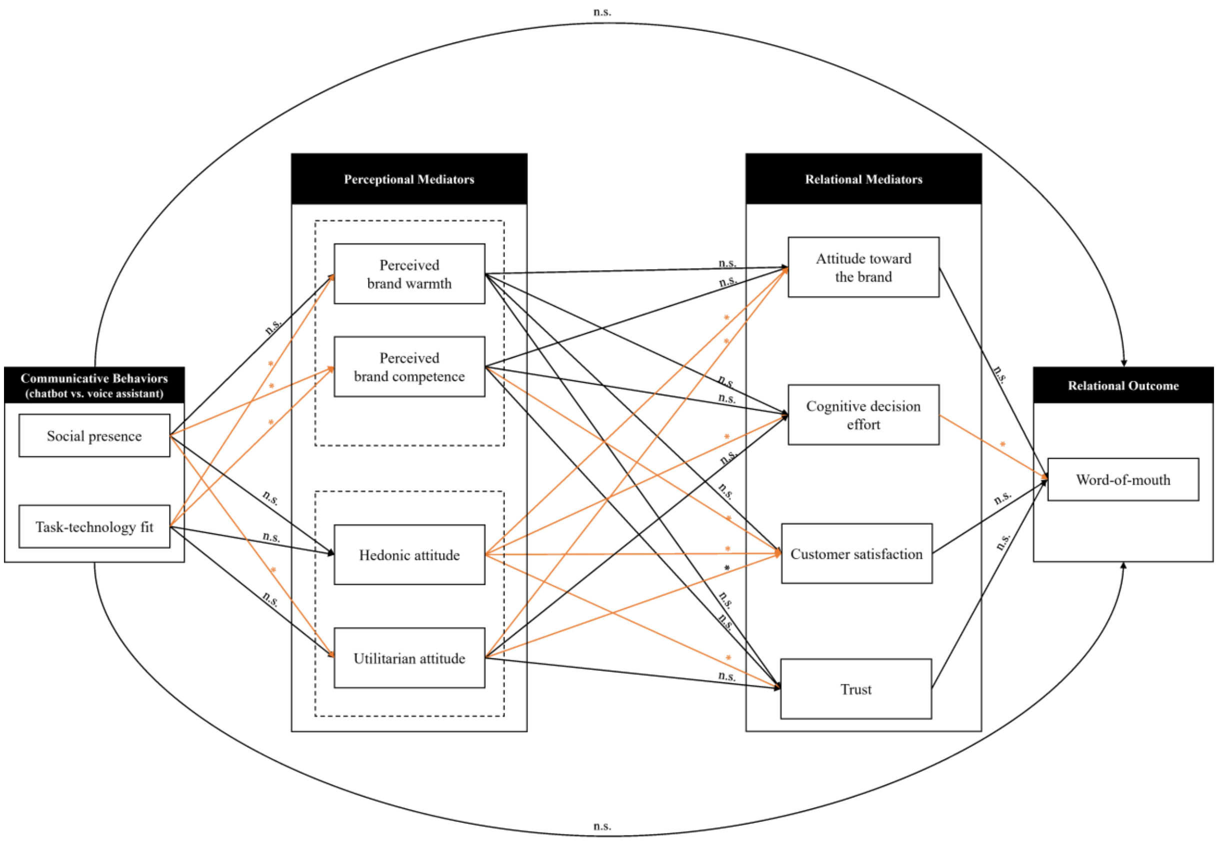
Table 15. T-test analysis results for the constructs of the sample groups

Construct	Mean values (chatbot / voice assistant)	T-value	Confidence interval (lower / higher value)	p-value
Attitude toward the brand	5.3 / 4.6	-5.946	-0.864 / -0.435	<0.001
Cognitive decision effort	2.1 / 2.7	3.060	0.109 / 0.511	<0.001
Customer satisfaction	6.8 / 5.7	-2.274	-1.321 / -0.096	<0.001
Hedonic attitude	4.4 / 3.8	-4,512	-0.852 / -0.335	<0.001
Perceived brand competence	4.9 / 4.7	-1.850	-0.415 / 0.012	0.063
Perceived brand warmth	4.3 / 3.9	-3.674	-0.641 / -0.194	<0.001
Social presence	3.6 / 2.8	-5.344	-1.039 / -0.481	<0.001
Task-technology fit	4.7 / 4.6	-0.817	-0.363 / 0.150	0.414
Trust	4.4 / 4.5	-0.311	-0.406 / 0.295	0.822
Utilitarian attitude	5.1 / 4.3	-6.014	-1.034 / -0.525	<0.001
Word-of-mouth	4.2 / 3.6	-4.084	-0.843 / -0.295	<0.001

Additionally, we examined the effects within the structural equation models for the chatbot and voice-assistant sample groups (see Figures 18 and 19) in more detail. To test whether the effect strengths differ significantly, we performed a multi-group confirmatory factor analysis (MGCFA). This analysis revealed that, in total, 12 effects differ significantly, which equals 40% of the model. A full overview of which effects differ significantly between the voice-assistant and chatbot sample groups is presented in Table 16 and visualized in Figure 20. Notably, Figure 20 focuses on displaying the relationships that differ significantly between the chatbot and voice-assistant sample groups. The effect strengths of the relations that differ significantly are displayed in Table 17 to improve the readability of Figure 20.

Table 16. Multi-group confirmatory factor analysis for the sample groups

Relation		**p-value**
Social presence	→ Perceived brand warmth	0.138
Social presence	→ Perceived brand competence	0.009
Social presence	→ Hedonic attitudes	0.274
Social presence	→ Utilitarian attitudes	0.003
Task-technology fit	→ Perceived brand warmth	0.004
Task-technology fit	→ Perceived brand competence	0.002
Task-technology fit	→ Hedonic attitudes	0.989
Task-technology fit	→ Utilitarian attitudes	0.477
Utilitarian attitudes	→ Attitude toward the brand	0.008
Hedonic attitudes	→ Attitude toward the brand	0.038
Perceived brand competence	→ Attitude toward the brand	0.818
Perceived brand warmth	→ Attitude toward the brand	0.481
Utilitarian attitudes	→ Cognitive decision effort	0.526
Hedonic attitudes	→ Cognitive decision effort	0.028
Perceived brand competence	→ Cognitive decision effort	0.082
Perceived brand warmth	→ Cognitive decision effort	0.090
Utilitarian attitudes	→ Customer satisfaction	0.000
Hedonic attitudes	→ Customer satisfaction	0.024
Perceived brand competence	→ Customer satisfaction	0.003
Perceived brand warmth	→ Customer satisfaction	0.108
Utilitarian attitudes	→ Trust	0.810
Hedonic attitudes	→ Trust	0.014
Perceived brand competence	→ Trust	0.945
Perceived brand warmth	→ Trust	0.836
Social presence	→ Word-of-mouth	0.776
Task-technology fit	→ Word-of-mouth	0.116
Attitude toward the brand	→ Word-of-mouth	0.198
Cognitive decision effort	→ Word-of-mouth	0.022
Customer satisfaction	→ Word-of-mouth	0.203
Trust	→ Word-of-mouth	0.134



Note: Orange arrows = effect strengths differ significantly ($p < 0.05$), n.s. = not significant.

Figure 20. Conceptual model for the sample groups in direct comparison

Table 17. Significantly differing relationships between the sample groups

Relation		**Chatbot effect strength (p-value)**		**Voice-assistant effect strength (p-value)**	
Social presence	→ Perceived brand competence	0.212	(<0.001)	0.429	(<0.001)
	→ Utilitarian attitude	0.262	(<0.001)	0.382	(<0.001)
Task-technology fit	→ Perceived brand warmth	0.372	(<0.001)	0.154	(0.006)
	→ Perceived brand competence	0.557	(<0.001)	0.327	(<0.001)
Perceived brand competence	→ Customer satisfaction	-0.111	(0.005)	0.097	(0.015)
Hedonic attitude	→ Attitude toward the brand	0.211	(<0.001)	0.389	(<0.001)
	→ Cognitive decision effort	0.304	(<0.001)	-0.020	(n.s.)
	→ Customer satisfaction	0.220	(<0.001)	0.409	(<0.001)
	→ Trust	0.283	(<0.001)	0.015	(n.s.)
Utilitarian attitude	→ Attitude toward the brand	0.327	(<0.001)	0.132	(0.012)
	→ Customer satisfaction	0.734	(<0.001)	0.555	(<0.001)
Cognitive decision effort	→ Word-of-mouth	0.131	(0.001)	-0.012	(n.s.)

Note: n.s. = not significant.

In a first step, we reviewed the strengths of the voice-assistant and chatbot sample groups displayed in Table 14. Thereby, we noticed that the influence of social presence on perceptional mediators is stronger for marketing communications through the voice assistant, whereas the influence of task-technology fit is stronger for chatbot marketing communications. In a second step, considering the MGCFA results more closely (see Figure 20 and Table 17), we can confirm that the effect of social presence on perceived brand competence and utilitarian attitudes is significantly stronger for voice-assistant marketing communications. Furthermore, the effect of the task-technology fit on perceived brand warmth and competence is significantly stronger for chatbot marketing communications.

Furthermore, for marketing communications through the chatbot, the utilitarian attitude plays a key role. We determine this finding because utilitarian attitude has the strongest impact on three of the four relational outcomes (an exception is the relational outcome of attitude toward the brand on which utilitarian attitudes has the second strongest influence). Moreover, the positive effects of the chatbot's utilitarian attitude on attitude toward the brand and customer satisfaction differ significantly from the positive effects aroused by marketing communication through voice assistants. However, the hedonic attitude of marketing communications through voice assistants arouses significantly stronger positive effects on attitude toward the brand and customer satisfaction than marketing communications through chatbots.

Proceeding, it should be noted that cognitive decision effort is crucial when comparing chatbot and voice-assistant marketing communications. While the cognitive decision effort of chatbot marketing communications has a positive effect on word-of-mouth, the effect is not significant for voice-assistant marketing communications.

Some high-effect strengths for both communication mediums are striking in the structural equation models. First, there is a strong and significant influence of utilitarian attitudes on cognitive decision effort (chatbot: $\beta = -0.728$, $p = < 0.001$; voice assistant: $\beta = -0.633$, $p = < 0.001$). Second, a strong relationship exists between social presence and hedonic attitudes (chatbot: $\beta = 0.629$, $p = < 0.001$; voice assistant: $\beta = 0.645$, $p = < 0.001$). Third, task-technology fit has a strong impact on utilitarian attitudes (chatbot: $\beta = 0.700$, $p = < 0.001$; voice assistant: $\beta = 0.551$, $p = < 0.001$). Finally, there is a strong and significant influence of utilitarian attitudes on customer satisfaction (chatbot: $\beta = 0.734$, $p = < 0.001$; voice assistant: $\beta = 0.555$, $p = < 0.001$). We return to these striking effects later in the discussion section (see Section 3.5), but before we do so, the research results are summarized below.

3.4.3 Summary of the research results

Our study presents significant structural equation models for the voice-assistant and chatbot sample groups. The hypotheses were tested, and H1 and H2 were fully accepted. Additionally, H3, H4, H5, H6, and H7 were partially confirmed. Altogether, the following key takeaways can be derived.

Overall, our study results highlight that marketing communications through conversational agents arouse positive marketing effects. Moreover, we reveal that differences exist in the use of text- versus speech-based conversational agents for marketing communications. This outcome emphasizes the need to distinguish research according to the two types of conversational agents. We summarize the key results of our study below by referring to the two research questions (RQ).

RQ 1. Which effects does marketing communication through conversational agents have on the brands that use them for marketing communications?

The study results for RQ 1 show that brands must transfer the right tasks to conversational agents. In other words, it is important that when conversational agents are used for marketing communications, they suit the functions of conversational agents (= task-technology fit). Furthermore, brands should create human-like marketing communications through conversational agents (= social presence). If both factors are ensured, brands can arouse positive effects through their marketing communications.

Regarding the specific effects of marketing communications through conversational agents, the study results reveal significant influences on conative and affective accomplishments. An example of conative accomplishments is that marketing communications through conversational agents help brands to be perceived as competent as well as friendly and kind (represented through brand warmth). Furthermore, creating human-like communications that suit the task improves the perception that brand marketing communications are fun and useful (equals hedonic and utilitarian attitudes). How brands and their marketing communications are perceived has further influence on attitudes toward the brands, consumers' brand satisfaction and trust, and how exhausting and frustrating communications with the brands are perceived to be. In this context, it should be mentioned that brands being perceived as competent lowers consumers' perceptions of frustrating and exhausting marketing communication. However, when brands that are perceived as competent use chatbots for marketing communications, consumer satisfaction is lowered. This result is contrary to our assumptions and will be discussed later (see Section 3.5). As an ultimate effect of conversational-agent marketing communications, we observe both indirect and direct influences on word-of-mouth for brands, which is an affective accomplishment.

Moreover, influencing factors that either directly or indirectly influence word-of-mouth can be identified through our study. Brands should consider user experience and the age of their target groups when evaluating marketing communications through conversational agents. For both conversational-agent mediums, we found that user experience positively influences trust and that age positively influences customer satisfaction. Moreover, depending on the medium of the conversational agent, user experience as well as age positively affect several other constructs and therefore have positive indirect influences on word-of-mouth.

In sum, our study results emphasize that marketing communications through conversational agents arouse positive conative and affective marketing effects. However, we noticed some differences in our analysis for perceptions of the chatbot and voice-assistant marketing communications. Thus, through the results for RQ 2, our study highlights that it is important for companies to be aware of the strengths and weaknesses of the two mediums of conversational agents (i.e., text and speech). Doing so may help companies decide which of the two communication mediums is more suitable to strengthen the core values of their product and service portfolios. To educate about the strengths and weaknesses of the two communication mediums, we now summarize the key study results for RQ 2.

RQ 2. Does the distinctiveness of chatbots and voice assistants lead to different effects on the brands?

Regarding RQ 2, we can conclude through the MGCFA results that the strength of voice-assistant marketing communications lies in their social presence. This social presence has a

strong positive influence on brands being perceived as competent and on marketing communications being perceived as useful. Furthermore, when consumers perceive brands as competent, the customers' satisfaction with them is also strengthened.
The strength of chatbot marketing communications lies in the fit between the task and chatbots as technology. The task in our study was an information search. By increasing the task-technology fit in chatbot marketing communications, brands can benefit from an improved perception of warmness and competence.
Furthermore, when chatbot marketing communications are perceived as being useful, they have a significantly stronger influence on attitudes toward brands and customers' satisfaction than voice assistants. In the context of marketing communications through voice assistants, the hedonic attitudes are more influential on brand attitudes and customer satisfaction than chatbots.

The greatest difference between chatbot and voice-assistant marketing communications is whether the communication is fun for consumers. When this is equally the case, brands benefit from using voice assistants for marketing communications, as doing so has stronger effects on brand attitudes and customers' satisfaction. If brands primarily want to influence consumer trust and lower the perception of frustrating and exhausting marketing communication, they can rely on chatbot marketing communications.

Moreover, our study results uncover that all construct values of the chatbot sample group that differ significantly from those of the voice-assistant sample group are higher. Regarding hedonic attitudes, this finding contradicts the study by Rzepka, Berger, and Hess (2022), which found that consumers have more fun searching for information via voice. However, an explanation for this disparity could be that (brand) marketing communications through voice assistants are still not as familiar to consumers as text-based ones through chatbots. Additionally, it is worth mentioning that communications through text- and speech-based conversational agents result in the same level of cognitive decision effort. According to Kock (2004), speech-based interactions require less cognitive effort compared to interactions through text. However, this seems not to be the case for AI-based marketing communications and is therefore a significant difference compared to human–human communications.

Ultimately, marketing communications through text-based chatbots and speech-based voice assistants arouse partly different effects. Therefore, they should be implemented consciously. Voice-assistant marketing communications have the advantage of a sense of social connection with consumers. On the other hand, marketing communication through chatbots helps brands by being suitable to providing information and helping customers with processes and services. We discuss the research results and deduce valuable contributions for academic researchers as well as implications for marketing practitioners in the following section.

3.5 Discussion

Recent publications highlight a relevant research gap regarding investigations about the influence of marketing communications through text- versus speech-based conversational agents on consumers (Diederich et al. 2022; Schwede et al. 2022). This study contributes to filling this research gap and compares brand marketing communication via text-based chatbots and speech-based voice assistants. By doing so, this study assesses the influence of these technologies on marketing outcomes related to brand communications. Therefore, this study extends current knowledge on interactive brand–consumer communications, contributing to the development of new knowledge in the expanding research field of AI-based marketing communications. In particular, this study contributes especially to the marketing and human–computer interaction literature and is beneficial for marketing practitioners who are interested in using AI-based technologies to create interactive marketing communications. Before outlining the implications for marketing practitioners, we describe the theoretical contributions of our study.

3.5.1 Theoretical contributions

Our study provides several theoretical implications, especially addressing the call of Diederich et al. (2022) to consider the distinctiveness of text- and speech-based conversational agents through direct comparison.

First, our study assessed the link between the distinctive traits of AI-based marketing communications and conative and affective marketing outcomes. Thereby, we prove task-technology fit is a relevant antecedent, which is especially significant for marketing communications through chatbots. Additionally, we tested the scale's validity of the construct of social presence for AI-based technologies in the marketing context. Therefore, our study reveals that the social presence brands evoke through chatbots and voice assistants is a significant antecedent that influences consumers' behavioral intentions.
In this regard, the strong effects of social presence and hedonic attitudes should be mentioned. These effects generally confirm the strength of conversational agents' social presence and its positive impact on perceiving fun during marketing communications. This research area should be further investigated to identify additional as well as the most relevant characteristics of brand marketing communication through AI-based technologies to generate positive brand effects. For example, we did not control perceived physical closeness toward conversational agents. However, this construct could foster consumer–brand relationships, which may have caused even stronger effect strengths.

Second, our study suggests that the effects of marketing communications through voice assistants and chatbots differ in strength. We found that marketing communications through voice assistants benefit from social presence, while the strength of marketing communications through chatbots lies in the task-technology fit. Furthermore, the effects of social presence and task-technology fit differ significantly for text- and speech-based marketing communications. Our study results extend the finding of Flavián, Akdim, and Casaló (2022), which states that voice is more efficient than text in the context of making product recommendations. Thus, we add the finding that voice is also more effective in shaping perceived brand competence and marketing communications' utilitarian attitude. Further investigations could extend this finding by comparing marketing communications through voice assistants with other interactive communication channels, such as social-media channels.

Third, we found an interesting relationship between perceived brand competence and customers' satisfaction with marketing communications through chatbots. Our study results show that the higher the perceived brand competence, the lower the customers' satisfaction. This could be a halo effect from products and services for which consumers expect and demand competent (personal) high-quality consultations. Examples of such products and services include high-involvement products, such as cars, or complex service portfolios from insurance companies. In these cases, consumers commit to spending high budgets or accepting a long-term liability in the form of a contract. German consumers, in particular, tend to be risk averse, which could explain this relationship.
Complex products and services are, in general, not recommended for communications through voice assistants. Therefore, this halo effect does not seem to exist for voice-assistant marketing communications. Moreover, consumers could expect seamless voice-dialogue flows only from brands that are perceived as competent, which would positively influence customers' satisfaction. This may explain the significant difference, but to fully understand this phenomenon, further studies are required.

Fourth, popular frameworks that are applied to investigate marketing-communication contexts are based on human–human interactions, but as technology-mediated communication becomes more common, suitable frameworks should follow (Dombi, Sydorenko, and Timpe-Laughlin 2022; Guzman and Lewis 2020). With our study, we addressed this issue by developing a model based on the social cognitive theory (Bandura 1986) to study human–computer marketing communications. Furthermore, we established brand perceptions (i.e., warmth and competence) and perceptions of communication (i.e., hedonic and utilitarian attitudes) as central mediating constructs in the context of AI-based marketing communications.

Fifth, our study results assessed the differences in cognitive decision effort between text- and speech-based conversational agents. Thereby, we measured the relationship between cognitive decision effort and word-of-mouth for AI-based marketing communications. We revealed that cognitive decision effort is crucial for marketing communications through chatbots in the sense that the higher the effort, the higher the word-of-mouth. In our study, a high value for cognitive decision effort indicates that the interaction is exhausting and frustrating. Therefore, word-of-mouth intentions tend to be aroused through marketing communications when consumers are unsatisfied with chatbots. This dissatisfaction leads to the question of whether the construct of word-of-mouth is associated only with positive emotions. Furthermore, this relationship is not significant for marketing communications through voice assistants. This distinction suggests that consumers expect to make cognitive decisions when interacting with voice assistants, which confirms that speaking with brands is still perceived as a relatively unfamiliar way of communicating.

Sixth, based on the striking effects identified in Section 3.4.2.2, we revealed which constructs are closely related in AI-based marketing communications. Our study shows that the task-technology fit, perceived usefulness of the interaction (i.e., the utilitarian attitudes) and cognitive decision effort are closely related. Furthermore, utilitarian attitudes are closely linked to customer satisfaction. This connection indicates that the usefulness of AI-based marketing communications is crucial for satisfying consumers with the interactions. Additionally, human-likeness, as one of the distinctive elements of AI-based marketing communications (expressed through the social presence), is a key factor in ensuring that consumers have fun during the interaction. This result validates the study findings of Brandtzaeg and Følstad (2017) and Guzman and Lewis (2020) that social presence is as a key relational component of AI-based communications.

Last, trust and privacy concerns are often discussed as issues for speech-based interactions. These factors tend to serve as an explanation for why voice assistants and smart speakers are not used. However, we found that consumers rate their trust in chatbots and voice assistants equally, which indicates that trust is a general issue for conversational agents and not voice assistants in particular. Furthermore, our study confirms that individual factors (e.g., user experience and age), as introduced by the UTAUT2 model, influence consumer evaluations of marketing communications through chatbots and voice assistants. However, we found that only user experience and age, but not gender, are influencing factors.

In addition to these theoretical contributions, our study reveals interesting findings for marketing practitioners. We delineate the core implications in the following section.

3.5.2 Managerial implications

Overall, this study shows that AI-based technologies can be used as effective marketing-communication channels. Therefore, our study encourages marketing practitioners to execute

AI-based marketing communications through chatbots or voice assistants because of their positive effects on conative and affective marketing outcomes, such as brand attitudes and word-of-mouth. Further implications are described hereinafter.

First, marketing practitioners may benefit from this study by gaining insights about the different effect strengths of communicating through chatbots and voice assistants on consumers' perceptions and behavioral intentions. While both communication mediums improve conative marketing accomplishments in the form of word-of-mouth, the effects on affective marketing accomplishments differ in some significant ways. Therefore, brands can benefit from the right media mix. Using human-like voice assistant marketing communications can help brands efficiently improve being perceived as competent and useful. Additionally, when brands ensure that the right communication tasks are processed by chatbots (= task-technology fit), they can also increase the perception of the brand competence. These findings can help brands make the most effective decisions about investments in financial and human resources for marketing communications. Regardless of the communication medium, marketing practitioners must always ensure that consumer–brand communications are being perceived as useful to generate a positive influence on customer satisfaction.

Second, this study reveals that when the primary goal of marketing communications is to reach higher brand awareness driven by word-of-mouth, marketers should focus on marketing communications via AI-based technology that evoke the feeling of social presence. This can be especially interesting for brands with lower marketing budgets. Marketers for low-involvement, fast-moving consumer goods can leverage this effect through chatbots or voice assistants because their positive effects on word-of-mouth do not differ significantly.
Additionally, when brands work to evoke the feeling of social presence in voice-assistant marketing communications, they can benefit from several positive effects. For example, social presence stimulates indirect positive effects on attitudes toward the brand and trust (mediated through the communication perceived as being warm and useful). Attitudes toward the brand and trust also further mediate positive effects on word-of-mouth.
When brands conduct marketing communications through chatbots and manage their social presence, they benefit from consumers perceiving the communication as fun and useful. This perception leads to positive effects on brand attitudes and lowers cognitive decision efforts which further results in improved word-of-mouth intention. However, marketing practitioners must address the relation of cognitive decision effort to word-of-mouth: the more frustrating and exhausting consumers perceive the interaction to be, the higher the word-of-mouth intention. Therefore, in the context of chatbot marketing communications, consumers are more likely to discuss it with family and friends if the experience is associated negatively.

Third, brands that aim for a kind and friendly positioning benefit from conversational-agent marketing communications that arouse social presence. However, if they want to achieve an image that reflects higher competence, marketing practitioners must differentiate between text- and speech-based marketing communications. Brand competence associations are strongly influenced by the social presence of speech-based communications, while for text-based communications, it is more important to ensure task-technology fit. Therefore, both communication mediums can support building a positive and high-quality brand image.

Fourth, providing consumers with the most suitable communication medium for executing certain tasks positively influences the communication's usefulness, which further positively influences consumers' attitudes toward brands, customer satisfaction, and trust. Therefore, companies address these considerations when developing their marketing communication strategies. In other words, it is important that marketers select the most suitable communication medium for certain tasks, which leads to an indirect positive effect on several marketing outcomes (especially brand attitudes and trust) and a word-of-mouth effect.

Finally, we recommend marketers be aware of their target groups' user experience and age because both influence several constructs of the conceptual model. Specifically, a higher user experience with chatbots or voice assistants has positive effects, for example, on task-technology fit and trust, while age influences, for example, the perception of communication. However, the target groups' gender does not play a relevant role for marketing practitioners considering marketing communications through chatbots or voice assistants.

Although our study provides several theoretical contributions and implications for marketing practitioners, our work is not free of limitations, which presents possible future research directions. Therefore, we describe these limitations in the following section.

3.5.3 Limitations and directions of future research

This study contributes to the marketing as well as human–computer interaction literature and reveals valuable findings. However, some limitations and future research opportunities should be considered.

First, it is possible that the use of a fictional sunscreen brand limits the generalizability of the results. This fictional brand represents the fast-moving consumer goods industry, with sunscreen as a low-involvement product. However, it remains unclear whether the effects for brands with high-involvement products (e.g., smartphones, laptops) or with products that require a higher degree of expertise (e.g., insurances) would remain the same. To allow generalization, the study should be repeated for other industries, low- and high-involvement products in comparison, and brands that are familiar versus unfamiliar to consumers. Additionally, brand heritage mediates the influence of warmth and competence on consumer intentions (Meyer and Orth 2023). Therefore, we recommend assessing brand heritage when investigating real brands to control inflated effects on warmth and competence.

Second, the interaction design may impact the effect strengths. The participants could only participate in the survey using their computer or laptop because of the technical limitations of the platform we used to build the voice-assistant stimulus. However, popular voice assistants like Apple Siri and Google Assistant are integrated into smartphones or smart speakers. Therefore, this study should be repeated by including an interaction with smartphones to test whether the results remain the same. Furthermore, the findings of Haugeland et al. (2022) state that chatbot interactions through buttons may strengthen the hedonic user experience compared to free-text interactions. In this study, the interaction with the brand's chatbot was based on buttons. It remains, therefore, unclear whether the effects would remain the same if the interaction was based on open text interactions. Additionally, we kept the voice of the voice assistant as neutral as possible. However, the voice used in our study may have sounded more female or male to the participants. Since we did not control the perception of gender, possible influences remain undetected.

Third, we limited our examination to the stimulus traits of social presence and task-technology fit. However, other characteristics, such as communication style (Rheu et al. 2021) and location during usage (Frijns, Schürer, and Koeszegi 2021), could also be influential. The survey participants in this study answered the questions on their laptops and were probably at home in a private setting. However, it may be possible that it is less fun to use voice assistants in public areas because of the less private environment. Additionally, the environment may matter less for the usage of chatbots as consumers are used to communicating through text in public areas and privacy is preserved. Therefore, the results may differ for participation in the survey through smartphones in public areas.

Fourth, we examined influences on attitudes toward the brand, customer satisfaction, cognitive decision effort, trust, and word-of-mouth. However, we did not investigate other possible marketing outcomes that are relevant for brands, such as brand loyalty. This choice raises the question of whether, for example, perceived brand competence and warmth have stronger effects on other marketing outcomes that are also relevant for brand managers. Additionally, further cognitive factors, such as privacy control, should be investigated as mediators to evaluate other possible (main) influencing factors on behavioral intentions. Future research could also investigate whether marketing communications through voice assistants evoke brand attachment, which is even stronger than brand attitudes (Park et al. 2010).

Fifth, we analyzed two communication mediums, text and voice, in direct comparison. However, the two sample groups in the comprehensive study were not fully equal. The Mann–Whitney U test showed that the sample groups differed significantly in terms of age. Since our study results indicated that the participant's age influenced the response values, the effect strengths of both structural equation models could be influenced by this disparity. Furthermore, marketing communications consist of a promising media mix and therefore combine different communication channels. This variety raises the question of whether communication strategies that combine both communication mediums have even stronger effects on brand outcomes and behavioral intentions.

Last, younger consumers, as digital natives, are assumed to be more used to the adoption of technology devices and may perceive a higher level of fun and usefulness when engaging with them (Wang, Myers, and Sundaram 2013). Brand managers often define their target groups by specifying segments, for example, based on demographic criteria such as gender and age (Kotler et al. 2020). Therefore, analyzing effect strengths divided into age groups that allow predictions for certain target groups may be helpful, as the effect strengths could vary. Furthermore, only Germans participated in the survey. To provide managerial implications for international brands and derive generalizable findings, the study should be repeated across countries.

3.6 Conclusion

In 2016, marketing practitioners emphasized the importance of conversational agents, which are still relevant today. Communications through AI-based conversational agents can be text-based or speech-based. However, there are knowledge gaps regarding the effects of marketing communications through these technologies. Additionally, researchers have recently noted a research gap in studies concerning revealing significant differences between text- and speech-based conversational agents.

In our study presented in Chapter 3, we addressed this gap by conducting an experiment in the form of a 1 x 1 between-subject design (n = 557). We evaluated the potential effects of conversational-agent marketing communications by having survey participants interact with either a text-based chatbot or a speech-based voice assistant. The allocation to the chatbot or the voice-assistant sample group was randomized. Furthermore, we created a fictional brand and programmed a neutral chatbot and voice assistant with a gender-neutral name and voice. As such, we were able to avoid potential biases in the responses through past experiences with specific brands or conversational agents.

The study revealed that marketing communications through voice assistants create a sense of social connection with consumers, while chatbots are convenient marketing-communication channels for providing information and helping customers navigate processes and services. The effects of marketing communications through chatbots and voice assistants differ in several significant ways.

Our work presented in Chapter 3 contributes to the fundamental understanding of conversational agents as marketing-communication channels. We highlighted the differences between text- and speech-based communication through AI-based conversational agents, closing existing research gaps in the marketing literature.

Subsequently, Chapter 4 develops the enhanced understanding of the fundamentals of voice-marketing communications and stimulated marketing effects presented in Chapter 3. Specifically, Chapter 4 presents a more in-depth analysis of the marketing effects of a particular voice-marketing activity: voice-assistant applications developed by brands or companies.

4. Exploring the marketing effects of voice assistant third-party skills[7]

A fast-paced world full of information evokes consumers' desires for applications and technologies that make their lives simpler and more convenient (Roy et al. 2019). Voice assistants address this need (Deloitte 2024) by answering consumers' requests, providing information quickly via voice to support consumers in decision-making, and helping them organize their daily lives (Moriuchi 2019; Smith 2020). Additionally, voice assistants also satisfy consumers' desires by addressing their demand for more natural communication (Zoghaib 2022).

Furthermore, voice assistants enhance the convenience of consumers' lives by offering several applications like Alexa Skills or Google Actions (Sabir, Lafontaine, and Das 2022). These applications can be developed by companies and brands and are called third-party skills (TPSs; Tuzovic 2022). An example is Gymondo, a fitness company that enables consumers to access daily five-minute workouts through the Gymondo Alexa Skill (Gymondo 2017). Since TPSs are designed with human-like voices and provide specific functions that respond to consumers' immediate demands, TPSs can arouse engaging interactive communications between brands and consumers (Batat 2019).

Marketing practitioners benefit from interactive communication as it can have positive influences, for example, on consumer–brand relationships (Kotler et al. 2020; Voorveld, van Noort, and Duijn 2013). However, these practitioners claim there is a lack of suitable methods to measure the marketing effects of digital audio activities (OnlineMarketing.de GmbH 2023), including TPSs. Nonetheless, they aim to measure whether the development and provision of their TPSs actually arouse the desired marketing effects. Since the interaction medium of voice marketing is currently evolving, well-suited models have not yet been sufficiently and comprehensively developed and tested (Pal and Arpnikanondt 2021). Therefore, we address marketing practitioners' need for a suitable measurement tool and the research gap of a theoretical model for voice-marketing effects in this chapter.

After presenting the research objective in Section 4.1, the theoretical frame is rendered in Section 4.2. Accordingly, the conceptual model is derived from the theoretical frame in Section 4.3. To do so, a suitable theory is selected as the foundation on which, according to marketing practitioners, relevant marketing effects are being integrated. We test the developed conceptual model empirically through quantitative online surveys in Section 4.4. The research results are discussed and limitations leading to further research opportunities are presented in Section 4.5. This chapter finishes with a conclusion in Section 4.6.

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[7] Parts of this chapter are taken from Hilgert et al. (2024) and Hilgert, Hillebrandt, and Ivens (2023b, in press).

4.1 Research objective

We derive the research objective for this chapter by referring to the research gaps in the voice-marketing research field identified in Chapter 2. The presented research gaps can be divided into two research streams. In Chapter 3, we addressed the first research stream of consumer–voice assistant interaction and perception (for details see Figure 13). Thereby, we clarified the distinctiveness of voice marketing as a communication tool, along with its strengths and weaknesses. We thus addressed investigations into the strategic perspective of voice marketing. We expand our view in this chapter by focusing on the second research stream, which contains issues related to voice-assistant adoption and acceptance. By doing so, we further explore existing voice-marketing activities for companies and brands, more specifically voice-assistant applications developed by brands or companies (referred to in the following as third-party skills, abbreviated TPSs).

As stated by several reports (Brocks and Bätjer-Gleitsmann 2021, p. 4; Klöß and Lange 2022, p. 26; Westwater 2021, p. 6), the adoption rate of voice assistants in general is around 50%. However, this number does not automatically represent the adoption rate of TPSs, which raises the question of identifying drivers of adoption intention for TPSs. This information is essential for companies and brands to design engaging TPSs and make the resources invested in these technologies worthwhile. This leads to our first research question (RQ):

RQ 1. What are the drivers of the adoption intention of third-party skills (TPSs)?

Marketing practitioners pursue specific marketing goals when they execute marketing activities or marketing communications. An example is Samsung, a company that develops and produces electronic devices such as smartphones and televisions. Samsung wanted to appeal Generation Z[8] as their new intended target group. Therefore, they launched YouTube Shorts to reach the awareness of the target group. This marketing activity was a great success since Samsung overachieved their predefined goals. (Think with Google 2023)

This outcome shows that marketing activities should be well-planned to clarify the expectations of which specific marketing effects are being pursued. However, to the best of our knowledge, studies that investigate the implementation of TPSs as marketing activities and determine which marketing effects can be successfully achieved through those activities are lacking. Furthermore, the question remains of which specific marketing effects companies pursue with the development of TPSs and whether the desired effects can be stimulated through them remains unanswered. Therefore, we formulate the following two research questions:

[8] People who are born between 1996 and 2010 belong to the Generation Z (McKinsey & Company 2023a).

RQ 2. Which marketing effects do companies pursue with the development of TPSs?

RQ 3. Which marketing effects do TPSs arouse?

To answer the presented research questions, we apply a two-part methodology in the form of a theory-building and a theory-testing method. Specifically, we explore existing models of technology acceptance and adoption that are suitable for the context of TPS investigations to answer RQ 1. In the case that no established model exists, an inductive theory-building method is required to select a suitable model as the basis. Additionally, we require a qualitative theory-building method to answer RQ 2 if the marketing effects are not already included in the selected basis model. We can apply the qualitative theory-building method to extend the model by considering the marketing effects that TPSs are supposed to arouse. Furthermore, through RQ 3, we aim to examine which marketing effects TPSs actually arouse. As such, we can verify whether TPSs contribute to the specific marketing effects desired by marketing practitioners. To do so, we need a deductive theory-testing method, which is usually a quantitative method. (Döring and Bortz 2016)

In the Section 4.2, we begin by reviewing the literature to render the theoretical frame required for addressing RQ 1. Therefore, we can discover and evaluate existing models of technology acceptance and adoption to build the foundation for our study's conceptual-model development.

4.2 Review of technology-acceptance and adoption models

Over the years, researchers have developed different models to investigate issues concerning technology acceptance and adoption. To detect established models, we reviewed the analysis of the voice-marketing research field conducted in Chapter 2. Section 2.3.3 presented which studies and therefore which theories have been applied to investigate technology acceptance or adoption. These theories include the TAM, the concept of privacy cynicism, decision avoidance theory, U & G theory, the stimulus-organism-response (S-O-R) framework, the theory of consumers search, and the TPB. Furthermore, the analysis uncovered that the TAM is by far the most often applied theory in voice-marketing research.

Additionally, we aimed to consider popular models for technology-adoption investigations, although they have not yet been applied in the voice-marketing context. Therefore, we broadened our view through an initial theory-based literature review (Paul and Criado 2020) to synthesize possible models. Hence, we performed an initial literature review using the Scopus database with the keyword string "("technology acceptance" or "technology adoption") and ("model" or "framework")". This resulted in a list of 22,304 papers, wherein we identified three core papers based on their citation count. The three most cited papers were as follows:

- Venkatesh et al.'s (2003) "User acceptance of information technology: Toward a unified view" (22,465 citations),
- Venkatesh and Davis's (2000) "Theoretical extension of the Technology Acceptance Model: Four longitudinal field studies" (12,414 citations), and
- Venkatesh, Thong, and Xu's (2012) "Consumer acceptance and use of information technology: Extending the unified theory of acceptance and use of technology" (7,062 citations).

In the most cited paper, Venkatesh et al. (2003) developed and introduced the UTAUT. An advanced UTAUT, named UTAUT2, was then developed and presented in the study of Venkatesh, Thong, and Xu (2012), which is the third most cited paper. Venkatesh and Davis's (2000) study is the second most cited paper on the TAM and focused on its extension, which resulted in the development and introduction of the TAM2.

After the three most cited papers in the result list, the citation count dropped to a total of 44 papers, with a citation count between 1,000 and 5,500. A closer look at the papers revealed that, in addition to the UTAUT, UTAUT2, TAM, and TAM2, the authors of the 44 less cited papers investigated or applied the TPB (e.g., Mathieson 1991; Pavlou and Fygenson 2006; Taylor and Todd 1995), the information system (IS) continuance model (Bhattacherjee 2001), the TAM3 (Venkatesh and Bala 2008), the innovation diffusion theory (Karahanna, Straub, and Chervany 1999; Wu and Wang 2005), the value-based adoption model (VAM; Kim, Chan, and Gupta 2007), the task-technology fit (TTF) model (Dishaw and Strong 1999), or the model of adoption of technology in households (MATH; Brown and Venkatesh 2005).

The initial analysis showed that various models have already been applied to investigate issues of technology acceptance and adoption. However, a closer examination of the different models was required to evaluate whether one could be a suitable model for investigating TPS issues. Therefore, in Section 4.2.1, we evaluate the models regarding their suitability for our study.

4.2.1 Determining the most suitable technology-adoption model for our study

To evaluate the listed models, we defined criteria that indicate their suitability for our study. Therefore, the following three criteria needed to be fulfilled:
1) The research objective in this study is to surpass the acceptance and adoption of technologies, more specifically TPSs. Since our research objective is to capture possible marketing effects aroused by TPSs, the assessment of their acceptance is not sufficient. Nevertheless, integrating marketing effects subsequently into an established model would be possible. Therefore, we

defined a model as suitable for our study when it measures at least the adoption (intention) of technologies, which leads to our first criterion: **model focus**.

2) Usually, research is focused on either the business-to-business (B2B) or business-to-consumer (B2C) context. As our study addresses interactions between consumers and brands through TPSs, a model fits our research when it is focused on B2C investigations. Therefore, we defined **model perspective** as our second criterion.

3) Voice assistants in research contexts are not fully new, but they are still in early stages. The variety of existing technologies is vast, and AI-based voice technologies as interaction mediums are unique to consumers. Therefore, we evaluate models as suitable when they have already been successfully applied for AI-based technologies or, even better, for voice technologies. As such, **model context** is our third criterion.

After defining which criteria were relevant to our study context, we evaluated the models listed in Section 4.2 accordingly. These models included the following: the concept of privacy cynicism (Choi, Park, and Jung 2018), decision avoidance theory (Anderson 2003), innovation diffusion theory (Rogers 1962), the IS continuance model (Bhattacherjee 2001), the MATH (Brown and Venkatesh 2005), the S-O-R framework (Mehrabian and Russell 1974), the TAM (Davis 1989), the TAM2 (Venkatesh and Davis 2000), the TAM3 (Venkatesh and Bala 2008), the theory of consumers search (Stigler 1961), U & G theory (Katz, Blumler, and Gurevitch 1973), the UTAUT (Venkatesh et al. 2003), the UTAUT2 (Venkatesh, Thong, and Xu 2012), the TPB (Ajzen 1991), the TTF Model (Goodhue and Thompson 1995), and the VAM (Kim, Chan, and Gupta 2007).

Some of all the listed models are striking in their inappropriate **model focus**. Decision avoidance theory as well as the concept of privacy cynicism investigate why consumers avoid using voice assistants. However, our study demands insights about the drivers of adoption: the influencing factors of the actual use of voice assistants, and TPSs in particular. Therefore, the model focus of both these models does not fit our research objective. The innovation diffusion theory illustrates how fast and why new technologies spread. However, our research aim is to identify the drivers of TPS adoption without considering how far the technology has already spread. Similarly, the IS continuance model is concentrated on the post-adoption phase and is therefore also not suitable for our research. The S-O-R framework is a more general model that explains the communication process. Therefore, the model is not concrete and specific enough to provide detailed insights about drivers for technology adoption and aroused marketing effects. The theory of consumers search concentrates on the pre-purchase phase, with a focus on consumers' search process but not on adoption intention or marketing effects. Therefore, we conclude that this model is also not suitable for our study. After examining model focus more closely, the MATH, TAM, TAM2, TAM3, U & G theory, UTAUT, UTAUT2, TPB, TTF model, and VAM were further discussed regarding the second defined criteria, which is model perspective.

Although the TAM is the most applied model for investigating voice-marketing issues thus far, its **model perspective** is not suitable for our study. The TAM is focused on organizational situations (i.e., on the B2B but not the B2C perspective; Kim, Chan, and Gupta 2007). Similarly, the TAM2 and TAM3 are both grounded in the TAM and extended by external influences on perceived usefulness and perceived ease of use, respectively. Consequently, the TAM, TAM2, and TAM3 do not fulfill the required B2C model perspective as one of our defined criteria.

We continued the evaluation process of the aforementioned models by examining their **model context**. To do so, we referred to the study of Pal et al. (2020), who recognized the research gap of examining which model is most suitable for investigating the growing area of voice-based technologies. They compared the TAM, TPB, UTAUT, and VAM and found that the VAM most effectively predicts consumers' intention to use voice-based technologies, such as voice assistants. Based on the study findings of Pal et al. (2020), we conclude that the TAM, the further developed TAM2 and TAM3, the TPB, and the UTAUT (including the advanced UTAUT2) are less suitable than the VAM regarding our research objective. Since the MATH is fundamentally grounded in the TPB, we also determine that this model is not the best fit for our study. At first glance, the U & G theory seems, with its focus on audience, to be an appropriate model for our research objective (Ruggiero 2000). However, the model is mainly used to investigate mass-communication media (Ruggiero 2000), which does not include interactive two-way communications through TPSs.

Overall, we conclude from the presented evaluation that the TTF model and the VAM seem to be best suited for our study. We refer to the results of the study presented in Chapter 3 to make our final decision, where we applied the task-technology fit to compare text-based chatbots and speech-based voice assistants. In our analysis, we revealed that the task-technology fit is decisive, especially for chatbots as a text-based communication medium. However, we aim to investigate speech-based voice-assistant applications in this study. As such, the VAM is the model that fulfills all the defined criteria and that we therefore identified as the most suitable model for addressing our research objective. We describe the VAM as the theoretical foundation for our study in more detail in the Section 4.2.2.

4.2.2 The value-based adoption model

The VAM, which was originally developed by Kim, Chan, and Gupta (2007), focuses on the perceived value of technologies and their significant positive influence on behavioral adoption intention. Perceived value can be understood as the individually interpreted cost-benefit balance when adopting technologies (Kim, Chan, and Gupta 2007). This value is influenced by two factors: the benefits and sacrifices of a technology.

The benefits comprise the perceived usefulness and enjoyment of a technology, both of which have a positive influence on perceived value. Two aspects influenced the selection of perceived usefulness and enjoyment as benefits in the VAM. First, the selection is grounded in cognitive evaluation theory, which distinguishes between extrinsic- and intrinsic-driven motivations (Deci 1971). Both motivation types further affect perceived value (Rogers 1995). Second, consumers are influenced by cognitive and affective factors when they select products (Dube-Rioux 1990). When both aspects are combined in terms of the VAM, perceived usefulness represents extrinsic and cognitive factors, while enjoyment implies intrinsic motivation and affective factors (Kim, Chan, and Gupta 2007).

Sacrifices, which correspond to the costs of the cost-benefit balance of perceived value in the VAM, comprise perceived technicality and the perceived fee. These factors negatively influence perceived value. Specifically, sacrifices are deduced from monetary and non-monetary costs (Kim, Chan, and Gupta 2007; Thaler 1985; Zeithaml 1988). While monetary costs are related to the price that consumers must pay, non-monetary costs encompass, for example, the time that consumers must invest to understand and become acquainted with a technology (Kim, Chan, and Gupta 2007). Notably, no specific price information is needed to evaluate monetary costs. Consumers mentally classify the price in the context of comparable products or categories and use it to evaluate monetary costs (Grewal, Monroe, and Krishnan 1998; Kim, Chan, and Gupta 2007). Consequently, Kim, Chan, and Gupta (2007) selected perceived technicality as the non-monetary costs and the perceived fee as the monetary costs to represent sacrifices in the VAM.

Perceived value is the central construct of the VAM and functions as a mediator. This value mediates the influence of the benefits and sacrifices on behavioral adoption intention. (Kim, Chan, and Gupta 2007) An illustration of the VAM is displayed in Figure 21.

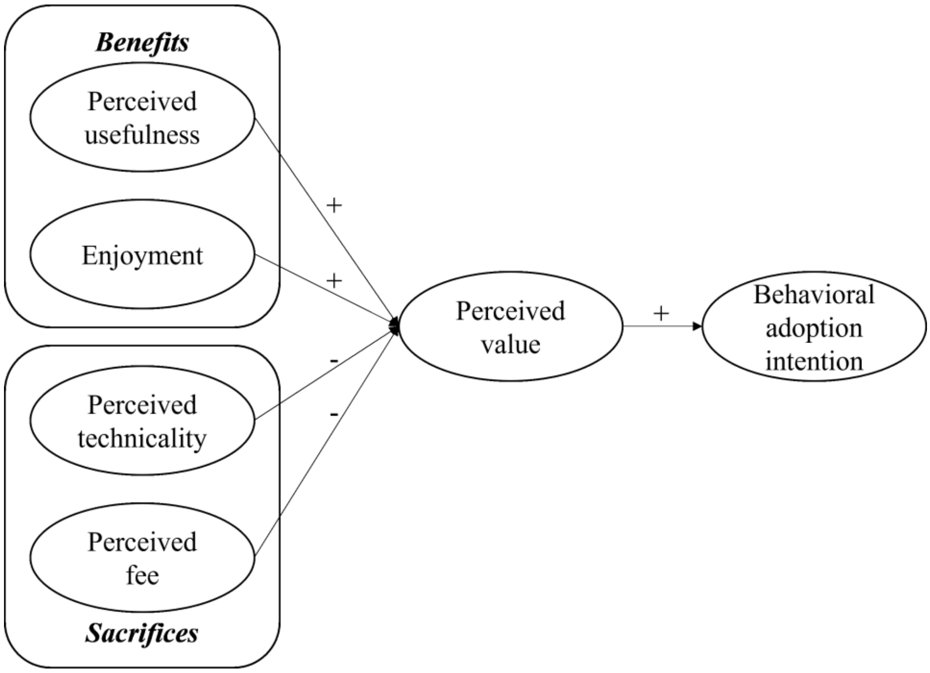


Figure 21. The value-based adoption model (own illustration based on Kim, Chan, and Gupta 2007, p. 115)

We conducted an initial bibliometric analysis to uncover existing research findings grounded in the VAM. To do so, we extracted a list of 760 papers from the Web of Science that cite the original paper of Kim, Chan, and Gupta (2007). Subsequently, we analyzed the bibliometric data using the software VOSviewer. The following criteria were then defined. We conducted a co-occurrence analysis based on the authors' keywords, including keywords that appeared at least five times. This resulted in 95 authors' keywords being distinguished into 10 clusters, as displayed in Figure 22. Since our focus was on the overall investigated issues, we concentrated on the 95 authors' keywords rather than the different clusters.

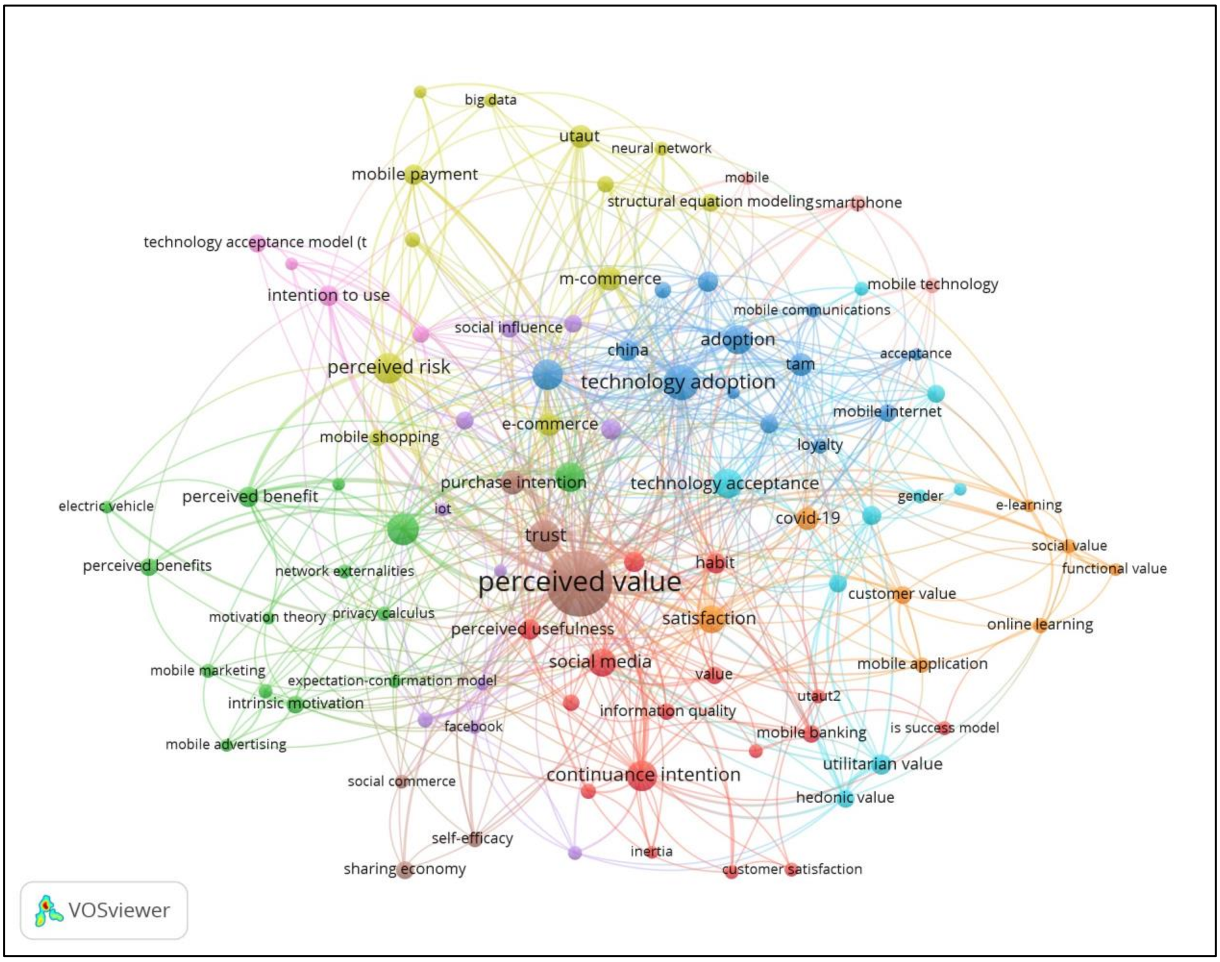


Figure 22. Bibliometric analysis of value-based adoption model research (derived from VOSviewer)

Upon closer examination, the authors' keywords can be differentiated into three areas: keywords about the model itself, investigated model variables, and investigated research contexts. A full overview of the keywords and the areas to which we assigned them can be found in Appendix 3.

The 46 keywords about the model itself comprise, for example, *value-based adoption model*, *perceived benefits*, *adoption*, or *UTAUT*. These keywords only imply that the model was applied in research without revealing insights about the details of existing study findings. Therefore, we do not evaluate them more in detail.

The 16 keywords that represent investigated model variables indicate which additional effects have been investigated by applying the VAM. This includes keywords such as *continuance intention*, *user satisfaction*, *service quality*, and *loyalty*. These keywords illustrate that several issues beyond the original VAM have been investigated thus far. However, the small number of keywords indicates that such research is expandable. We will address these keywords later in this chapter.

The 33 keywords concerning investigated research contexts indicate which contexts have been studied thus far based on the VAM. This group comprises keywords such as *social media*, *mobile advertising*, *mobile application*, and *augmented reality*. Since these keywords provide an overview of existing research areas that draw on the VAM, we briefly summarize them below.

The VAM has mainly been applied to investigate issues about smartphone usage. This concern is indicated by a total of 18 keywords, which include *mobile banking*, *mobile advertising*, *mobile marketing*, *mobile commerce*, *mobile communication*, *mobile services*, *mobile payment*, and *mobile shopping* (e.g., Ashraf et al. 2021; Kim and Kim 2022; Tseng et al. 2022). Additionally, we can derive from the keywords *social media*, *facebook*, *social commerce*, and *social networking sites* that research on different social-media-channel aspects referring to the VAM has been conducted (e.g., Hu, Ma, and Bai 2022; Lv et al. 2022; Rahardja et al. 2021). Furthermore, the VAM builds the basis for research regarding e-based education, as indicated by the keywords *e-learning* and *online learning* (e.g., Liao et al. 2022; Watjatrakul 2019); information technologies, as indicated by the keywords *big data* and *neural network* (e.g., Maeng, Lee, and Yun 2023; Villarejo-Ramos et al. 2021); consumer-to-consumer platforms, as indicated by the keywords *sharing economy* and *network externalities* (e.g., Hsieh, Yang Lin, and Huang 2021; Kim and Kim 2020); and AI-based technologies, as indicated by the keywords *service robots*, *augmented reality* (e.g., Kang, Koo, and Chung 2023; Koo et al. 2020), *electric vehicle* (e.g., Hu et al. 2023; Mustafa, Zhang, and Li 2021), and *e-commerce* (e.g., Cabrera-Sánchez et al. 2020; Huang and Chang 2019).

The presented overview illustrates that the original VAM can be used as a reference for several research issues in the field of technology. While this overview suggests that a wide range of studies about mobile research exist, studies that have applied the VAM to investigate future-oriented technologies like augmented reality are still in their infancy. Moreover, voice assistant and smart speaker—representing the central topics of this dissertation—do not even appear as authors' keywords in Figure 22. The reason for this absence is that we limited the results to keywords that appear at least five times. By examining the 760 papers that formed the data basis for the bibliometric analysis more closely, "smart speaker" appears two times as an authors' keyword (Hsu and Lin 2023; Park et al. 2018), and "voice assistant" appears four times (Cao et al. 2022; Liu et al. 2023; Pal et al. 2020; Pawar and Vispute 2023). These numbers reinforce the infancy of this research field, which emphasizes the valuable contribution of our study to expanding its body of literature.

Despite the low number of studies about voice assistants or voice marketing that refer to the VAM, the study results of Pal et al. (2020) highlight the suitability of the VAM to investigating such issues. Additionally, we disclosed in Section 4.2.1 that the VAM was the most promising model for our study. Therefore, the VAM forms its theoretical framework.

As displayed in Figure 21, the VAM helps to predict the behavioral adoption intentions of consumers for smart voice-based technologies, which include voice assistants (Pal et al. 2020). However, the VAM is limited by predicting only behavioral adoption intentions without encompassing constructs that measure possible marketing effects. As the effects of using voice-based technologies on companies and brands surpass the intentions of voice-assistant usage, the current VAM cannot sufficiently measure and fully capture those effects. Consequently, extending the VAM with constructs that represent marketing effects relevant to brands and companies is required. We address this necessity by developing the conceptual model for our study accordingly in Section 4.3.

4.3 Conceptual-model development

We developed the conceptual model for our study using the VAM as a basis. First, the original VAM was extended by conducting interviews with companies that plan to implement or already have implemented TPSs. We then extracted which marketing effects companies pursue when implementing TPS. Second, we deduced from the literature how to implement the identified relevant marketing effects in the original VAM to successfully assess them. The exact procedure is described below.

4.3.1 Company interviews to determine pursued marketing effects

To obtain a broad and representative picture of the market, we used the Industry Classification Benchmark (ICB) as the basis for selecting our interview partners. The ICB is an industry-classification taxonomy developed and published by Dow Jones and the Financial Times Stock Exchange (FTSE) in 2005 to subdivide the market into industry sectors and sub-sectors (FTSE Russell 2023). An overview of the ICB is displayed in Figure 23.

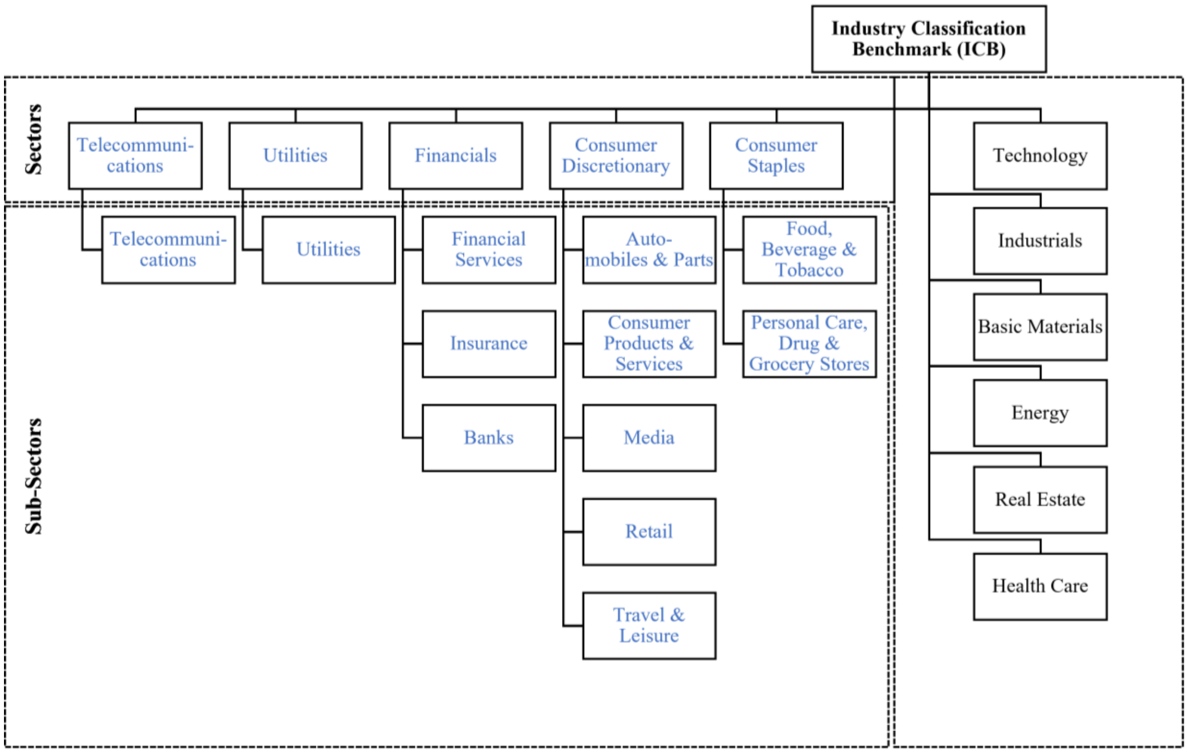


Figure 23. Industry Classification Benchmark (ICB) with industry sectors and sub-sectors (own illustration)

We differentiated the industry sectors into their focus on B2B (written in black in Figure 23) or B2C (written in blue in Figure 23). We decided not to recruit interview partners of companies from sectors with a B2B focus since our study focused on the marketing activities of companies with end consumers (i.e., B2C communications). As such, possible interview partners from the industry sectors of technology, industrials, basic materials, energy, real estate, and health care were excluded.

Furthermore, we divided the industry sectors with a B2C focus into the categories “consumers with own households,” “young adult,” and “all legally competent consumers.” The category “consumers with own households” comprises the industry sectors telecommunication and utilities. These sectors include companies that are relevant for consumers who demand, for example, electricity and energy providers, which is the case for consumers with their own households.

The category “young adults” concerns the industry sector financials. Companies in this industry sector are relevant for all young consumers as soon as they have their own bank accounts and insurances (e.g., health insurance).

The category “all legally competent consumers” encompasses the industry sectors consumer discretionary and consumer staples. Companies from these industry sectors are relevant for consumers as soon as they are legally allowed to conclude purchase agreements.

For our study, we aimed to cover most consumers in the total market, which allowed us to approach a generalizable measurement model without exceeding a reasonable research scope. Since not all consumers have their own households, we excluded the category “consumers with own households” and concentrated our further investigations on the industry sectors with target groups from the categories “young adults” and “all legally competent consumers.”

Consequently, we interviewed marketing experts from companies in the three industry sectors—financials, consumer discretionary, and consumer staples—following grounded theory (Glaser and Strauss 2017). Hence, we conducted interviews until they no longer provided any new insights, resulting in discussions with a total of 10 experts from nine different companies. Six of the experts had already developed and implemented their own TPS, while three of the interviewees were experts from service companies who reported that their customers developed TPSs. One expert interviewed was interested in and planned the implementation of his own TPS.
The interviewed marketing experts can be assigned to the industry sectors as follows. Two belonged to (service) companies from the financials industry sector, one to a company from the consumer-staples industry sector (which includes fast-moving consumer goods), and four to companies from the consumer-discretionary industry sector (which includes slow-moving consumer goods). Therefore, our interviewed marketing experts covered the three largest B2C industry sectors (calculated by the number of sub-sectors) of the ICB (see Figure 23). Additionally, we interviewed three marketing experts from consultancies that provided an overarching picture of pursued marketing effects through TPSs independently from specific industry sectors. This approach ensured gaining industry- and sector-specific insights without losing the broader perspective. To ensure the anonymity of the interviewed marketing experts, we assigned a number to each interview. Which of the interviewed marketing expert numbers belonged to which industry sector is presented in Table 18.

Table 18. Overview of the marketing expert interviews with industry-sector assignments

Marketing expert interview number	Industry sector	Industry sub-sector
Interview 1	Consumer discretionary	Travel & leisure
Interview 2	Consumer discretionary	Travel & leisure
Interview 3	Overarching (consultancy)	./.
Interview 4	Consumer discretionary	Retail
Interview 5	Consumer staples	Food, beverage & tobacco
Interview 6	Consumer discretionary	Consumer products & services
Interview 7	Financials	Insurance
Interview 8	Financials	Financial services
Interview 9	Overarching (consultancy)	./.
Interview 10	Overarching (consultancy)	./.

We conducted eight interviews through digital conversations using the communication platform Teams, and two interviewees responded to our interview request by answering the interview questions via email. The interviews lasted between 45 min and 60 min. The anonymized transcripts were used as the basis for further analyses. We conducted the qualitative content analysis according to Mayring (2000) and inductively derived six categories to deduce which marketing effects companies pursue when they develop TPSs. The six categories are described below. We refer hereafter to the 10 interviews using the abbreviations I for interview and the number of the interview (e.g., "I1") to distinguish the answers of the 10 interviewees.

Brand experience. Some of the interviewees stressed the overall relevance of the brand experience. TPSs can be beneficial to generating a seamless experience (I8), especially when the goal is to combine several brand touchpoints (I1). Furthermore, the companies use TPSs with the goal of enabling a hyper-personalization experience (I2) and creating a more emotional communication atmosphere (I3). Moreover, TPSs can result in more convenient experiences in daily life by aiding the implementation of routines (I6). For example, a coffee machine may start every morning at 7 o' clock when the consumers begin their days (I6). Therefore, we derived the first category, namely (seamless) **brand experience** based on quotes like "[…] we see a value in combination with the other channels, especially […] because the topic seamless experience increases in importance […]" (I1) and "For us, of course, the customer is always in the foreground, that they have the perfect premium experience with our devices […]" (I6).

Customer satisfaction. During the interviews, we recognized the importance of service orientation and customer satisfaction as desired marketing effects. Thus, TPSs are implemented in customer service or to relieve employees (I10). Furthermore, TPSs should expand and improve service levels to enhance customer satisfaction and loyalty (I3). These changes are possible, for example, by focusing the TPSs' communication to process customers' requests as quickly and successfully as possible (I9). Another way is to increase convenience for customers, for example, by starting a robot vacuum or oven through voice demands (I6). Therefore, the core attribute of TPSs is to increase customer satisfaction (I4). For the second category, **customer satisfaction**, quotes like "[…] we pursue the goal [with the implementation of TPSs] of making people happier and companies more efficient […]" (I9) and "[…] that they can improve […] the satisfaction" (I3) formed the basis of this category.

Image. The interviewees emphasized that by listening to consumer needs and translating them into innovative solutions, companies can build their reputations (I6). Furthermore, TPSs can serve as applications, but the content of the TPSs may also serve as a tool to transmit brand attributes (I7). Additionally, the interviewees emphasized that, when planning the development of TPSs, younger consumers (I5) or persons with disabilities (I2) may be target groups to focus on. Although it is not the goal to limit consumer–TPS interactions to younger consumers (I7), it is likely that these consumers are reached because they are the main user groups of voice assistants (I5). Generally, companies strive to reach new target groups, likely groups that are digitally affined and innovative (I6) and can, in turn, shape the company's perception. Therefore, we derived the third category, namely **image**, from quotes like "[…] we are of course aiming at a different target group, perhaps a target group that has a digital affinity, that is innovative, that likes to try things out" (I6) and "[…] in the best case, it should confirm the image that the customer may already have of us, or bring it closer to him" (I7).

Innovativeness. Some of the interviewees specified the characteristics that companies want to convey through TPSs. They highlighted that a TPS had been developed to contribute to their company being perceived as innovative (I1). Additionally, the novelty effect is striking when discussing this topic with customers (I8). Creating an innovative perception is not only a goal for end consumers but also the companies' own employees (I2). Furthermore, the shaping of innovative perception is twofold. On the one hand, companies want to foster the perception of innovativeness, but on the other hand, it is possible that consumers expect companies to be innovative (I6). Thus, we identify **innovativeness** as a fourth category based on quotes like "[…] we are, of course, looking after our current customers, i.e., our premium customers, who naturally expect [us] to keep up with the times and be innovative" (I6).

Loyalty. The interviewees predicted that the voice medium would gain importance for customer interactions (I1). Therefore, voice is another (optional) consumer touchpoint (I3). Moreover, voice as a barrier-free touchpoint (I8) is seen as a touchpoint that is accessible around the clock and therefore represents a promising touchpoint for increasing consumer loyalty (I3). Furthermore, companies aim to create TPSs that arouse continuous usage (I7). Thus, their goal is to devise a brand touchpoint with which consumers interact daily (I4). This brand touchpoint allows companies to provide consumers with as many points of contact as needed (I5). Therefore, we deduced the fifth category, **loyalty**, from quotes like "[…] so the desired situation [is] to really be with the consumers on a daily basis" (I4) and "[…] just to create a bond" (I3).

Sales. Some of the interviewees emphasized that their goal with TPSs was to increase sales. Doing so is possible, on the one hand, by (re-)ordering daily consumer goods, such as dishwasher tabs (I6), recipe ingredients, or tools (I5). On the other hand, TPSs can contribute to reducing costs (I9), which can be achieved, for example, by outsourcing tasks like answering service hotlines. Therefore, we conclude the sixth category, namely **sales**, from quotes like "[…] of course, we know that we make so much return on investment per recipe that we put online. And, of course, we are pursuing the same goal with the recipe skill" (I5).

Overall, our qualitative content analysis of the interviews resulted in six categories. We concluded that, with TPSs, the companies' aim to arouse positive marketing effects regarding brand experience, customer satisfaction, image, innovativeness, loyalty, and sales. The number of the interviewed experts who mentioned each of the marketing effects is displayed in Figure 24 (in alphabetical order).

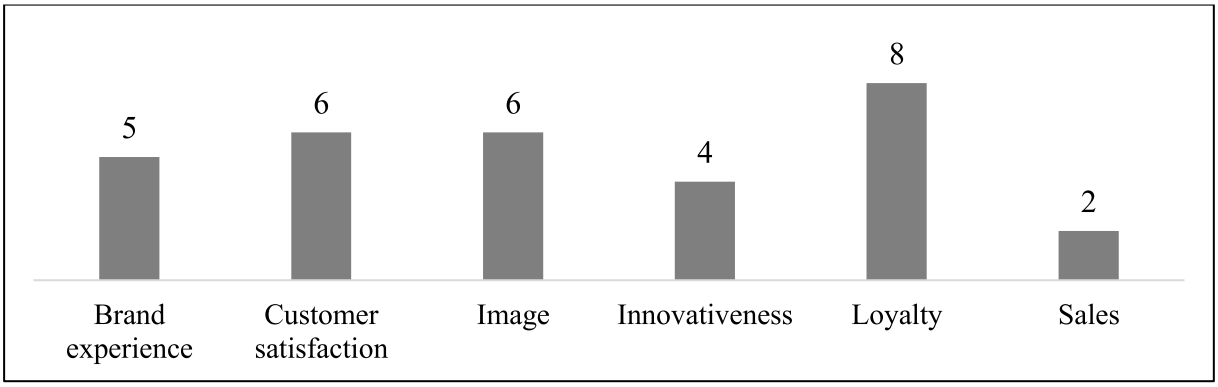


Figure 24. Number of the mentioned pursued marketing effects

We can distinguish the identified marketing effects by drawing on advertising-effectiveness research that identifies two categories. One category encompasses psychological advertising impact, while the other comprises economic advertising impact. Psychological advertising impact can be further subdivided into cognitive, emotional, and conative levels and is measured through variables such as brand awareness, willingness to buy, and involvement. Economic advertising impact, on the other hand, encompasses tangible indicators, such as turnover and sales. (Pusler 2011)

Referring to the advertising-effectiveness research, the marketing effects mentioned by the interviewed experts can be assigned to these two categories. All marketing effects can be classified as psychological advertising impacts, except for sales, which represent economic advertising impacts. We focused our study on only the psychological impact of advertising for the following two reasons. First, sales are not the primary goal of marketing but rather a consequence of successful marketing and therefore a secondary metric (Blattberg and Deighton 1996). Sales in the context of voice assistants is called voice commerce. Voice commerce is used by approximately 12% of German consumers and has thus still not been adopted by the majority (Brocks and Bätjer-Gleitsmann 2021, p. 13; PwC 2019). Furthermore, almost half of users stated that they would refuse to shop again via voice assistants (Brocks and Bätjer-Gleitsmann 2021, p. 13). Therefore, we exclude the marketing effect of sales from our study, even though it was mentioned by the interviewees.

Having identified which marketing effects companies pursue through TPSs, we now finalize the development of the conceptual model for our study in Section 4.3.2. To do so, we draw on the original VAM (Kim, Chan, and Gupta 2007) and integrate the marketing effects determined in this section. Furthermore, we derive the hypotheses.

4.3.2 Hypotheses

We based the conceptual model for our study on the original VAM. Therefore, we adopted the relationships between the constructs from the original VAM (Kim, Chan, and Gupta 2007) and formulated the following hypotheses accordingly:

H1a. Perceived usefulness positively influences perceived value.
H1b. Enjoyment positively influences perceived value.
H1c. Perceived technicality negatively influences perceived value.
H1d. Perceived fee negatively influences perceived value.
H1e. Perceived value positively influences behavioral adoption intentions.

To integrate the five identified marketing effects in the original VAM, we reviewed findings from the literature. The interviewees mentioned that it is relevant that their company is perceived as innovative because of their TPSs. The literature differentiates mainly between consumer innovativeness, as a trait of consumers, and organizational innovativeness, which represents the internal organization of innovativeness (Hauser, Tellis, and Griffin 2006). Consumer innovativeness, indicating consumers' intention to adopt innovative products, has been studied broadly (e.g., Shahid et al. 2022; Varma Citrin et al. 2000; Yang 2005), and the same applies to organizational innovativeness (e.g., Hult, Hurley, and Knight 2004; Ruvio et al. 2014; Wang and Ahmed 2004). However, studies on the external view of whether organizations and brands are perceived as innovative (i.e., the consumers' perspective) are expandable (Shams, Alpert, and Brown 2015). In the context of voice assistants, in particular, only a small number of studies have examined consumer innovativeness (e.g., Hasan, Shams, and Rahman 2021; Molinillo et al. 2023). Moreover, to the best of our knowledge, no study has examined perceived brand or organizational innovativeness in the context of voice assistants thus far.

To develop an applicable hypothesis for our study, we broadened our view and considered literature about innovativeness from a general perspective. Existing literature focuses on the influence of perceived innovativeness as an independent variable with influence, for example, on brand loyalty (Pappu and Quester 2016) and brand equity (Nørskov, Chrysochou, and Milenkova 2015) or as a moderator on e-word-of-mouth (Ruiz-Alba et al. 2022). However, our study aims to examine the possible impact that the provision of TPSs has on the perception of companies as innovative (i.e., as a dependent variable). Thus, to derive the hypotheses for our study, we draw on the statement of Aaker (2004). She highlights the importance of companies providing value to their customers by being innovative. We adapt this key message to our study by assuming that perceived value leads consumers to perceive companies as innovative, which drives customer value from a long-term perspective. Therefore, we concluded the following for our study:

H2a. Perceived value positively influences brand innovativeness.

The interviewees highlighted the importance of evoking positive brand experiences through TPSs. Engaging interactions with consumers fuel consumer–brand relationships (Kotler et al. 2020). However, the interactions must be relevant, which means that they should provide value to consumers (Edelman Trust Institute 2023, p. 27). To successfully build relationships with consumers, marketers aim to create positive experiences for consumers with their brands (Morgan-Thomas and Veloutsou 2013).
Although the importance of brand experiences is addressed in several studies (e.g., Jeon and Yoo 2021; Jiang, Luk, and Cardinali 2018; Shukla et al. 2021), the construct has scarcely been examined in the context of voice assistants. Therefore, the question remains: how can brand experiences be evoked? Hwang et al.'s (2021) study examined this question for stationary coffee shops with staff, either robots or humans, as a stimulus. The authors revealed that perceived value forms brand experiences. Therefore, we assumed that this is also the case for TPSs. Thus, we concluded that the perceived value of a TPS positively contributes to brand experiences with the brand that developed the TPS. Therefore, we formulated the following hypothesis:

H2b. Perceived value positively influences brand experiences.

Furthermore, the qualitative content analysis of the interviews revealed that companies aim to foster customer satisfaction through their TPSs. In their study, Ilyas et al. (2021) revealed that perceived value fosters customer satisfaction. This finding was confirmed for several research areas, such as e-services (Karimi Rad, Elahi, and Gholami Tazeabad 2014), the restaurant industry (Tarn 1999), and the chemical industry (Samudro et al. 2020). Therefore, we derived the following hypothesis:

H2c. Perceived value positively influences customer satisfaction.

Additionally, the study of Ray et al. (2021) demonstrated a positive influence of brand experiences on customer satisfaction in the context of e-learning platforms. Since TPSs are digital services, like e-learning platforms, we derived the following hypothesis:

H3a. Brand experiences positively influence customer satisfaction.

Loyalty is mentioned in the interviews as another relevant marketing effect of TPSs. Brand loyalty is necessary for building long-term relationships with consumers (Maduretno and Junaedi 2022). According to Oliver (1999), consumer loyalty describes consumers' intention to reuse or repurchase a specific product or service. Therefore, loyalty is key for the long-term survival of brands facing competitive environments.

Since engaging interactions with consumers fuel consumer–brand relationships (Kotler et al. 2020), brand loyalty can be developed by generating regular interactions between brands and consumers (Hasan, Shams, and Rahman 2021). This required regularity of brand experiences may be encouraged through TPSs because of their integration into consumers' daily lives (Poushneh 2021a). This assumption is confirmed through a study that revealed that voice assistants can positively influence brand loyalty (Huh, Kim, and Lee 2023). Therefore, we assumed the following for our study:

H3b. Brand experiences positively influence brand loyalty.

The interviewees also mentioned the desired marketing effect of TPSs influencing the image of their brand or company. Altogether, they described that, in the best case, TPSs will convey brand attributes to influence their reputation or image. Brand attitude encompasses brand attributes and further influences brand image (Faircloth, Capella, and Alford 2001). Therefore, we decided to capture the first level of brand image in our study: brand attitude. To include the construct in the original VAM, we further examined the literature.

The Edelman Trust Barometer report stated that consumers' experiences shape expectations for brand performance (Edelman Trust Institute 2023, p. 25). This assumption is supported in the voice-assistant context through a study that revealed that evoking engaging interactions with consumers through voice assistants (Smith 2020; Tsai, Liu, and Chuan 2021) can positively influence consumers' attitudes toward brands (Kotler et al. 2020). Therefore, we examined possible effects by testing the following hypothesis:

H3c. Brand experiences positively influence attitudes toward brand use.

In addition to the marketing effects mentioned above, the interviewees stressed the relevance of voice assistants as a provider of TPSs. Voice assistants were emphasized, for example, in the following two quotations: "That means the Alexa has to be used [...] because that's just the biggest provider" (I5) as well as "And customers and consumers have become very accustomed to Amazon Alexa, for example" (I6). The influence of the voice assistant Amazon Alexa in the context of usage and perception of TPSs has not yet been examined from a consumer perspective. However, a recent study uncovered the importance of a voice assistant's personalization and authenticity as two relevant criteria for reusing intentions (Alimamy and Kuhail 2023). While Amazon Alexa allows the settings for Alexa Skills to be personalized (Amazon 2023), whether the voice assistant is perceived as authentic remains unclear. Since the personalization criterion is given, for our study, we assumed the overall positive effect of the voice assistant that provides access to TPSs on behavioral adoption intentions. Additionally, an initial study on user interactions with 19 Amazon Alexa users revealed that the experience with the voice assistant is more important than the output of the interaction (Lopatovska et al. 2019). Therefore, we assumed that the voice assistant positively influences perceived value, which we understand as the sum of consumers' positive and negative usage experiences with TPSs. We controlled possible effects through the following hypotheses:

H4a. Attitude toward the voice assistant positively influences perceived value.
H4b. Attitude toward the voice assistant positively influences behavioral adoption intentions.

We summarize the derived hypotheses in Figure 25, which presents the conceptual model for the following empirical investigations.

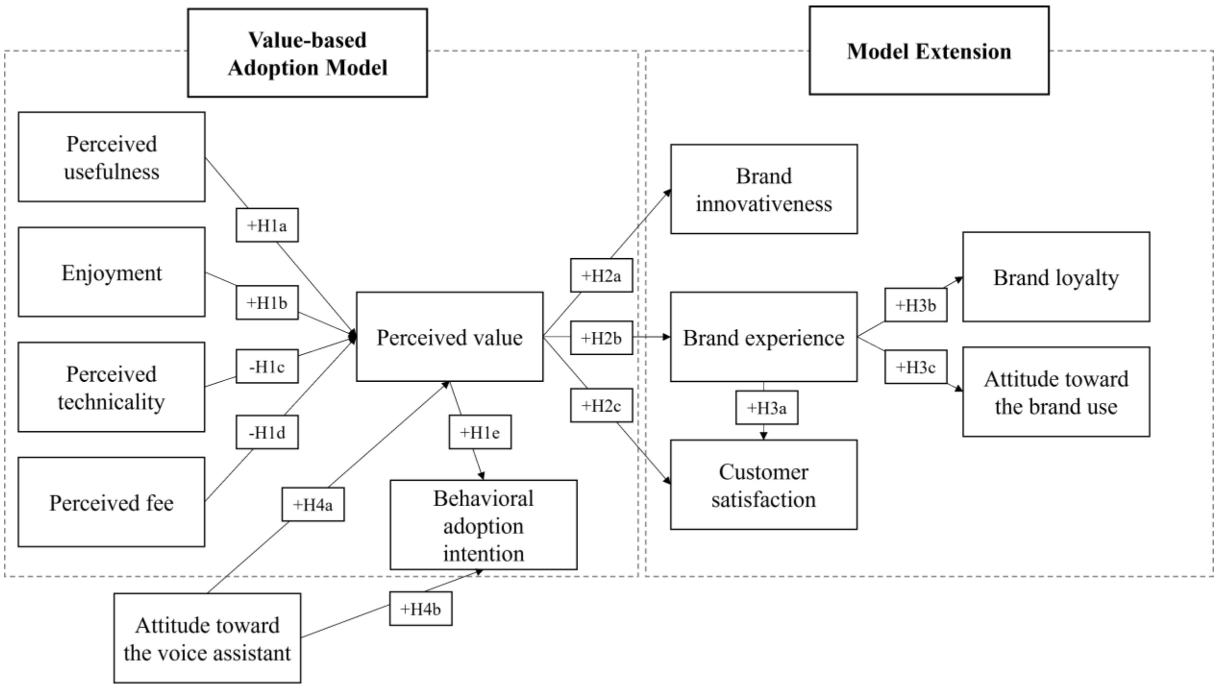


Figure 25. Conceptual model to assess the marketing effects of third-party skills

We assessed the constructs of the conceptual model through scientifically developed scales. We measured the constructs of the original VAM based on the scales of Pal et al. (2020), who adapted the original scales of Kim, Chan, and Gupta (2007) to the context of voice-based technologies. The adapted scales include the constructs "perceived fee," "perceived technicality," and "enjoyment" with three items each; "perceived usefulness" with five items; "perceived value" with four items; and "behavioral adoption intention," which is also usually measured by four items. Because of the TPS context in our study, we excluded the fourth item of "behavioral adoption intention," which is "I intend to buy [TPSs] in the future." The reason for this exclusion is that voice assistants are bought by consumers, but TPSs are only activated on voice assistants, not purchased separately. Therefore, we excluded this specific item and assessed "behavioral adoption intention" through three items.

We investigated possible marketing effects by including the construct “brand experience,” which we measured through the 12-item scale developed by Brakus, Schmitt, and Zarantonello (2009). Additionally, we measured the 4-item construct “brand loyalty” and the 5-item construct “attitude toward the brand use” based on the scales developed by McLean et al. (2020), who adapted the scale for brand loyalty from Zeithaml, Berry, and Parasuraman (1996) and the scale for attitude toward the brand use from Kim, Yoon, and Han (2016). We controlled for possible effects of the voice assistant that provides access to TPSs using the scale “attitude toward the brand use” again (Kim, Yoon, and Han 2016) and adapted the questions to the context of Amazon Alexa. Furthermore, we assessed the constructs “customer satisfaction” (Voss, Parasuraman, and Grewal 1998) and “brand innovativeness” (Eisingerich and Rubera 2010) on 3-item scales. Finally, we measured all items on 7-point Likert scales. A full overview of the constructs and their items is presented in Appendix 4. Additionally, we asked for the gender, family status, and employment situations of the participants through single-choice options and for their age through an open text field.

We executed the study in Germany, which is why we translated all constructs to German using the TRAPD method (Behr, Braun, and Dorer 2015, pp. 7–8). We empirically tested the conceptual model and describe the details in Section 4.4 below.

4.4 Empirical study

We tested the conceptual model by conducting quantitative online surveys. We chose this method because our conceptual model is based on hypotheses that are subject to testing. Therefore, we applied a deductive theory-testing method for which a quantitative method is appropriate (Döring and Bortz 2016). Furthermore, we needed samples that were large enough to conduct statistical analyses to test the conceptual model. As such, we planned to distribute the survey online.

We performed three steps to test the conceptual model. First, we designed the survey structure and executed a stimulus pre-test (described in Section 4.4.1). Second, we conducted two survey pre-tests (see Section 4.4.2.1), which allowed us to uncover required adjustments—if any—in the survey structure. Third, after completing and analyzing the pre-tests, we adapted, where necessary, the survey structure and tested the conceptual model on large sample sizes (presented in the Sections 4.4.2.2 and 4.4.2.3).
The objective of our study was to test the conceptual model’s significance and, therefore, its suitability to capturing marketing effects aroused through TPSs. Thus, we needed to ensure that the survey was designed in a way that would allow us to capture consumer perceptions of TPSs. The process of designing our survey according to these requirements is now described in Section 4.4.1.

4.4.1 Research design

Our study has the objective of assessing the marketing effects aroused by TPSs. Therefore, it was necessary that the survey participants either had previous experience with TPSs or that we ensured they gained those experiences through our survey. We wanted to avoid the risk of narrowing down the number of possible participants too drastically. Therefore, we decided that it was not a prerequisite that participants already had real interactions with TPSs. Nonetheless, to ensure that the participants could realistically evaluate TPSs, we decided to include a stimulus in the survey in the form of an audio recording demonstrating TPSs. The details of this process are described below in Section 4.4.1.1.

4.4.1.1 Developing and testing the stimulus

We integrated a stimulus into the survey in the form of an audio recording. The audio recording demonstrated an interaction between a consumer and the TPS of a company accessed through the voice assistant Amazon Alexa. As such, we ensured that the survey participants had the same TPS in mind, and comparable experiences with it, when responding to the survey questions. We self-recorded three audio files, one for each of the selected ICB industry sectors (i.e., financials, consumer discretionary, consumer staples). Each audio recording was approximately one minute in length. We chose this duration because it was long enough to present the essential aspects of TPS functions without being overly long and therefore risking losing the participants' awareness. Additionally, we adjusted the wakeup-word from "Alexa" to "Echo." Therefore, we reduced the risk that initial biases toward the voice-assistant provider, which in our case was Amazon Alexa, would influence the responses. A written example of the audio recording can be found in Appendix 5.

We ensured that the survey responses were not influenced by the audio recording as a stimulus type by conducting a stimulus pre-test with a convenience sample ($n = 26$). As a stimulus, we used an audio recording of a TPS from a company that belongs to the largest industry sector, namely consumer discretionary. We divided the convenience sample into two groups: One group had a real interaction with the specific TPS through a smart speaker in a user-experience laboratory ($n = 12$), and the other group listened to the audio recording of an interaction between a consumer and the same TPS ($n = 14$). Afterwards, both groups answered the item questions of the original VAM.

We compared and analyzed the responses of both groups by conducting a t-test analysis. As a prerequisite for the t-test, we needed to test whether a normal distribution was given. To do so, we conducted the Shapiro–Wilk test. The results indicated that a normal distribution was given with p-values above 0.05 for all constructs (perceived usefulness: $p = 0.139$, enjoyment: $p =$

0.610, perceived technicality: p = 0.253, perceived value: p = 0.323) except for perceived fee (p = 0.024) and adoption intention (p = 0.002). Since two of the constructs did not fulfill the prerequisite, we tested the possible variance between the responses through the Mann–Whitney U test instead of the t-test. Furthermore, as our sample size was below 30, we reported the exact significance value to validate possible variances. The results of the stimulus pre-test (presented in Table 19) show p-values for all constructs above 0.05. As such, the responses of both groups did not show significant variances. Therefore, we concluded that the responses were not influenced by the audio recording as a stimulus type.

Table 19. Mann–Whitney U-test results for the stimulus pre-test

Construct	**Test group**	**Mean value**	**Standard deviation**	**Mann–Whitney U test result (p-value)**
Adoption intention	Audio stimulus	2.8	1.291	0.374
	Real interaction	2.6	1.918	
Enjoyment	Audio stimulus	3.9	0.701	0.304
	Real interaction	3.7	0.806	
Perceived fee	Audio stimulus	4.4	0.789	0.462
	Real interaction	4.5	0.770	
Perceived technicality	Audio stimulus	2.9	1.153	0.860
	Real interaction	3.3	1.853	
Perceived usefulness	Audio stimulus	2.8	1.200	0.820
	Real interaction	2.9	1.536	
Perceived value	Audio stimulus	4.0	0.953	0.462
	Real interaction	3.5	1.568	

4.4.1.2 Structure of the questionnaire

Based on the successful stimulus pre-test, we further developed the questionnaire structure. At the beginning of the questionnaire, we assessed the participant's familiarity with the company whose TPS we presented later. We then included a brief description of TPSs in general, which ensured that the participants had a common understanding of the research subject. The participants then listened to the audio recording. The way in which we assigned the TPS audio recording to each participant varied in the pre-tests and subsequent studies. Therefore, we describe the specific assignment in the corresponding sections. After listening to the audio recording, the questionnaire continued with questions assessing the constructs' items to test the hypotheses. At the end of the questionnaire, we asked for the participants' demographics and concluded with the option to provide feedback on the questionnaire.

We included two control questions in the questionnaire to ensure data quality. The first question ensured that the participants listened carefully to the entire audio recording and was thus included immediately after presenting the audio recording. This question consisted of asking the participants for a specific detail that was mentioned in the audio recording, which was important because we distributed the survey online. Therefore, it was not possible to observe the participants while they were answering the questions, so we implemented a validation check to ensure that participants listened carefully to the audio recording. We included a second control question at the end of the questionnaire. This question was an attention check and asked participants to mark a specific answer to ensure that participants were still reading the questions carefully. If participants gave an incorrect answer to any of the control questions, the questionnaire ended immediately.

We programmed the questionnaire using the software UNIPARK and tested it through two pre-tests. The pre-tests are presented generally in Section 4.4.2 and more precisely in Section 4.4.2.1.

4.4.2 Data analysis

We examined the conceptual model in two separate parts: first, through pre-tests and second, based on larger sample sizes in cross-culture and cross-industry-sector studies. The main reason for pre-testing the conceptual model in two separate parts was the high number of constructs to assess. We wanted to keep the completion time of the online survey short and therefore ensure high awareness and concentration among the participants throughout its entirety. This helped us gain initial insights about significant effects throughout the conceptual model and generate information about possible required adjustments in the survey. Furthermore, we used the pre-tests to validate the functionality of the survey and the constructs' items.

The focus of the two pre-tests differed. We provide a detailed description of the different pre-test foci in the following section.

4.4.2.1 Pre-tests

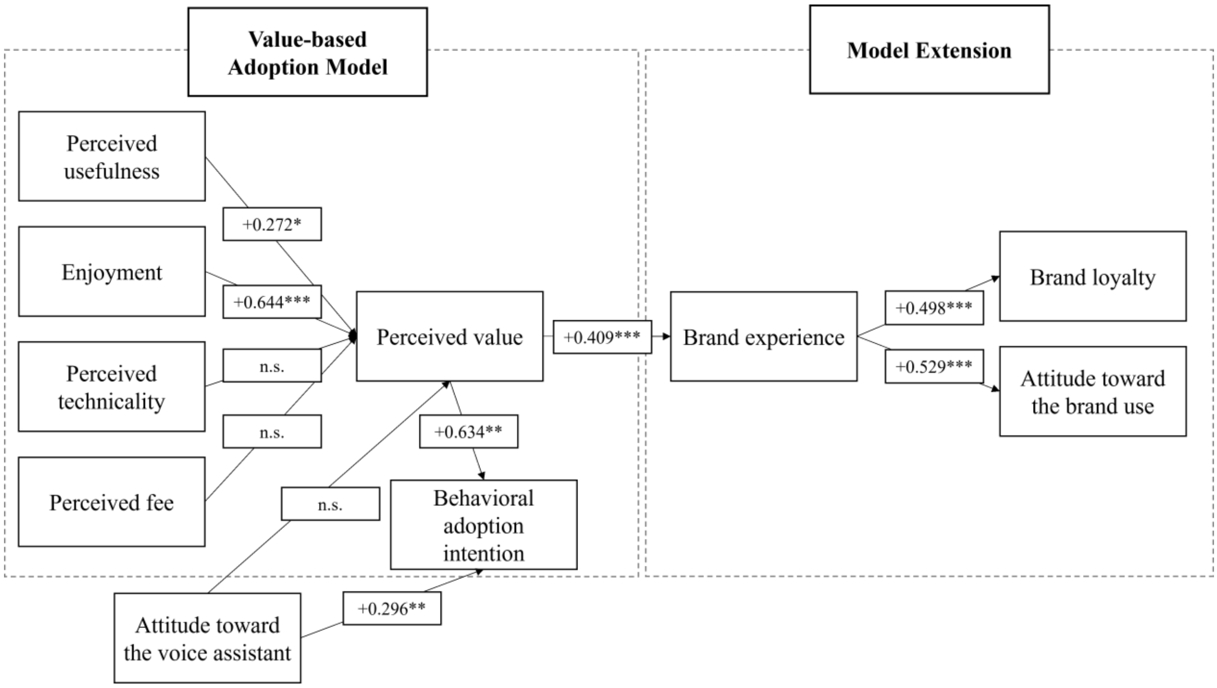
For the pre-tests, we used two different TPS audio recordings of companies from the largest industry sector, namely consumer discretionary (for details, review Figure 23). Through the **pre-test I,** we assessed the integration of the constructs of brand experience, brand loyalty, and attitude toward the brand use in the conceptual model. We also tested possible effects of consumers' attitudes toward the use of the voice assistant at this time. The data collection for pre-test I was based on the snowball principle and generated, after cleaning the data by excluding one participant who was unable to listen to the audio recording, a sample of 62 participants.

We analyzed the data through a confirmatory factor analysis (CFA). We excluded one item of the perceived-fee scale to achieve reliable scales for all constructs through values of >0.7 for Cronbach's α (Streiner 2003): perceived technicality with $\alpha = 0.852$; perceived fee with $\alpha = 0.915$; enjoyment with $\alpha = 0.826$; perceived usefulness with $\alpha = 0.967$; perceived value with $\alpha = 0.892$; adoption intention with $\alpha = 0.989$; brand experience with $\alpha = 0.855$; brand loyalty with $\alpha = 0.951$; attitude toward the brand use with $\alpha = 0.954$; and attitude toward the voice assistant with $\alpha = 0.957$.

Additionally, the exclusion of four items from the brand-experience scale was required to achieve the internal consistency of each construct by ensuring a composite reliability (CR) of >0.6 (Bagozzi and Yi 1988) and an average variance extracted (AVE) of >0.5 (Bagozzi and Yi 1988). This process resulted in an adjusted Cronbach's α of 0.904 for the brand-experience scale. Additionally, we applied the Fornell and Larcker criterion to ensure discriminant validity (Fornell and Larcker 1981).

We calculated the conceptual model using structural equation modeling in IBM SPSS AMOS, which revealed that the effects of perceived technicality ($p = 0.376$), perceived fee ($p = 0.245$), and perceived usefulness ($p = 0.196$) on the perceived value were not significant. Additionally, attitude toward the voice assistant had no significant effect on the perceived value ($p = 0.326$). Therefore, we tested whether adjustments to the model led to improvements. We thus excluded, step by step, the relations with the lowest significance level. First, we deleted the relation between perceived technicality and perceived value, which resulted in a significant effect of perceived usefulness on perceived value. We then removed the relation between perceived fee and perceived value. We kept both constructs (perceived technicality and perceived fee) in the conceptual model to control for covariances across the independent variables of the original VAM (i.e., enjoyment and perceived usefulness).

Eliminating the relation between attitude toward the voice assistant and perceived value resulted in significant effects throughout the conceptual model, but model-fit indices remained insufficient ($\chi2 = 1{,}461.562$, $df = 806$, p-value = 0.000, $\chi^2/df = 1.813$, TLI = 0.773, CFI = 0.787, RMSEA = 0.115). The root-mean-square error of approximation (RMSEA) is supposed to have a threshold of >0.08 (Browne and Cudeck 1992), the Tucker–Lewis index (TLI) a threshold of >0.90 (Bentler and Bonett 1980), and the comparative fit index (CFI) a value of >0.90 (Rigdon 1996). The analysis results are presented in Figure 26.



*Note: * = p < 0.05, ** = p < 0.01, *** p < 0.001, and n.s. = not significant.*

Figure 26. Data-analysis results of pre-test I for the partly tested conceptual model

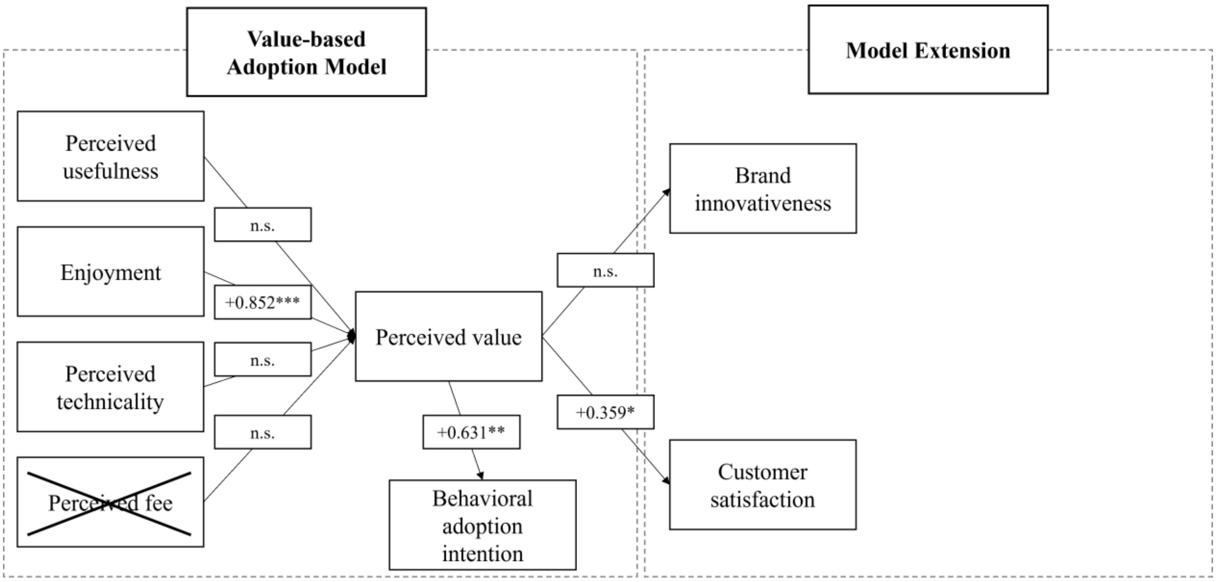
The objective of pre-test I was to assess the functionality of the survey and the constructs' items in the context of TPSs as well as to gain initial insights about significant effects in the conceptual model. Since the sample size was acceptable but still small, and we did not test the full conceptual model, we refrained from precise model-fit indices at this point. We will focus on them in a later section when we test the full conceptual model on large sample sizes. Nevertheless, we can conclude that our pre-test I was successful in confirming the significant effects of perceived value on brand experience, which further positively influences attitudes toward the brand use and brand loyalty. Furthermore, we revealed a positive effect of attitude toward the voice assistant on adoption intention. Altogether, despite improvable model-fit indices, we received promising initial results regarding our conceptual model, especially in terms of the integrated marketing effects. We continued testing the rest of the conceptual model in pre-test II. Therefore, we gained comprehensive insights before examining the full conceptual model with large sample sizes.

In **pre-test II** we focused on the integration of the suggested conceptual model's other constructs, namely brand innovativeness and customer satisfaction. We collected data based on the snowball principle and generated, after excluding one participant due to invalid data, a sample of 56 participants.

Once again, we executed a CFA and tested the reliability of the scales through Cronbach's α (Streiner 2003). We excluded one item of the perceived-fee scale and two items of the brand-innovativeness scale due to Cronbach's α values below the threshold of 0.7. This exclusion resulted in reliable values of Cronbach's α >0.7: perceived usefulness with α = 0.938; enjoyment with α = 0.825; perceived technicality with α = 0.835; perceived fee with α = 0.719; perceived value with α = 0.880; adoption intention with α = 0.952; customer satisfaction with α = 0.864; and brand innovativeness with α = 0.849.

Furthermore, we confirmed the internal consistency of each construct through a CR of >0.6 (Bagozzi and Yi 1988) and an AVE of >0.5 (Bagozzi and Yi 1988). However, the construct perceived fee did not show plausible values (AVE of 19.429 and CR of 9.6). Additionally, we tested the discriminant validity through the Fornell and Larcker criterion.

We then completed structural equation modeling and revealed that the effects of perceived fee, perceived technicality, and perceived usefulness on perceived value were again not significant. The effect of perceived value on brand innovativeness was also not significant. We tested possible model improvements again by removing the insignificant relations step by step, starting with the most insignificant, which was perceived fee on perceived value ($p = 0.974$). However, this time, we deleted the full construct perceived fee from the structural equation model because of its insufficient AVE and CR values. Additionally, we removed the relation between perceived technicality and perceived value ($p = 0.712$) as well as between perceived usefulness and perceived value ($p = 0.280$). We again retained the constructs perceived usefulness and perceived technicality in the statistical calculation, which both had sufficient AVE and CR values, to control the covariances between the independent variables of the original VAM. Furthermore, we kept the borderline relation of perceived value on brand innovativeness ($p = 0.058$), which resulted in a significant model with acceptable model-fit indices ($\chi 2 = 304.965$, df = 223, p-value = 0.050, $\chi^2/df = 1.368$, TLI = 0.910, CFI = 0.920, RMSEA = 0.082). The analysis results of pre-test II are presented in Figure 27.



*Note: * = p < 0.05, ** = p < 0.01, *** p < 0.001, and n.s. = not significant.*

Figure 27. Data-analysis results of pre-test II for the partly tested conceptual model

The objective of pre-test II was to test parts of the conceptual model again. This test confirmed the pre-test I's results of insignificant influences of perceived technicality and perceived fee on perceived value. The results of pre-test II showed that, in contrast to the results of pre-test I, perceived usefulness had no significant influence on perceived value. Furthermore, the effect of perceived value on brand innovativeness was not significant.

We summarize the key findings of both pre-tests to identify required adjustments for the subsequent studies based on large sample sizes. First, the pre-tests revealed promising initial results for the successful extension of the original VAM with marketing effects that are relevant for companies. However, the pre-tests revealed that it is required to exclude the marketing effect of brand innovativeness from the subsequent studies due to an insufficiency of promising analysis results.
Second, we uncovered that the negative influences of perceived technicality and perceived fee on perceived value seem to be irrelevant in the context of TPSs. However, since both constructs are part of the original VAM and play relevant roles regarding the covariances between the independent variables, we justify this assumption in the subsequent studies with larger sample sizes.
Third, we showed that attitude toward the voice assistant is relevant to the adoption intention of TPSs. Therefore, we retain this construct in the subsequent studies to further control this effect.

In Figure 28, we present the adjusted conceptual model, which we test hereafter on large sample sizes. We first investigate the conceptual model in Study 1 across industry sectors to test its robustness for the German B2C market. Subsequently, we examine the conceptual model in Study 2 across countries to reveal possible cultural differences.

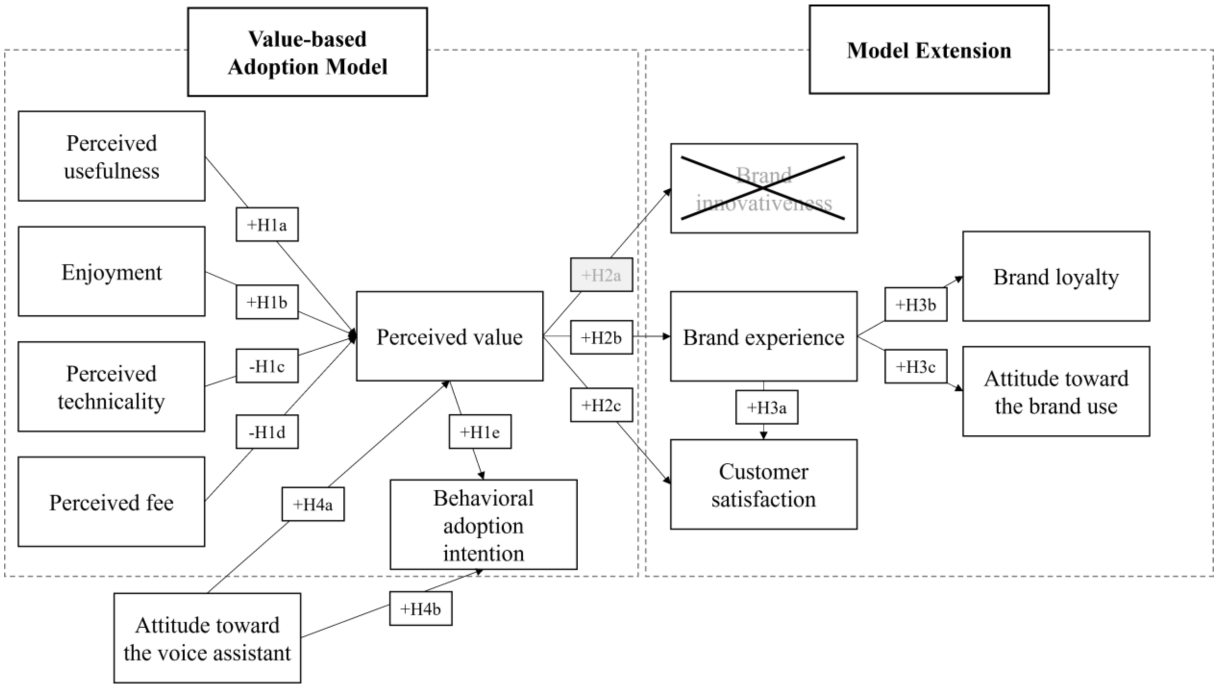


Figure 28. The adjusted conceptual model based on the pre-test analysis results

4.4.2.2 Study 1: Comparison across industry sectors

We tested the conceptual model for most of the German B2C market as derived in Section 4.3.1. To do so, we conducted a quantitative online survey, wherein we included three different audio recordings as stimuli at the beginning of the survey. All audio recordings demonstrated an interaction between a consumer and a company's TPS. The three audio recordings represented the three major industry sectors, namely financials, consumer discretionary, and consumer staples, for which we aimed to test the conceptual model. We randomly assigned the survey participants to one of the audio recordings. Afterwards, all participants responded to the same survey questions. We included two control questions in the survey to ensure high data quality, as described in the research-design section (see Section 4.4.1).

We calculated a survey completion time of 13 minutes. This calculation was based on several times when we completed the survey carefully. We then collected data based on the snowball principle by distributing the survey link through personal contacts, online survey platforms, and student classes. This process resulted in a total sample size of 411 participants who fully completed the survey. We excluded 36 data sets because of a survey completion time that was at least twice as long as our calculation. An overly long completion time held the risk of the participant not comprehensively remembering the audio recording from the beginning of the survey. The risk of insufficient data quality due to an overly short completion time was prevented through the control questions in the survey. Thus, our final sample size consisted of 375 participants, of which 120 were assigned to the TPS audio recording for the financials industry sector, 133 to the consumer-discretionary industry sector, and 122 to the consumer-staples industry sector.

The sample consisted of 59% female and 39% male participants, but 1% indicated diverse as their gender, and 1% avoided a statement. Most participants were between 25 and 34 (46%) or between 18 and 24 (41%). Furthermore, most indicated they were single (84%), a student (65%), and employed (22%). A detailed overview of the descriptive data of the sample is presented in Table 20.

Table 20. Descriptive data of Study 1's sample

Gender	**Absolute**	**Relative**
Male	146	39%
Female	222	59%
Diverse	4	1%
No answer	3	1%
Total	375	100%
Age	**Absolute**	**Relative**
<18	2	1%
18–24	152	41%
25–34	173	46%
35–44	18	5%
45–54	10	3%
>54	15	4%
No answer	5	1%
Total	375	100%
Family status	**Absolute**	**Relative**
Single	313	84%
Married	50	13%
Registered life partnership	4	1%
Divorced	4	1%
Widowed	3	1%
No answer	1	0%
Total	375	100%
Employment situation	**Absolute**	**Relative**
Pupil	4	1%
Student	244	65%
Apprentice	8	2%
Employee	83	22%
Civil servant	11	3%
Self-employed person	14	4%
Retired	5	1%
Others	1	0%
Currently not employed	4	1%
No answer	1	0%
Total	375	100%

We tested the conceptual model across the industry sectors through a CFA and structural equation modeling using the software IBM SPSS AMOS. We first confirmed the reliability of the scales through Cronbach's α (Streiner 2003) for each of the industry sectors separately as well as across them. However, to ensure the internal consistency of each construct through a CR of >0.6 (Bagozzi and Yi 1988) and an AVE of >0.5 (Bagozzi and Yi 1988) in a second step, some adjustments were needed. We removed one item from each of the scales: enjoyment, perceived technicality, perceived fee, perceived value, and customer satisfaction. Furthermore, it was required to eliminate six items from the brand-experience scale. This process resulted in acceptable values for the AVE, CR, and Cronbach's α across the industry sectors (see Table 21) and for each of them individually (see Appendices 6, 7, and 8).

Table 21. Scales' reliability values for the data of Study 1

Construct	AVE	CR	Cronbach's α
Adoption intention	0.898	0.96	0.967
Attitude toward the brand use	0.718	0.93	0.926
Attitude toward the voice assistant	0.863	0.97	0.969
Brand experience	0.491	0.85	0.875
Brand loyalty	0.734	0.92	0.915
Customer satisfaction	0.796	0.89	0.888
Enjoyment	0.875	0.93	0.933
Perceived fee	0.840	0.91	0.902
Perceived technicality	0.749	0.86	0.856
Perceived usefulness	0.855	0.97	0.967
Perceived value	0.733	0.89	0.905

Note: AVE = average variance extracted, CR = composite reliability, and α = alpha.

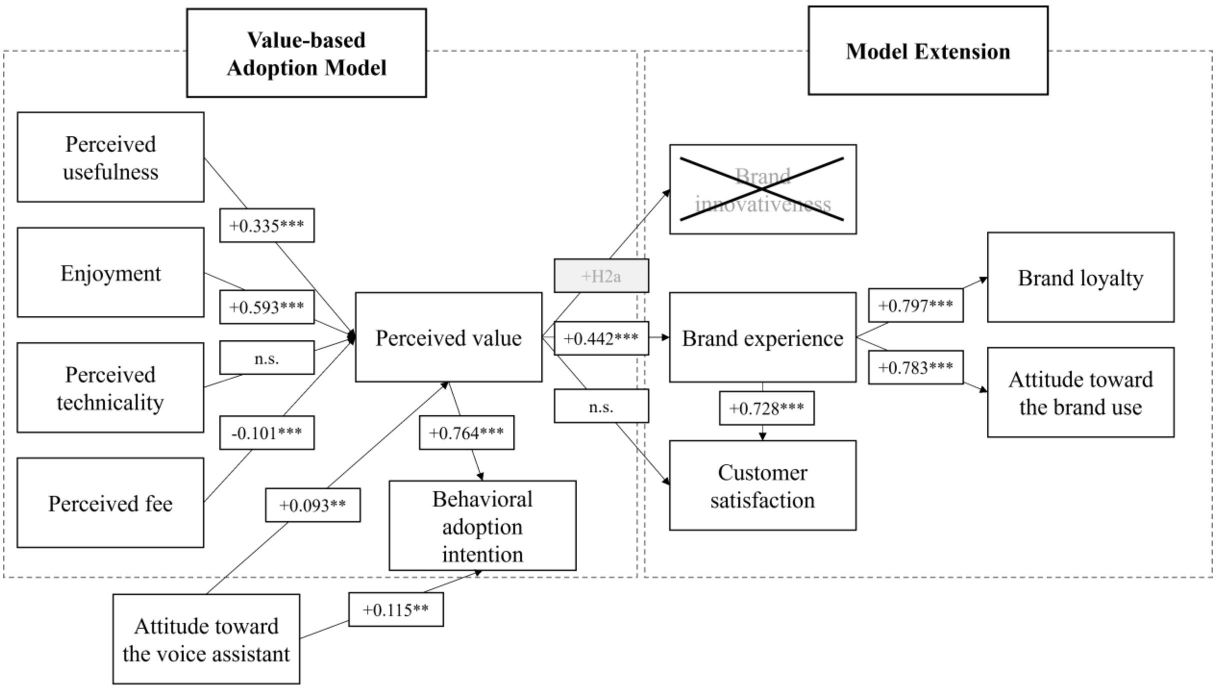
Furthermore, we confirmed the Fornell and Larcker (1981) criterion, which expects that the inter-correlation scores are lower than the AVE score. As displayed in Table 22, all constructs met this criterion. The figures are deconstructed into individual industry sectors and presented in Appendices 9, 10, and 11.

After confirming the reliability within and between the constructs, we can also report sufficient model-fit indices that meet the thresholds ($\chi2$ = 1,990.758, df = 684, p-value = 0.000, χ^2/df = 2.910, TLI = 0.907, CFI = 0.914, RMSEA = 0.071). The results of the structural equation modeling with effect strengths and significant levels are displayed in Figure 29.

Table 22. Inter-item correlation matrix for the data of Study 1

	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.
1. Adoption intention	**0.898**										
2. Perceived value	0.530	**0.733**									
3. Perceived usefulness	0.417	0.549	**0.855**								
4. Enjoyment	0.594	0.616	0.487	**0.875**							
5. Perceived technicality	0.004	0.015	0.003	0.011	**0.749**						
6. Perceived fee	0.033	0.139	0.042	0.077	0.031	**0.840**					
7. Customer satisfaction	0.130	0.075	0.063	0.126	0.000	0.035	**0.796**				
8. Brand experience	0.207	0.123	0.138	0.213	0.044	0.007	0.274	**0.491**			
9. Brand loyalty	0.200	0.086	0.066	0.138	0.002	0.018	0.450	0.375	**0.734**		
10. Attitude toward the brand use	0.180	0.108	0.082	0.165	0.000	0.037	0.558	0.350	0.624	**0.718**	
11. Attitude toward the voice assistant	0.281	0.306	0.276	0.281	0.005	0.038	0.046	0.050	0.027	0.054	**0.863**

Note: The bolded elements are the AVEs.



*Note: * = p < 0.05, ** = p < 0.01, *** p < 0.001, and n.s. = not significant.*

Figure 29. Conceptual-model results of Study 1

Examining the effect strengths distinguished by industry sector (see Appendices 12, 13, and 14), we can confirm significant influences for all of them for the following relations: perceived usefulness and enjoyment on perceived value, attitude toward the voice assistant on adoption intention, perceived value on brand experience, and brand experience on brand loyalty and attitude toward the brand use. Furthermore, we can validate that the influence of perceived technicality on perceived value is not significant for each of the three industry sectors.
However, the influence of perceived value on customer satisfaction is insignificant for the consumer-discretionary and consumer-staples industry sectors, while it is significant for the financials industry sector. Furthermore, we can only observe a significant influence of attitude toward the voice assistant on perceived value for the TPS of the financials industry sector: This effect is not significant for the TPSs of the other industry sectors. While the perceived fee does not significantly influence the perceived value of TPS in the consumer-staples industry sector, this is the case for both other industry sectors.

Additionally, we conducted a MCFGA using IBM SPSS AMOS. This allowed us to identify possible significant differences across the industry sectors, which could reveal industry-specific effects. Based on the MCFGA analysis results (presented in Table 23), we can conclude that the effect strengths of each of the three industry sectors differ significantly compared to the full industry.

Notably, some effect strengths regarding the financials industry sector TPS are striking. First, the effect of enjoyment on perceived value is weaker for the TPS of the financials industry sector than for the TPSs of the other two industry sectors. Second, perceived attitude toward the voice assistant has a strong negative influence on the perceived value of the TPS in the financials industry sector, while the influence is positive for the TPSs in the other two industry sectors. Third, the perceived value of the financials industry sector's TPS plays a crucial positive role in customer satisfaction, which is not the case for the other two industry sectors. Fourth, the positive influence of brand experience on customer satisfaction is weaker for the financials industry sector's TPS than for the other industry sectors.

Beyond the particularities of the financials industry sector, some slight but nonetheless significant differences in the effect strengths across the industry sectors can be observed for the influence of brand experience on brand loyalty. Additionally, slight differences across the industry sectors in the effect of perceived value on customer satisfaction are noticeable. Furthermore, the effect strengths of the influence of perceived value on brand experience vary strongly across the industry sectors.

Table 23. Multi-group confirmatory factor analysis for the data of Study 1

Relation			Full industry (effect strength)	Financials industry sector (effect strength / p-value)	Consumer-discretionary industry sector (effect strength / p-value)	Consumer-staples industry sector (effect strength / p-value)
Perceived usefulness	→	Perceived value	0.335	0.417 (n.s.)	0.324 (n.s.)	0.480 (n.s.)
Enjoyment	→	Perceived value	0.593	0.441*	0.607 (n.s.)	0.508 (n.s.)
Perceived technicality	→	Perceived value	-0.047	-0.018 (n.s.)	-0.016 (n.s.)	-0.026 (n.s.)
Perceived fee	→	Perceived value	-0.101	-0.160 (n.s.)	-0.165 (n.s.)	-0.007 (n.s.)
Perceived value	→	Adoption intention	0.764	0.818 (n.s.)	0.685 (n.s.)	0.804 (n.s.)
Attitude toward the brand use	→	Perceived value	0.093	0.270 (n.s.)	0.156 (n.s.)	-0.035 (n.s.)
Attitude toward the brand use	→	Adoption intention	0.115	-0.142*	0.284 (n.s.)	0.234 (n.s.)
Perceived value	→	Brand experience	0.442	0.573**	0.242**	0.757*
Perceived value	→	Customer satisfaction	0.009	0.370**	-0.029 (n.s.)	-0.023*
Brand experience	→	Customer satisfaction	0.728	0.341**	0.772 (n.s.)	0.728 (n.s.)
Brand experience	→	Brand loyalty	0.797	0.669*	0.881 (n.s.)	0.772*
Brand experience	→	Attitude toward the brand use	0.783	0.671 (n.s.)	0.877 (n.s.)	0.716 (n.s.)

*Note: * = p < 0.05, ** = p < 0.01, *** p < 0.001, and n.s. = not significant.*

To summarize this section, we investigated the conceptual model for the German B2C market for the three largest industry sectors. We illuminated the full market but also each of the industry sectors individually. These analyses uncovered several findings to answer the defined research questions of this study (described in Section 4.1), which we address in detail in Section 4.4.3. However, before comprehensively answering the research questions and summarizing the results of the hypothesis tests, we must first examine the conceptual model in a country comparison between Germany and the United States of America (USA) in Section 4.4.2.3.

4.4.2.3 Study 2: Comparison across countries

The objective of the study at hand was to increase the generalizability of our analysis results. As such, we repeated our survey in the USA. We chose the USA because this country is reported as a key player in the voice-assistant market (Future Market Insights 2022; Matveeva 2019). Additionally, Germany and the USA are economically closely related (Auswärtiges Amt 2023). Therefore, many brands and companies operate across both countries, so a direct comparison could provide interesting information and reveal relevant culturally driven insights.

We once again executed a quantitative online survey with audio recordings as stimuli. In Study 2, our study across countries, we focused on the largest industry sector, which is consumer discretionary (see Figure 23). We initially included two different TPS audio recordings of companies in the consumer-discretionary industry sector. We randomized the allocation of the stimuli to the survey participants and controlled for brand familiarity at the beginning of the survey (1 = not at all familiar; 5 = totally familiar). Therefore, we gained data about the TPSs of brands that were familiar (brand familiarity ≥3) as well as unfamiliar (brand familiarity <3) to the survey participants. As such, we excluded biases in the average response values due to participants' knowledge about and attitude toward brands in the different countries (mean values: brand familiarity$_{(USA)}$ = 3.98 and brand familiarity$_{(Germany)}$ = 3.50).

Furthermore, we included several constructs at the end of the survey to control for possible culturally driven differences in the responses. These constructs included "affinity for technology" measured on an 8-item scale (Franke, Attig, and Wessel 2019), "trust" measured on a 4-item scale (Chaudhuri and Holbrook 2001), "privacy control" measured on a 4-item scale (Esmark Jones et al. 2020), and "long-term orientation" measured on an 8-item scale (Bearden 2006). We assessed the items again through 7-point Likert scales. A full overview of the constructs' items can be found in Appendix 15. The selection of the constructs was based on the cultural country-comparison tool published by Hofstede Insights Oy (2024).[9] The rest of the online-survey structure remained the same.

We distributed the survey link in both countries, Germany and the USA, through snowball sampling. This process resulted in a sample size of 391 participants. We deleted 12 data sets because of an overly long completion time and two data sets because of straightlining. Since the audio recording was at the beginning of the survey, an overly long completion time held the risk of the participant not remembering the audio recording comprehensively. The risk of insufficient data quality due to an overly short completion time was avoided through the control

[9] For our survey the construct "long-term orientation" was derived from Hofstede dimension long-term orientation, the construct "trust" from the dimension indulgence, and the constructs "privacy control" and "affinity for technology" from the dimension uncertainty avoidance. The differences of the dimensions between the countries are presented in the Appendix 16, the definition of the dimensions can be found at Hofstede Insights Oy (2024).

questions in the survey. Altogether, the final sample size was n = 377, of which 188 participants were from the USA and 189 participants were from Germany. A detailed overview of the descriptive data for both sample groups is presented in Table 24.

Table 24. Descriptive data of Study 2's sample

Gender	**Absolute (Germany)**	**Relative**	**Absolute (USA)**	**Relative**
Male	89	47%	88	47%
Female	96	51%	97	52%
Diverse	3	2%	1	1%
No answer	1	1%	2	1%
Total	189	100%	188	100%
Age	**Absolute (Germany)**	**Relative**	**Absolute (USA)**	**Relative**
<18	0	0%	1	1%
18–24	135	71%	178	95%
25–34	50	26%	5	3%
35–44	1	1%	0	0%
45–54	0	0%	4	2%
>54	1	1%	0	0%
No answer	2	1%	0	0%
Total	189	100%	188	100%
Family status	**Absolute (Germany)**	**Relative**	**Absolute (USA)**	**Relative**
Single	181	96%	170	90%
Married	7	4%	12	6%
Registered life partnership	0	0%	1	1%
Divorced	0	0%	3	2%
Widowed	1	1%	1	1%
No answer	0	0%	1	1%
Total	189	100%	188	100%
Employment situation	**Absolute (Germany)**	**Relative**	**Absolute (USA)**	**Relative**
Pupil	0	0%	0	0%
Student	155	82%	162	86%
Apprentice	6	3%	2	1%
Employee	26	14%	15	8%
Civil servant	0	0%	0	0%
Self-employed person	2	1%	2	1%
Retired	0	0%	1	1%
Others	0	0%	2	1%
Currently not employed	0	0%	3	2%
No answer	0	0%	1	1%
Total	189	100%	188	100%

In both countries, 47% of the participants identified as male, while approximately 52% reported to be female. Around 2% declared diversity as their gender or gave no answer. Furthermore, 95% of the participants in the USA were between 18 and 24, while most participants in

Germany were between 18 and 24 (71%) or between 25 and 34 (26%). In both countries, most participants reported being single (Germany: 96%; USA: 90%) and students (Germany: 82%, USA: 86%).

We once again executed the Mann–Whitney U test to validate the comparability of the two country-specific sample groups. The analysis revealed that a significant difference regarding the participant's ages was noticeable ($p < 0.001$). Furthermore, it was striking that the survey participants from both countries were mainly younger, between 18 and 24 years old (especially the participants from the USA). We consider these findings later during the data analysis and interpretation of the analysis results.
To test comparability regarding the gender of the participants, we executed the chi-square test. The p-value of 0.709 indicated that the sample groups did not differ significantly in terms of the participant's gender and were therefore comparable.

Furthermore, we captured possible cultural differences. To do so, we repeated the Mann–Whitney U test with the culturally specific constructs of trust, privacy control, long-term orientation, and affinity for technology. This analysis uncovered that the culturally specific constructs from Germany and the USA differed significantly in all figures (see Table 25). Moreover, the mean values of all constructs were higher for the USA, except for affinity for technology. As such, consumers in the USA have higher trust in voice assistants and a greater sense of privacy control when using them. However, they have a lower affinity for (innovative) technology than Germans. Furthermore, consumers in the USA are more long-term oriented than Germans. We will return to these figures when interpreting the analysis results in Section 4.4.3.

Table 25. Analysis results of the Mann–Whitney U test for Study 2

Variable	Group	Sample size	Mean value	Standard deviation	Mann–Whitney U test result (p-value)
Affinity for technology	Germany	189	4.39	1.14	< 0.001
	USA	188	4.06	0.79	
Long-term orientation	Germany	189	4.65	0.88	< 0.001
	USA	188	5.39	0.95	
Privacy control	Germany	189	3.53	1.27	< 0.001
	USA	188	4.41	1.16	
Trust	Germany	189	3.11	1.27	< 0.001
	USA	188	3.55	1.30	

To test the conceptual model in more detail, we analyzed the data through a CFA and structural equation modeling using IBM SPSS AMOS. First, we confirmed reliable Cronbach's α values for all constructs in both countries. Since all constructs showed reliable values >0.7 (Streiner

2003), we continued the data analysis. We tested the constructs for a CR of >0.6 (Bagozzi and Yi 1988) and an AVE of >0.5 (Bagozzi and Yi 1988). Some adjustments were needed to receive acceptable values. We excluded one item each from the perceived-technicality and perceived-fee scales as well as two items of the brand-experience scale. However, despite these adjustments, the AVEs of the brand-experience scale remained below the threshold. A full overview of the values is displayed below in Table 26.

Table 26. Scales' reliability values for the data of Study 2

Construct	**AVE (Germany / USA)**	**CR (Germany / USA)**	**Cronbach's α (Germany / USA)**
Adoption intention	0.917 / 0.884	0.97 / 0.96	0.974 / 0.958
Attitude toward the brand use	0.781 / 0.817	0.95 / 0.96	0.948 /0.954
Attitude toward the voice assistant	0.858 / 0.864	0.97 / 0.97	0.968 / 0.969
Brand experience	0.315 / 0.301	0.86 / 0.85	0.876 / 0.871
Brand loyalty	0.773 / 0.842	0.93 / 0.96	0.931 / 0.955
Customer satisfaction	0.776 / 0.732	0.91 / 0.89	0.908 / 0.877
Enjoyment	0.671 / 0.604	0.85 / 0.81	0.838 / 0.800
Perceived fee	0.571 / 0.847	0.92 / 0.92	0.916 / 0.918
Perceived technicality	0.515 / 0.636	0.87 / 0.77	0.856 / 0.706
Perceived usefulness	0.775 / 0.859	0.95 / 0.97	0.944 / 0.968
Perceived value	0.572 / 0.671	0.84 / 0.89	0.854 / 0.898

Note: AVE = average variance extracted, CR = composite reliability, and α = alpha.

Furthermore, we tested the Fornell and Larcker (1981) criterion. This analysis showed overall acceptable values. However, it revealed that the brand-experience scale was highly correlated with the scales of brand loyalty and attitude toward the brand use in both countries. Additionally, for the data from the USA, the analysis uncovered a high correlation between the brand-experience and the customer-satisfaction scales. A detailed overview is presented for the data from Germany in Table 27 and for the USA in Table 28.

Table 27. Inter-item correlation matrix for Study 2's data from Germany

	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.
1. Adoption intention	**0.899**										
2. Perceived value	0.585	**0.513**									
3. Perceived usefulness	0.327	0.514	**0.775**								
4. Enjoyment	0.582	0.632	0.349	**0.560**							
5. Perceived technicality	0.046	0.088	0.038	0.047	**0.636**						
6. Perceived fee	0.108	0.168	0.052	0.100	0.042	**0.584**					
7. Customer satisfaction	0.032	0.008	0.011	0.049	0.003	0.070	**0.517**				
8. Brand experience	0.031	0.032	0.018	0.081	0.022	0.037	0.212	**0.169**			
9. Brand loyalty	0.073	0.012	0.021	0.040	0.021	0.045	0.345	0.383	**0.706**		
10. Attitude toward the brand use	0.081	0.019	0.015	0.082	0.000	0.042	0.500	0.307	0.604	**0.722**	
11. Attitude toward the voice assistant	0.500	0.469	0.316	0.452	0.127	0.045	0.033	0.021	0.035	0.066	**0.864**

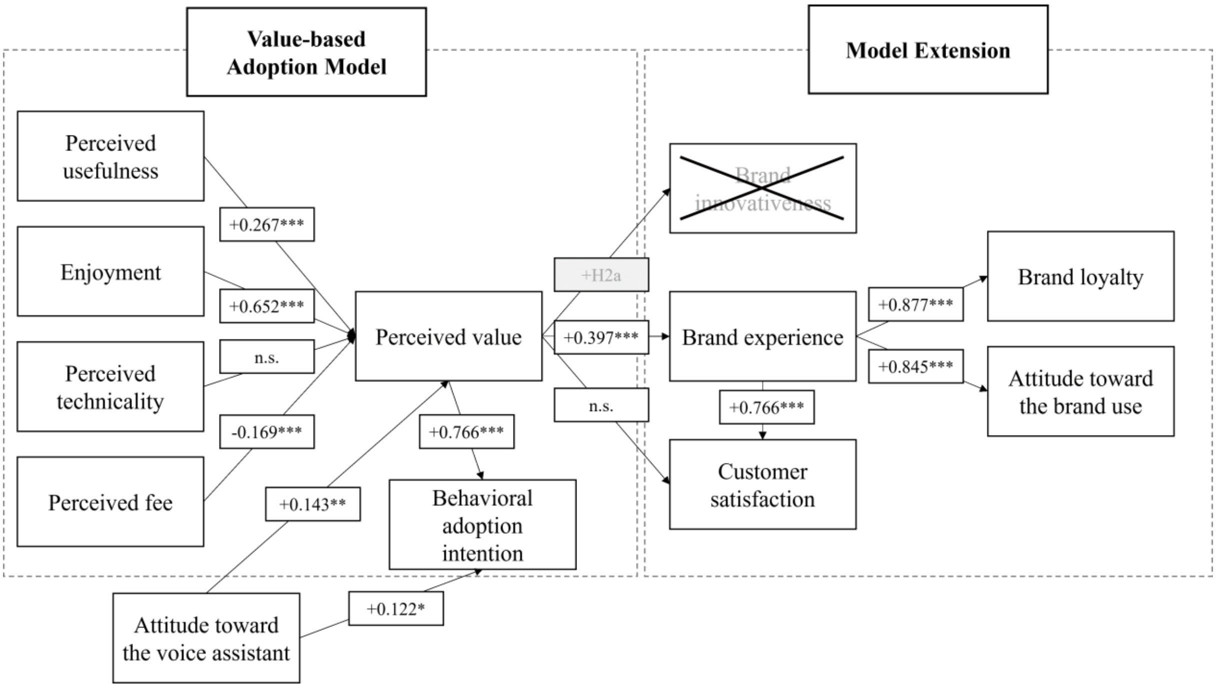
Note: The bolded elements are the AVEs.

Table 28. Inter-item correlation matrix for Study 2's data from the USA

	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.
1. Adoption intention	**0.879**										
2. Perceived value	0.458	**0.739**									
3. Perceived usefulness	0.216	0.336	**0.876**								
4. Enjoyment	0.458	0.514	0.432	**0.748**							
5. Perceived technicality	0.004	0.062	0.004	0.016	**0.500**						
6. Perceived fee	0.042	0.147	0.054	0.078	0.028	**0.843**					
7. Customer satisfaction	0.173	0.106	0.048	0.057	0.004	0.120	**0.895**				
8. Brand experience	0.139	0.118	0.070	0.081	0.014	0.091	0.482	**0.365**			
9. Brand loyalty	0.166	0.076	0.031	0.029	0.003	0.063	0.692	0.472	**0.846**		
10. Attitude toward the brand use	0.127	0.079	0.022	0.037	0.009	0.111	0.721	0.461	0.738	**0.841**	
11. Attitude toward the voice assistant	0.151	0.266	0.261	0.215	0.054	0.063	0.005	0.002	0.000	0.000	**0.887**

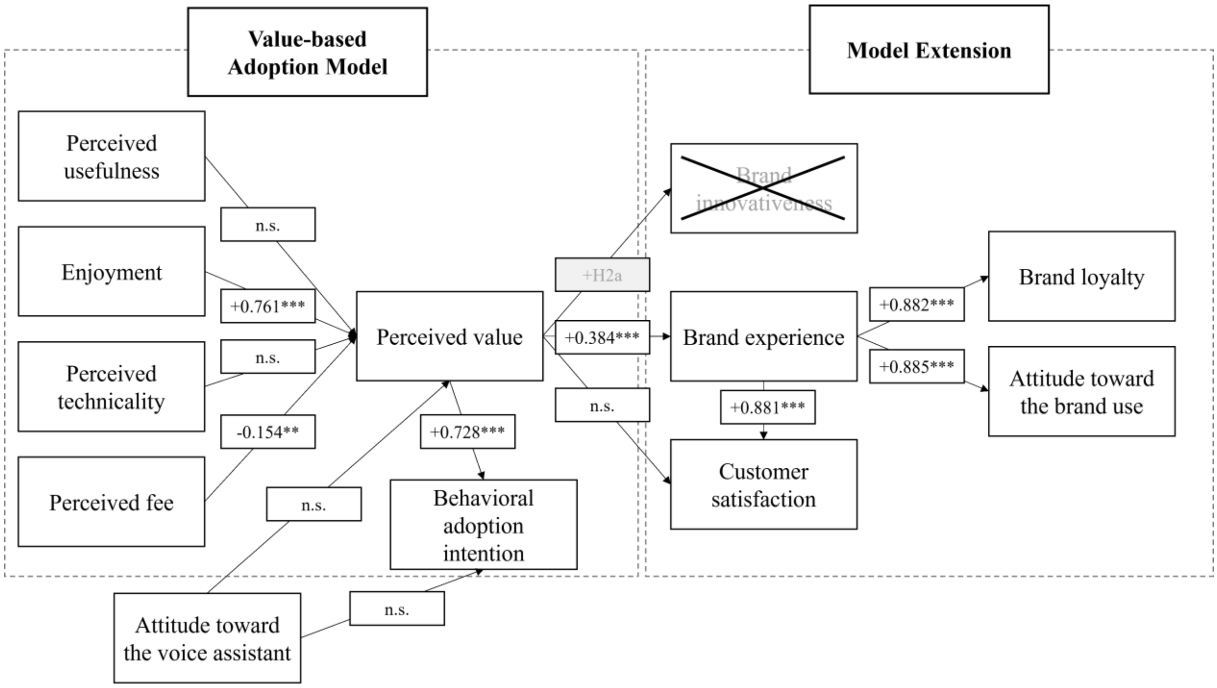
Note: The bolded elements are the AVEs.

After reviewing reliability within and between the constructs, we executed structural equation modeling. We can confirm acceptable model fits for both countries (Germany: $\chi2$ = 1,764.803, df = 971, p-value = 0.000, χ^2/df = 1.818, TLI = 0.897, CFI = 0.904, RMSEA = 0.066; USA: $\chi2$ = 1,829.259, df = 971, p-value = 0.000, χ^2/df = 1.884, TLI = 0.895, CFI = 0.901, RMSEA = 0.069). The results of the structural equation modeling with effect strengths and significant values are displayed in Figure 30 for the data from Germany and in Figure 31 for the data from the USA.



*Note: * = p < 0.05, ** = p < 0.01, *** p < 0.001, and n.s. = not significant.*

Figure 30. Conceptual-model results of Study 2 (Germany)



*Note: * = p < 0.05, ** = p < 0.01, *** p < 0.001, and n.s. = not significant.*

Figure 31. Conceptual-model results of Study 2 (USA)

Furthermore, we executed an MGCFA to identify whether the relations and their effect strengths throughout the conceptual model differ significantly between the countries. The results are presented in Table 29. The analysis revealed that three relations throughout the conceptual model differ significantly across the countries: perceived usefulness on perceived value ($p = 0.006$), enjoyment on perceived value ($p = 0.045$), and brand experience on customer satisfaction ($p = 0.003$). The influence of perceived usefulness on perceived value is significant for TPSs in Germany, but this is not the case for the USA. The two other relationships are both significant and show higher effect strengths for the TPSs in the USA than in Germany. Furthermore, the different significance levels of the relations of attitude toward the voice assistant on perceived value and adoption intention are striking.

Table 29. Multi-group confirmatory factor analysis for the data of Study 2

Relation		**Germany: effect-strength (p-value)**	**USA: effect-strength (p-value)**	**p-value for the effect-strength difference**
Perceived usefulness	→ Perceived value	+0.267***	+0.018 (n.s.)	0.006
Enjoyment	→ Perceived value	+0.652***	+0.761***	0.045
Perceived technicality	→ Perceived value	-0.027 (n.s.)	-0.090 (n.s.)	0.131
Perceived fee	→ Perceived value	-0.169***	-0.154**	0.881
Attitude toward the voice assistant	→ Perceived value	+0.143**	+0.066 (n.s.)	0.367
Attitude toward the voice assistant	→ Adoption intention	+0.122*	+0.011 (n.s.)	0.232
Perceived value	→ Adoption intention	+0.766***	+0.728***	0.467
Perceived value	→ Brand experience	+0.397***	+0.384***	0.447
Perceived value	→ Customer satisfaction	-0.058 (n.s.)	0.009 (n.s.)	0.394
Brand experience	→ Customer satisfaction	+0.766***	+0.881***	0.003
Brand experience	→ Attitude toward the brand use	+0.845***	+0.882***	0.167
Brand experience	→ Brand loyalty	+0.877***	+0.885***	0.093

*Note: * = p < 0.05, ** = p < 0.01, *** p < 0.001, and n.s. = not significant.*

To identify possible reasons for these differences, we tested whether the culturally specific constructs moderated the relations that differed significantly. Thus, we included the constructs as moderators in the conceptual model.
For the data from the German sample group, the analysis showed that the relation between enjoyment and perceived value is moderated through all culturally specific constructs. The relationship between perceived usefulness and perceived value is influenced by trust, affinity for technology, and privacy control but not long-term orientation. The relationship between brand experience and customer satisfaction is only moderated by trust and long-term orientation.
For the data of the sample group from the USA, the analysis revealed that all constructs moderate the relations between perceived usefulness and enjoyment and perceived value. However, the relationship between brand experience and customer satisfaction is only moderated by affinity for technology and long-term orientation.

Since the influence of perceived usefulness on perceived value is not significant in the USA sample, we refrain from further interpretations of the moderation effect. The influence of enjoyment on perceived value and brand experience on customer satisfaction both have higher effect strengths in the USA sample group than in the German sample group. We assume that the significantly higher values in the USA sample group for trust, long-term orientation, and privacy control result in the stronger effect of enjoyment on perceived value. Furthermore, the influence of brand experience on customer satisfaction is moderated in the German sample group through trust and long-term orientation. We can explain the significant difference in the relationship between the countries because both moderators show significantly higher values in the USA sample group.

Overall, we conclude that the different effect strengths can be explained by the fact that the relations that differ significantly are moderated through culturally specific constructs that also vary markedly between the countries (see Table 25). However, only three out of the total 12 relations differ significantly. Therefore, although some culturally driven differences exist, most of the conceptual model and effect strengths are comparable between the two countries.

To summarize, we presented the data analyses to test the conceptual model across the industry sectors in Section 4.4.2.2, and we tested the conceptual model across Germany and the USA in this section. We summarize and interpret the key analysis results below in Section 4.4.3.

4.4.3 Summary of the research results

As we analyzed several issues in the previous sections in detail, we present and interpret the key analysis results in this section in a structured manner. To do so, we present the results alongside the research questions and by referring to the conceptual model (presented in Figure 32).

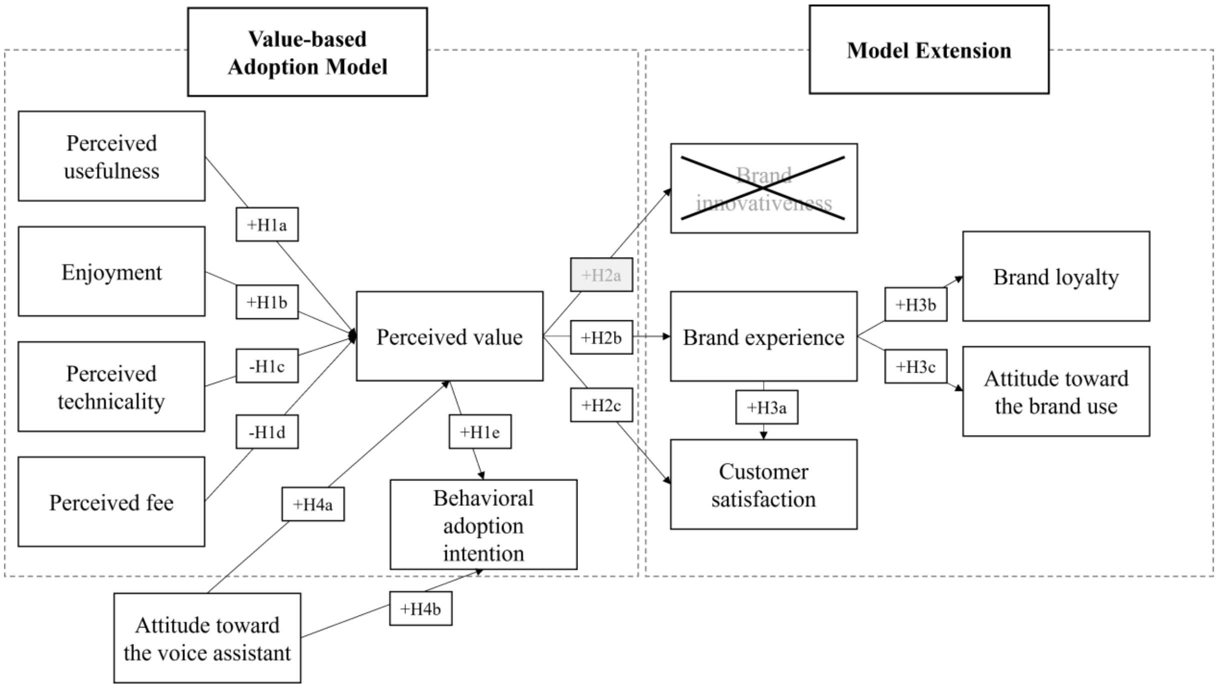


Figure 32. Conceptual model assessing marketing effects of third-party skills

RQ 1. What are the drivers of the adoption intention of third-party skills (TPSs)?

To reveal the drivers of adoption intention for TPSs, we illuminate several models and frameworks applied in technology-adoption studies. Through a well-founded review, we concluded that the VAM was the most suitable model for our study to investigate TPSs. Thus, from a theoretical perspective, the drivers for the adoption intention of TPSs are that consumers enjoy the interactions and perceive them as useful. However, negative influences in the form of perceived technicality and consumers' fees must also be considered. The influences are mediated by consumers' perceptions of value regarding TPSs. We empirically tested the drivers for TPS adoption intention by formulating hypotheses H1a, H1b, H1c, H1d, and H1e through online surveys.

Analyses of the data collected through the online surveys confirm H1b and H1e independently from the industry sector and country. Furthermore, we reject H1c because of insignificant relations for all industry sectors across Germany and the USA. While H1a can be confirmed for the context of TPSs in Germany across all industry sectors, we reject it for the USA. Furthermore, H1d can be confirmed in general for both countries, but not specifically for the German consumer-staples industry sector. Thus, the results of the two pre-tests, which reported that H1d is not significant, are refuted through the online surveys based on large sample sizes.

In sum, when brands or companies develop TPSs, it is crucial to ensure that consumers enjoy the interaction. Since the perceived technicality in both countries has no significant indirect influence on the adoption intention, brands can assume that consumers know how to activate and interact with TPSs. While it is important that German consumers perceive the interaction with TPSs as useful, it is not relevant for consumers in the USA. Furthermore, the perceived fee is not important for TPSs in the German consumer-staples industry sector.

RQ 2. Which marketing effects do companies pursue with the development of TPSs?

We interviewed marketing experts from companies in the largest industry sectors across the German B2C market. This allowed us to gain insights about which marketing effects companies pursue through TPSs. The qualitative content analysis of the interview transcripts revealed that companies strive to positively affect brand experience, loyalty, and customer satisfaction through TPSs. Furthermore, companies aim to improve their image and be perceived as innovative. A comparison of these marketing effects with previous studies that have drawn on the VAM highlights the existing research gap that we address with our study. Although previous studies have investigated individual variables such as loyalty and satisfaction (see Section 4.2.2), most of the marketing effects mentioned by marketing practitioners have not been investigated thus far, affirming a relevant gap in the literature that we address in our study.

RQ 3. Which marketing effects do TPSs arouse?

We included the determined marketing effects from RQ 2 in the VAM, which served as the basis for our investigations, to develop a conceptual model for our study. To do so, we derived hypotheses from the literature, resulting in H2a, H2b, H2c, H3a, H3b, H3c, H4a, and H4b. We tested the conceptual model through quantitative online surveys to investigate which marketing effects companies can influence through the development of TPSs. Below, we summarize which of the hypotheses can be confirmed or rejected.
First, we reject H2a because of the pre-test II, as it revealed that the assumed relation in the conceptual model is not significant. We tested the other hypotheses across the three largest German industry sectors and the two countries, Germany and the USA. The analyses confirmed H2b, H3a, H3b, and H3c independently of the industry sector and country. H2c is mostly insignificant and therefore rejected, except for the German financials industry sector. H4a and H4b depend on the industry sector and the country: While the voice assistant that provides access to the TPSs plays no crucial role in the USA (therefore we reject H4a and H4b), it has a relevant role in Germany. However, this effect depends on industry sector in Germany. While both hypotheses are significant with negative influences (instead of the assumed positive influences) for TPSs from the financials industry sector, the influences are positive for TPSs from the consumer-discretionary industry sector. Thus, we accept H4a and H4b for the consumer-discretionary industry sector and reject them for the financials industry sector. Furthermore, only H4b can be accepted in the consumer-staples industry sector, while H4a is

not significant and therefore must be rejected. We visualize the analysis results of the hypothesis tests in Table 30.

Table 30. Overview of the hypothesis test results

Hypothesis	Consumer-discretionary industry sector	Consumer-staples industry sector	Financials industry sector	Germany	USA
H1a	accepted	accepted	accepted	accepted	rejected
H1b	accepted	accepted	accepted	accepted	accepted
H1c	rejected	rejected	rejected	rejected	rejected
H1d	accepted	rejected	accepted	accepted	accepted
H1e	accepted	accepted	accepted	accepted	accepted
H2a	rejected	rejected	rejected	rejected	rejected
H2b	accepted	accepted	accepted	accepted	accepted
H2c	rejected	rejected	accepted	rejected	rejected
H3a	accepted	accepted	accepted	accepted	accepted
H3b	accepted	accepted	accepted	accepted	accepted
H3c	accepted	accepted	accepted	accepted	accepted
H4a	accepted	rejected	rejected	accepted	rejected
H4b	accepted	accepted	rejected	accepted	rejected

Overall, we successfully extended the value-based adoption model (VAM) by incorporating marketing effects, as shown in Figure 33. We now introduce this updates model as the value-based adoption and marketing effects model, abbreviated VAMEM. Some industry- and sector-specific effects of the VAMEM should be considered when the VAMEM is applied. We note them by dotting the relation between perceived value and customer satisfaction and leaving the plus/minus indication for the influence of the attitude toward the voice assistant in brackets.

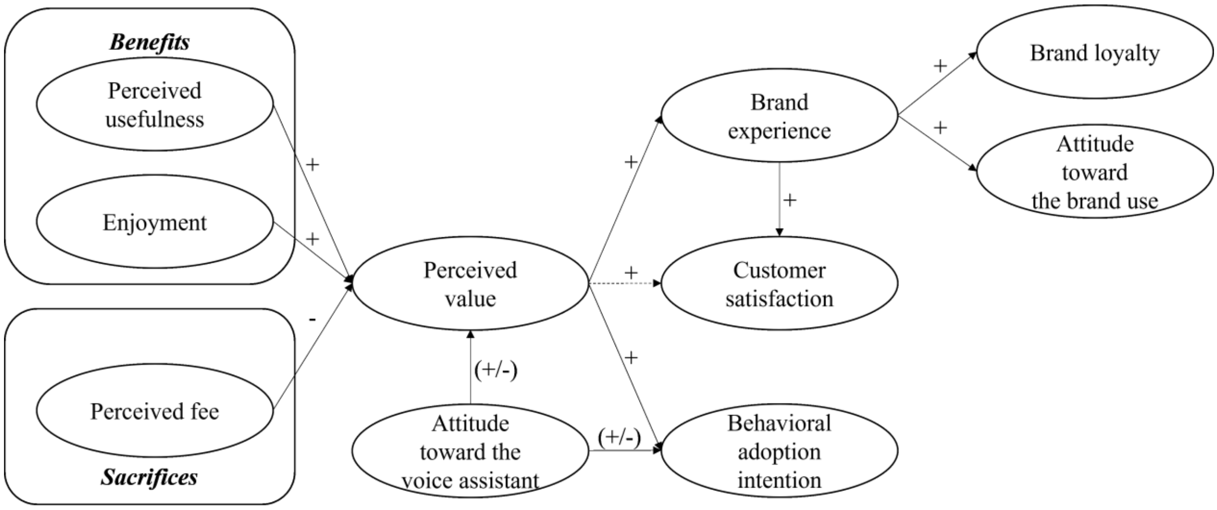


Figure 33. The value-based adoption and marketing effects model (VAMEM)

To summarize the research results, our study showed that companies can influence several marketing effects through TPSs. Independent of industry sector and country, is it possible to positively influence brand experiences as well as improve brand loyalty and attitudes toward brands. Companies can also increase customer satisfaction with brands through their TPSs. Furthermore, existing and popular voice assistants, such as Amazon Alexa, can be used for the development and distribution of TPSs since they have no influence (in the USA) or a positive influence (in Germany) on the TPSs' adoption intention. Furthermore, we can conclude that perceived technicality plays no significant role in TPS usage.

However, it should be noted that when the VAMEM is applied to one specific industry sector or country, there may be differences in the relevant benefits and sacrifices. For example, the perceived usefulness of TPSs is country specific: it plays a relevant role in Germany but not in the USA, at least not for the consumer-discretionary industry sector, which we examined in detail in our study. Thus, validation of the robustness of the study results requires further industry- and sector-specific investigations in the USA.

Furthermore, for TPSs from companies in the consumer-staples industry sector in Germany, the perceived fee is not significant and therefore not important to consumers. We assume that products in this industry sector are inexpensive, so the perceived fee in relation to the positive effects is not consequential to consumers.

Additionally, there are two striking differences when the VAMEM is applied to the financials industry sector in Germany. First, making the TPSs accessible through popular voice assistants that do not belong to the financial company has a negative influence on adoption intentions. This effect is contrary to the results for the other industry sectors. Furthermore, the perceived value of TPSs in the financials industry sector has a significant direct positive effect on customer satisfaction, and this effect is not significant for the other industry sectors.

Our study results are discussed further in Section 4.5. We also present the theoretical contributions of our study as well as implications for marketing practitioners.

4.5 Discussion

The relevance of TPSs is not entirely new. Many DAX30 companies have already developed TPSs, including the sports company Adidas, the insurance company Allianz, and medical companies such as Bayer and Beiersdorf (Schaad 2021, pp. 9–10). However, the contribution of TPSs to desired marketing achievements has remained unclear. Therefore, we addressed this need in our study and developed a model that makes it possible to capture the potential influences of TPSs on marketing effects: the VAMEM. This work presents several contributions for academic researchers as well as implications for marketing practitioners, which are highlighted below in Sections 4.5.1 and 4.5.2.

4.5.1 Theoretical contributions

Our study contributes to the theory in several ways. Most importantly, we developed a model that captures the marketing effects of TPSs and is robust across industry sectors. Moreover, the model can be used not only for the German market but also in other countries with high voice-assistant-usage rates, such as the USA.

Nonetheless, we highlight the importance of considering possible influencing factors on the VAMEM. We found that country- and culture-specific characteristics are critical to TPS investigations and therefore should be controlled when the VAMEM is applied across countries. We revealed that consumers from the USA are relatively long-term-oriented, trust more in voice assistants, and have higher sense of privacy control when interacting with them, but they are less affined to (innovative) voice technology than German consumers. Thus, affinity for technology, perceived privacy, trust, and long-term orientations are constructs that play a relevant role in the adoption of TPSs in these countries. Since the constructs can significantly influence specific relations throughout the VAMEM, we recommend identifying and assessing culturally specific constructs for investigations of TPSs across countries.

Additionally, our work notes effects in the VAMEM that are industry- and sector-specific. For Germany, the financials industry sector is a striking example. We found that German consumers evaluate some constructs of the VAMEM differently, which is the case for the financials industry sector in particular but may also be possible for other countries because of culturally driven characteristics. However, since we did not test TPSs of the financials industry sector across countries, we refuse to derive specific implications for countries other than Germany. Regarding Germany, German consumers' trust in the financials industry sector is low, with only 25% saying they somewhat or highly trust the banking and insurance sectors (Temporale and Maas 2023, p. 5). Therefore, these consumers may be reserved about sharing financial-related information with voice assistants such as Amazon Alexa. This reservation could explain the negative influences of attitude toward voice assistants on perceived value and adoption intention of TPSs in this industry sector. Moreover, our work shows that the perceived value of TPSs in the financials industry sector has a high significant influence on customer satisfaction. Furthermore, German users expect high value from the TPSs of the financials industry to use them. When that prerequisite is given, there is a strong positive influence on customer satisfaction. Thus, we recommend researchers consider possible connections when investigating TPS issues.

The two previous paragraphs highlight that individuals' characteristics can be crucial for TPS investigations. This is consistent with a study by Liu et al. (2023) about our central construct, perceived value. The authors reported that the perceived value of voice assistants depends on users' psychological factors. Based on our findings described above, we recommend controlling psychological factors as possible influencing factors in the future.

Furthermore, in our study, we comprehensively applied and tested the brand-experience scale of Brakus, Schmitt, and Zarantonello (2009). However, adjustments were always required. Thus, we conclude that the established scale is not fully adequate for TPS investigations. Therefore, we support the call of Konttinen, Karjaluoto, and Shaikh (2021) to develop a brand-experience scale that is suitable for the context of studies that address digital applications like TPSs.

Academic researchers should not limit their research to theoretical contributions. It is also important to identify relevant findings that support marketing practitioners. Therefore, the following section presents the implications we derive from our study for marketing practitioners.

4.5.2 Managerial implications

Our work contributes to the successful implementation of TPSs in practice. Most importantly, our work provides the VAMEM model, which marketing practitioners can use to capture the marketing effects that their TPSs arouse. These practitioners can therefore measure whether the costs and resources used to develop their TPSs are balanced against the effects. Moreover, the study results confirm the positive influences of TPSs on marketing effects, which may encourage marketing practitioners to develop TPSs. We also provide several findings that will help marketing practitioners determine what to consider for TPS development and implementation, which are now described.

Companies must be aware of cultural differences. Understanding the cultures and individual characteristics of people helps to focus on the correct features when developing TPSs. This knowledge is especially crucial when companies operate internationally. For example, while consumers in Germany pay attention to the usefulness of TPSs, consumers in the USA do not. However, when consumers in the USA enjoy interactions with TPSs, there is a stronger positive influence on perceived value than for consumers in Germany. Therefore, companies should not launch the same TPS across countries without analyzing possible country-specific influences and considering these influences during the development of their TPSs.

Additionally, our study highlights the relevance of industry sector for TPS development. When companies belong to the financials industry sector, they should avoid using popular voice assistants to make their TPSs accessible to consumers due to the negative influence of attitudes toward voice assistants. These attitudes not only negatively influence the perceived value of the TPSs but also intention to use them. Furthermore, the enjoyment factor plays a less important role for TPSs of companies in the financials industry sector. Customer satisfaction with the company is also influenced more by the perceived value of the TPSs than by the brand experience with them. By considering these findings, companies in the financials industry sector can improve the success of their TPSs.

Moreover, our study shows that companies from different industry sectors use TPSs to contribute to comparable marketing effects. Therefore, companies can also benefit and learn from best-practice examples that are not from their specific industry sector. Doing so may allow them to improve their provided TPSs, which could potentially increase overall consumer experiences with TPSs. From a long-term perspective, improved consumer experiences can result in a higher number of TPS users and, therefore, an increased potential for TPSs as marketing touchpoints.

Last, we show marketing practitioners that consumers generally know how to activate and use TPSs. We derive this implication from the analysis result that perceived technicality was removed from the VAMEM. Therefore, our work encourages companies to develop TPSs because the technical foundation on which users can use them is established.

Although our study has several implications for marketing practitioners, it is not free of limitations. Furthermore, some future research is required to validate our study findings. Therefore, we present the limitations of our study and future research directions in the following section.

4.5.3 Limitations and directions of future research

Despite its valuable contributions to theory and practice, our work is not free of limitations. Additionally, we identified some interesting research streams that we recommend addressing in future studies.

First, we derived the constructs for capturing cultural differences from Hofstede Insights Oy (2024). However, these may not be the only significant culturally specific constructs that distinguish German users from those in the USA. We also did not include all dimensions from Hofstede Insights Oy (2024). Moreover, the selected constructs represent specific cultural differences between Germany and the USA. Thus, a generalized applicability of the constructs to other country-comparison studies is not recommended. It is rather recommended to define the characteristics individually for each country. Therefore, future studies about TPSs in different countries conducted together with cultural scientists could create further interesting insights. It may even be possible to develop a set of universal criteria that are applicable across countries.

Second, we successfully developed the VAMEM with significant effects throughout the conceptual model. However, our study revealed that several adjustments were needed for the brand-experience scale as one of the central constructs in the VAMEM. Furthermore, in Study 2, the construct's AVE did not reach the threshold, perhaps because of the selected industry sector. However, as the field of voice interaction emerges and future studies are in demand, we recommend addressing the need of developing a voice-specific brand-experience scale.

Third, we confirmed the VAMEM's significance. However, further extensions of the VAMEM could increase the model's value. For example, we did not control the perceived warmth and competence of the TPSs. However, both constructs could influence perceived value (Kolbl et al. 2020). Furthermore, since we removed perceived technicality as an independent sacrifice variable of the VAMEM because of its insignificant influence on the perceived value, a replacement could be required. For instance, privacy concerns and security issues play crucial roles in voice technologies and could therefore be relevant influencing factors (Tuzovic 2022). Additionally, the adoption of smart speakers is strongly impacted by constructs that are platform related, such as perceived service availability (Park et al. 2018). Therefore, the VAMEM could be validated in more detail against this finding. Moreover, when voice-assistant usage further increases, voice assistants as possible daily used technologies could trigger techno-stress (Kumar et al. 2022). Further inspiration can be derived from the overview of Kamoonpuri and Sengar (2023, p. 2) about consumer-related barriers to adopting voice assistants.

Fourth, the research design of our quantitative online surveys could have influenced the analysis results. All the participants of our samples were relatively young in age. Therefore, it is possible that they are used to innovative technologies, which could explain why perceived technicality does not play a significant role. However, when companies develop TPSs for older people, for example, to provide medical assistance, the relevance of perceived technicality should be re-evaluated. Furthermore, we used a female consumer voice for the audio recordings as stimuli, which could have influenced the user responses. Although the study of Cowell and Stanney (2003) reported that no gender is preferred for embodied conversational agents, Romero et al. (2021) showed contrary results for smart speakers. Therefore, comparing the results with a male consumer voice is recommended. Moreover, our research design was focused on the B2C context. However, as voice interaction emerges, the implementation of voice interactions in the B2B context could follow. Therefore, we encourage researchers to consider the development of a B2B-specific VAMEM in the future.

As an outlook for future research directions, we encourage researchers to investigate the effects of TPSs on consumer–brand relationships in long-term studies. Because of the possible daily interaction between consumers and TPSs, it may be possible to observe the mere-exposure effect, which describes an increasing positive evaluation of stimuli as exposure increases (Zajonc 2001).
Additionally, in the interviews conducted in this study, the experts highlighted the importance of multimodality (I8), which does not concern voice alone, although voice is or will be the first preference. Therefore, it could be interesting to investigate the impact of voice marketing and TPSs in the context of the whole marketing mix. To do so, studies could build on Mari and Algesheimer's (2021) research, which addresses the voice-marketing and commerce communication-mix strategy.

4.6 Conclusion

Voice interaction is growing and becoming an increasingly important part of consumers' daily lives. Such interaction is therefore an interesting brand touchpoint that is currently being evaluated in practice. A relevant touchpoint in this context is TPSs, which are voice-assistant applications developed by companies or brands that are usually accessible through well-known voice assistants, such as Amazon Alexa. However, there has been a lack of suitable models to evaluate the resources spent on developing TPSs.

Therefore, in the study presented in Chapter 4, we addressed the need to develop a model that marketing practitioners can use to assess the marketing effects aroused through TPSs. To do so, we comprehensively analyzed the literature and identified the VAM as a suitable basis. We then interviewed experts from the marketing practice to reveal which marketing effects they pursue through TPSs. Accordingly, we extended the original VAM to account for the mentioned effects by drawing on findings from the literature.

We tested the developed model extensively across the three largest B2C industry sectors in Germany using quantitative online surveys. Additionally, we tested the model's robustness across Germany and the USA, countries with high voice-assistant-usage rates. Our analysis results showed that our newly developed model, the value-based adoption and marketing effects model (abbreviated VAMEM), is significant and can be used in practice to measure the performance of TPSs and their influence on specific marketing effects. With the VAMEM, we show that companies can positively arouse marketing effects such as brand experience, brand loyalty, customer satisfaction, and brand attitudes through their TPSs.

Although our work is not free of limitations, the study results make a valuable theoretical contribution and offer helpful implications for marketing practitioners. The need for future research, described throughout this chapter, may encourage researchers to advance our work and further refine the findings.

In the next chapter, Chapter 5, this dissertation concludes with a summary of the key findings and implications. Furthermore, future research directions from a meta perspective as well as an outlook for the topic of voice marketing are presented.

5. Summary and outlook

Despite the increasing importance of voice marketing for both marketing practitioners and academic researchers, only a few investigations into voice-marketing issues exist. To improve the state of knowledge, we conducted empirical research on the area of voice marketing, as presented in Chapters 2, 3, and 4. Here, in Chapter 5, the key findings are summarized. Furthermore, in Chapter 5 are the studies' theoretical contributions and managerial implications described. Additionally, the limitations of this dissertation are acknowledged, and future research directions are suggested. Finally, this chapter concludes with an exploration of the future of the voice-marketing field. First, the following section provides the research summary.

5.1 Research summary

Chapters 2, 3, and 4 present studies that investigate specific voice-marketing issues and extend knowledge on relevant research objectives. Below, the research approaches are outlined, and the key findings of each study are summarized.

The overall research objective of the study presented in Chapter 2 was to expand the voice-marketing research field, which is still in its infancy, by addressing the following two research questions: Which dimensions does the research field of voice marketing encompass, and which research gaps currently exist in the published voice-marketing literature?
To address these questions, we followed a hybrid review (Paul and Criado 2020). Thus, as a first step, we analyzed the research field quantitatively through a bibliometric analysis. We therefore executed a broader analysis from a meta-perspective. The well-considered keyword string resulted in 673 papers, which we used for the analysis. As such, it was possible to objectively structure the voice-marketing research field into three dimensions: strategy, usage, and device. Furthermore, it was possible to identify two research streams in the field of voice marketing, namely 1) voice-assistant acceptance and adoption and 2) consumer–voice assistant interaction and perception. Additionally, the bibliometric analysis enabled us to identify research gaps in the form of under-researched topics. In the strategy dimension, research related to digital marketing, echo chambers, and voice commerce were determined to be expandable. For the usage dimension, we identified the need for more research about voice-assistant applications developed by brands or companies, e-commerce, perceived value, and security. We also concluded that the device dimension would benefit from extensive research about branding and customer-engagement issues.
Building on these findings, we adopted a more detailed perspective on existing literature about voice-marketing issues. Thus, in a second step, we conducted a qualitative semi-systematic

literature review. Screening according to strict criteria resulted in 35 papers to which we had full reading access. This review facilitated a comprehensive detailed analysis of the literature and existing research results. To proceed in a structured manner, we used the TCCM framework for the analysis.

We combined the results of the quantitative bibliometric analysis and the qualitative semi-systematic literature review to provide answers to the two research questions. This process resulted in a comprehensive research agenda for each dimension of the voice-marketing research field. Moreover, we formulated several research questions for each of the voice-marketing dimensions, which encouraged a structured and, thus, holistic examination of the research field. We developed the study findings presented in Chapter 2 in Chapter 3.

We decided upon the research objective for the study presented in Chapter 3 by reviewing the research agendas developed in Chapter 2. Since the voice-marketing research field is still in its infancy, we aimed first to develop fundamental knowledge. Voice assistants as communication tools for voice marketing are often also called conversational agents. In the literature, this term is used not only for voice-based but also for text-based conversational agents. Conversational agents in general are gaining attention from both marketing practitioners and academic researchers. Experts from companies such as Microsoft and Forbes have emphasized the practical relevance of these agents, listing them as part of the top 10 breakthrough technologies in 2016 and continuing to highlight their relevance today. As marketing touchpoints, conversational agents facilitate interaction and enable engaging communication between consumers and brands or companies. However, knowledge about the effects that conversational agents arouse needs to be improved. From a theoretical perspective, existing research on conversational agents lacks investigations regarding their use as marketing-communication channels for brands or companies. Moreover, research highlights the distinctiveness of voice interactions, suggesting that text- and voice-based conversational agents may differ significantly in their functions as marketing-communication channels. Therefore, it is important to distinguish the research on conversational agents and, thereby, close the gap of research on text- and voice-based agents in direct comparison. As such, we addressed this research gap, which is also on the research agenda of the strategy dimension in Chapter 2, in our study presented in Chapter 3. The two research questions investigated in Chapter 3 were as follows: Which effects does marketing communication through conversational agents have on the brands that use them for marketing communications, and does the distinctiveness of chatbots and voice assistants lead to different effects on the brands?

We examined the research questions by applying an experiment in the form of a 1 x 1 between-subject design. Thus, the participants explored, as part of a quantitative online survey, a real interaction with a text-based chatbot or voice-based voice assistant. To exclude biases in the responses based on earlier experiences with specific brands, chatbots, and voice assistants, we developed 16 fictional brands and programmed neutral conversational agents (a chatbot as well as a voice assistant). We tested the brands' fictiveness through a pre-test in which we mixed them with nine real brands. Finally, we selected one of the confirmed fictional brands, called "Senjoysoft," for our online survey. A pre-test of 94 participants ensured the functionality of the survey and, once again, the brand's fictionality. We then collected data on a larger sample size of 557 participants, and we analyzed the data through structural equation modeling and using MGCFA. Finally, we found that marketing communications through text- and voice-based conversational agents arouse positive effects. However, the agents differ significantly in their core effects. Marketing communication through voice-based conversational agents is unique in its ability to connect with consumers socially, whereas the use of text-based conversational agents is better suited for providing information and assisting customers with processes and services. The study findings from Chapter 3 contribute to closing research gaps in theory and provide guidance to marketing practitioners on what type of conversational agent to implement. Furthermore, we developed fundamental knowledge about conversational agents, including voice assistants, as marketing-communication channels.

In our study presented in Chapter 4, we ground on the expanded fundamental knowledge of voice assistants as marketing-communication channels by investigating a specific voice-marketing communication tool: voice-assistant applications developed by brands or companies (in the following called third-party skills, abbreviated TPSs). In doing so, we addressed another research gap identified in the study presented in Chapter 2, this time for the usage dimension.
Voice interaction is growing and becoming increasingly important in consumers' daily lives. Therefore, marketing practitioners are interested in and have begun testing TPSs to contribute to their marketing goals. However, there is a lack of suitable measurement instruments to evaluate the efficiency of resources spent on developing TPSs. To address and close this gap, we formulated three research questions: What are the drivers of the adoption intention of third-party skills (TPSs), which marketing effects do companies pursue with the development of TPSs, and which marketing effects do TPSs arouse?
To answer these research questions, we followed a three-step approach. First, we analyzed the literature extensively to identify a suitable model to use as the basis for our study. Our analysis revealed that the VAM could serve as a foundation for our study.
Second, we conducted qualitative interviews with marketing experts from companies across the three largest industry sectors of the German B2C market, according to the ICB. The interviews delivered insights into the marketing effects that companies pursue through TPSs, which include brand attitude, brand experience, brand loyalty, customer satisfaction, and brand innovativeness. We integrated these marketing effects into the VAM by connecting the constructs using findings from the literature, thus developing our conceptual model.
Third, we conducted quantitative online surveys to test the conceptual model across industry sectors and for Germany and the USA, two countries with high voice-assistant-usage rates. The sample size was 375 for the study across the industry sectors and 377 for the study across the countries. We analyzed the data using structural equation modeling and MGCFA. Our key findings suggest that TPSs have positive marketing effects on brand experience, brand loyalty,

brand attitude, and customer satisfaction, regardless of the industry sector or country. However, we cannot observe positive effects on brand innovativeness. Additionally, we found that for TPS adoption perceived technicality does not play a significant role, and the significance of the effect of perceived usefulness varies depending on the country. Our study resulted in the development of the VAMEM (the value-based adoption and marketing effects model) as a measurement instrument to capture the marketing performance of TPSs moving forward.

This research summary outlined the revealed research results. Section 5.2 now highlights the theoretical contributions of the presented research results.

5.2 Academic research contributions

This dissertation focuses on the research field of voice marketing. Since voice marketing relies on the functionality of AI technology, advancements in AI have therefore had a significant impact on the development of voice marketing. Currently, AI is highly relevant to both companies and society, leading to the ongoing development of AI technology and AI-based applications. Consequently, voice marketing is an emerging research field that is constantly evolving.

In our study presented in Chapter 2, we discovered several studies that have investigated the research field of voice marketing. However, an overarching analysis was still lacking, even though the first voice assistant, Apple Siri, was launched in 2011. The most important theoretical contribution of this dissertation is thus the overarching analysis of the voice-marketing research field. Through this analysis, we revealed the three-dimensional structure of voice marketing with two research streams. Therefore, the voice-marketing research field revolves around the three dimensions of strategy, usage, and device. These dimensions are connected through the following two research streams: 1) voice-assistant acceptance and adoption and 2) consumer–voice assistant interaction and perception. We identified research gaps for each dimension and encouraged researchers to address them. Furthermore, our study provides a structure for voice marketing as a research field that is of growing importance. This structure can be used to organize future research in the field of voice marketing, providing a comprehensive overview of studies and findings on voice-marketing issues and existing research gaps. Voice marketing is a rapidly evolving topic due to advancements in AI, making it vital to monitor new developments.
Furthermore, the analysis of the applied theories using the TCCM framework showed that no established theory is established to investigate voice-marketing issues specifically. Using the TCCM framework, we identified the variables (antecedents, outcomes, mediators, and moderators) that have been studied for voice-marketing issues thus far. These provide a

foundation for developing a promising fundamental theory in the interdisciplinary field of voice-marketing research.

The study presented in Chapter 3 makes a theoretical contribution by assessing relevant characteristics of AI-based marketing communications. Previous research has shown significant differences between speaking and writing as forms of communication, but this knowledge has not been sufficiently applied to the context of AI-based marketing communication. Our study has closed this gap and, therefore, made a valuable contribution to the theory. The study findings presented in Chapter 3 emphasize that analyses and knowledge about communication cannot be generalized. Additionally, the communication medium, such as speech versus text, is highly relevant and should be considered during investigations about communication and marketing issues.
Furthermore, our study validates the scale for assessing social presence in AI-based marketing communications. As such, we confirmed that conversational agents have the relevant characteristic of imitating the presence of a social being. Moreover, our study results show that text- and speech-based marketing communications through AI-based conversational agents require different levels of cognitive decision effort. This variation highlights the importance of considering the distinctiveness of these two communication mediums in studies. Additionally, our study demonstrates the relevance of mediating factors, such as warmth and competence, as well as hedonic and utilitarian attitudes, for AI-based marketing communication.
In summary, our study emphasizes the significance of incorporating the concepts of social presence and cognitive decision effort in studies that involve conversational agents. Additionally, our study findings reinforce the importance of researchers being mindful of mediators for AI-based marketing communication through conversational agents.

Our study presented in Chapter 2 revealed that there is currently no established theory for investigating voice-marketing issues. Additionally, common frameworks used to study marketing-communication issues are predominantly based on human–human interactions; however, as technology-mediated communications become more common, suitable frameworks must be developed (Dombi, Sydorenko, and Timpe-Laughlin 2022; Guzman and Lewis 2020). We contribute to the theory and to closing this research gap with our study presented in Chapter 4, which develops a conceptual model called VAMEM. The VAMEM assesses the influence of voice-marketing communication on marketing effects. Although our study focused on voice-marketing communication through TPSs, the VAMEM can serve as a basis for further voice-marketing studies. Additionally, we discovered that established frameworks developed before the launch of voice assistants must be revised. The study by Pal et al. (2020) shows that the VAM is the most effective predictor of adoption intention for voice assistants. However, the model was developed in 2007, prior to the launch of Apple Siri as the first voice assistant in 2011. Our study showed that perceived technicality, which is an independent variable of the VAM, has no significant effect on the perceived value, and therefore on the adoption intention, of TPSs. People seem to have become so familiar with different technologies that they are not concerned about how to use them. Therefore, it is essential to develop and increase the popularity of suitable models for voice-marketing investigations that consider the evolution of consumer behavior. Doing so is especially important because of the ongoing development of AI technology and its impact on voice-marketing issues.

Academic research should be beneficial for academic researchers and marketing practitioners alike. Therefore, this dissertation adds value not only to the theory but also provides implications for marketing practitioners. The implications and most important aspects of this dissertation are presented in Section 5.3.

5.3 Managerial research implications

Although voice assistants for private use have existed for over 10 years, applications for voice assistants are in a nascent stage (Brocks and Bätjer-Gleitsmann 2021). Therefore, research and analysis findings that guide the successful development and implementation of voice assistants and voice-assistant applications are required. This dissertation contributes to closing existing knowledge gaps and provides valuable findings in this area.

The study presented in Chapter 2 provides an overview of the different dimensions of voice marketing for marketing practitioners. The findings demonstrate that voice-marketing strategies, consumers' usage of the technology, and the device used to execute voice marketing play relevant roles in practice. Therefore, marketing practitioners should consider all three dimensions to be well-informed and prepared to evaluate the relevance of voice-marketing activities for their companies. In terms of voice-marketing strategies, voice marketing should align with a company's current short- and long-term strategies. Furthermore, resources are necessary to develop compelling voice-marketing activities that provide value for customers. Therefore, the implementation of voice marketing in a company should be well-considered. Companies should understand their target audience and how they use new technologies. In this context, our study shows that consumers' perceptions of the value of voice assistants are crucial. This knowledge can serve as a basis to individually validate the specific needs and potential success of voice-marketing activities. Regarding the device used to execute voice marketing, companies can use popular voice-assistant providers, such as Amazon Alexa and Google Assistant, for voice marketing. However, cooperation with these providers can bring both opportunities and risks since another stakeholder with its own interests is involved. Additionally, there may be limitations, such as dependencies on the platform of the voice-assistant provider, which could limit access to performance analyses. Therefore, when planning to execute voice marketing, it is important to carefully consider suitable devices.

We conclude that voice marketing is an emerging mode for companies to connect with consumers, creating new customer touchpoints and allowing companies to enrich the overall brand experience. By using voice assistants as AI-based technologies, companies can interact with their customers in real time through voice-marketing activities. Therefore, voice marketing has the potential to help companies become a part of their customers' daily lives. The presented research agendas provide an initial overview of the insights that marketing practitioners can expect in the future. Therefore, we encourage marketing practitioners to remain informed by monitoring new research publications in the field of voice marketing.

The study presented in Chapter 3 suggests that AI-based technologies, in particular conversational agents, are effective tools for brand management. Our study shows that marketing practitioners benefit from implementing conversational agents as marketing-communication channels because of their positive impact on conative and affective marketing achievements, such as word-of-mouth intentions and customers' attitudes toward brands.
Furthermore, our study shows that brands can benefit from using the correct media mix in their marketing communications. Marketers can make specific use of text- and speech-based conversational agents, depending on the marketing goals they are seeking to achieve. For example, text-based marketing communications through chatbots help to positively influence consumers' perception of brand competence. Similarly, speech-based marketing communications through voice assistants reinforce the brand perception of competence and add the positive influence of usefulness to consumers. Therefore, our study provides valuable implications for decisions regarding the media mix for marketing communications.
Additionally, marketing communications through conversational agents are particularly beneficial for brands with limited marketing budgets and lower brand awareness. Using conversational agents for marketing communications has a positive impact on word-of-mouth intentions, resulting in free promotions for the brand. To achieve this, our study shows that it is important to make consumers feel like they are communicating with a social being. This feeling has the positive side effect of shaping the brands' positioning to be kind and friendly.
Our study emphasizes the importance of marketing practitioners being aware of their target groups' user experience and age. While age influences the perceptions of marketing communications, a higher user experience with conversational agents has a positive effect on trust toward them.

As the study findings presented in Chapters 2 and 3 show, voice marketing can be valuable to both consumers and brands. However, the potential of voice-marketing activities has not been fully assessed. Our study presented in Chapter 4 aims to contribute to closing this research gap by developing a model that enables the assessment of the marketing effects of voice-marketing activities. As a study result, we present the VAMEM, a model that suggests the positive marketing effects that voice marketing, in particular TPSs as a voice-marketing activity, can arouse. Our study demonstrates that these positive effects are not limited to specific industry sectors or countries. Therefore, several marketing practitioners in the B2C market can benefit from the development and provision of TPSs. However, we recommend that companies in the financials industry carefully consider using an external voice-assistant provider to make their TPSs accessible. It may be advantageous to rely on in-house development to reduce the negative effect on the adoption of TPSs.

Additionally, we found that consumers are generally aware of how to activate and use TPSs. Therefore, we encourage companies to develop TPSs and take advantage of the positive marketing effects, as consumers have the technical foundation to use TPSs. Furthermore, interviews with marketing experts from companies from various industry sectors indicate that the desired marketing effects of TPSs are relatively similar. Therefore, companies can learn from best-practice examples, even if they belong to a different industry sector. In doing so, all companies can improve their TPSs and therefore enhance consumers' overall experiences of TPSs.

Moreover, our study shows that positive influences on the marketing effects are stable across Germany and the USA, as countries with high voice-assistant-usage rates. As such, it is not required that international acting companies develop fully novel TPSs for each country. Therefore, generating scaling effects is possible. However, the voice-assistant-usage habits of consumers should be considered. While the voice-assistant provider, more specifically the voice assistant Amazon Alexa, plays no crucial role for consumers from the USA, it influences the TPS adoption intention of German consumers. Therefore, when companies evaluate launching their TPSs in countries with high voice-assistant-usage rates, we recommend controlling this factor. Furthermore, companies can take less care regarding the usefulness of TPSs when they launch them in the USA, while the usefulness of TPSs is relevant for consumers in Germany.

Despite several implications that this dissertation provides to marketing practitioners and academic researchers, our studies are not free of limitations. Furthermore, different research directions for further exploring the voice-marketing research field are presented in Section 5.4 below.

5.4 Limitations and future research directions

Specific limitations in our studies, which lead to the need for further research, should be mentioned. First, the analysis of published voice-marketing research presented in Chapter 2 encompassed the state of the art of the voice-marketing research field. However, the research field is rapidly and constantly evolving, as are published voice-marketing studies (review Figure 4). Therefore, we recommend monitoring the development of the voice-marketing research field by regularly repeating the analysis.

Second, we revealed several research gaps as study findings in Chapter 2. In this dissertation is addressed one specific research gap in each research stream. However, several research gaps concerning the three voice-marketing dimensions (i.e., strategy, usage, device) remain to be considered. These gaps include, for example, branding issues, security in the voice-marketing context, and questions regarding customer engagement and voice commerce (see Figure 13).

Third, in Chapter 3, the focal points of our empirical investigation were AI-based conversational agents and in Chapter 4, TPSs as a specific voice-marketing activity. This scope ensured that we remained focused and extracted specific insights and effects from voice marketing. However, in marketing practice, the planning and performance measurement of marketing activities include all marketing channels. Therefore, marketing activities through social media, websites, or magazines are considered together, which raises several questions. For example, which effects arouse voice-marketing activities when they are connected to other marketing-communication channels? Can voice marketing strengthen overall marketing performances, or are cannibalization effects observable? Therefore, grounding the findings from this dissertation can guide future studies on the whole marketing mix.

Fourth, specific elements of our research designs should be noted. We derived the interviewees for our study presented in Chapter 4 from the ICB. Thus, we focused on industry sectors that represent most consumers and excluded industry sectors that have, in particular, the target group of consumers with their own households. However, it could be possible that this target group is of special interest because consumers in their own households decide independently whether to implement smart speakers in their homes. Therefore, these consumers' perceptions of and usage behavior with smart speakers and, thus, with TPSs may differ from those of others. We thus recommend that our study be repeated with a special focus on consumers with their own households.
Additionally, the environments of the research situations were somewhat unnatural. For example, the survey participants in the study presented in Chapter 3 interacted with the fictional voice assistant through a laptop but not via voice assistants implemented in smartphones or smart speakers. Additionally, the survey participants of the study presented in Chapter 4 listened to TPS audio recordings instead of having real interactions with them. Although we pre-tested the stimuli and possible influences on the survey responses, repeating the studies in more realistic environments, for example, through in-home studies, could be valuable. This could also facilitate long-term studies for several weeks.
Furthermore, the empirical studies presented in Chapters 3 and 4 were mainly executed in Germany with German consumers. An exception is the study presented in Chapter 4, which also considered consumers from the USA. Nevertheless, these two countries are well-developed and have high voice-assistant-usage rates. Furthermore, we used the snowball principle several times to distribute the surveys, but this process does not result in samples that represent the

populations. As such, it is necessary to verify our study results with representative study samples across countries.

Altogether, we revealed several valuable and interesting findings for the voice-marketing research field. Therefore, we contributed to theory and marketing practices alike (see Sections 5.2 and 5.3). However, this dissertation captured only a small portion of the state of the art. During the time in which we conducted our studies, the topic of voice technology has undergone a major evolution—from a technological perspective and in terms of consumers' perceptions of voice technology in general. As AI technology, which underpins voice marketing, continues to improve at a rapid pace, so do the capabilities of voice marketing. This progress creates not only several opportunities but also the need for further studies. Issues that could be of interest in the future are now described.

The study findings presented in Chapter 4 indicate that the value consumers perceive in the usage of voice assistants is crucial for adoption intentions. However, existing studies show that consumers' voice-assistant usage intentions are still negatively influenced by privacy concerns (Barone and Stagno 2023). These concerns reduces both adoption intentions and trust in voice assistants (Pitardi and Marriott 2021). Although privacy concerns can be reduced through specific actions such as giving the voice assistant a human name (Voorveld and Araujo 2020), they cannot be fully eliminated. However, due to technological advancements, improvements in voice technology are already observable. These developments could increase consumers' perceived value of voice assistants, which further reduces or even eliminates the factors that negatively influence their behavioral adoption intentions. Therefore, continuous studies, especially longitudinal studies, about consumers' perceptions of voice assistants and voice marketing, including effects on consumer–brand relationships, are recommended. If the added value of voice marketing reaches the level of smartphones, researchers should be attentive to the phenomenon of techno-addiction or techno-stress. Techno-addiction describes a dependency on technology (Young 2017), while techno-stress means that consumers have difficulties using new (computer) technologies or managing them in a healthy way (Brod 1984).

Moreover, some aspects related to the field of voice marketing are worth discussing. As explained in Section 1.1, characteristics of voices and, therefore, voice assistants have the power to influence consumers feelings. Thus, voice assistants' characteristics can impact consumers' behavior and interactions (Poushneh 2021a), which raises the question of whether actively and conscientiously influencing these characteristics is justifiable from an ethical perspective. For example, the study of Huang and Labroo (2020) showed that low-pitched voices lead to the selection of larger product sizes. However, whether consumers intrinsically want to purchase larger product sizes remains unclear. Even though, for example, the law against unfair competition protects consumers, it is ambiguous whether the law already considers voice-marketing-specific situations. The details of the first draft for an AI law, the so-called AI Act, have been the subject of heated debate (Horizont 2024). Nonetheless, the regulation was comprehensively accepted by the European member states in February 2024 (Landesvertretung Rheinland-Pfalz in Brüssel 2024). However, despite initial regulations through the AI Act, comprehensive rules and regulations are lacking. Therefore, conscious adjustment and implementation of AI-based voices and their interaction with consumers are possible but could lead to behaviors that consumers regret afterwards. Several studies have also shown that humanizing voice assistants increases consumers' adoption intentions (e.g., Chérif and Lemoine 2019; Moriuchi 2021; Zhong and Ma 2022). Additionally, the risks that come with this humanization must be considered. Anthropomorphized voice assistants can endanger the identity of consumers and raise their privacy concerns, consequently eroding their well-being (Uysal, Alavi, and Bezençon 2022). This danger highlights the importance of researching voice-marketing issues from both ethical and legal perspectives. Doing so will not only help to inform consumers about possible effects but also provide implications for marketing practitioners to prevent them from engaging in unethical activities.

It has become clear that options for voice marketing will continue to evolve. Therefore, interesting developments can be expected in the future. The following section concludes this dissertation by providing an outlook for the field of voice marketing.

5.5 Outlook

As this dissertation shows, voice marketing possesses significant potential, and its development phase is still far from over. Further technological advancements driven by generative AI can be expected. Not only has Amazon included AI technology in their Amazon Alexa voice assistant (Heuck 2023), but ChatGPT is also available as a voice assistant in specific cases (e.g., Volkswagen 2024). These examples emphasize potential future developments in voice marketing, the extent of which can currently only be guessed at.

Voice interactions are likely to form future customer experiences, and, as such, they will probably be embedded throughout the entire customer journey (Torres and Doherty Áine 2022). For example, social-media platforms such as Snapchat and Instagram are testing the implementation of AI-based chatbots (i.e., text-based conversational agents; Business Insider 2023). If this development is accepted by consumers, the next step could be the integration of speech-based conversational agents into further social-media channels and other smartphone applications. Therefore, consumers could not only interact with each other via WhatsApp using voice messages, but communication on Instagram and other social-media channels could also be voice-based or at least supported by voice-based communications. This shift would pave the way for voice marketing in these channels and thus extend the opportunities for two-directional

interactions between brands and consumers. Therefore, voice marketing could also appear in several other customer touchpoints.
Since Generation Z and Millennials have increasingly shorter interaction spans with brands (Schwarz 2023), there are growing challenges for brands and companies in marketing communications. Embedding voice marketing into additional customer touchpoints could provide a solution for this issue by enabling so-called content snacking (Schwarz 2023). Content snacking means absorbing information in a digestible and sometimes amusing way (t3n 2018), and this form of communication is preferred by younger generations (Schwarz 2023). Therefore, implementing voice marketing in further customer touchpoints to enable content snacking could enhance brand experiences and therefore contribute to extending interaction spans with brands.

Currently, there is a growing interest in voice marketing in the B2C market, which is targeted toward end consumers. However, the possibility of implementing voice marketing in the B2B market is also increasing. Recent developments in AI technology have resulted in promising AI-based applications, such as ChatGPT and Bing Image Creator, which influence today's working lives (van Lengen 2023). For example, the company Volkswagen integrated ChatGPT in the form of a voice assistant in their new cars (Volkswagen 2024). Moreover, OpenAI launched an app-store for ChatGPT in January 2024, which includes applications that advise and support users in almost every conceivable situation (Business Insider 2024). These advancements highlight that these applications, including voice-marketing activities, have the power to shape the working environment of the future. For example, voice marketing could increase efficiency or employee retention in production and logistic departments through work relief. In this context, the implementation of TPSs that support employees in using specific machines and devices in production halls and distribution centers would be beneficial. Furthermore, TPSs could also support employees in using software applications during their working days, either acquiring information through TPSs on how to use and navigate the software applications or benefiting from the opportunity to multi-task. For instance, while using the software application through a laptop keyboard, employees could ask TPSs for required information, such as delivery schedules. An existing example of this process is Salesforce, a company that implemented a voice assistant called Einstein that allows users to access and use the customer-relationship-management software of Salesforce through voice (Salesforce n.d.). Furthermore, for people with office jobs, TPSs could support them in planning and booking business trips, including hotels and transportation, as well as business lunches (Goryachev 2018). The company Cisco has already implemented such a voice assistant, called Cisco Spark Assistant (Cisco 2017).

Beyond the implementation of voice technology in familiar applications of the existing reality, or the real world, such technology could also become part of new realities, including augmented reality, virtual reality, and mixed reality. Augmented reality enables the implementation of

digital elements into the real world (e.g., Milgram et al. 1995; Rauschnabel et al. 2022), while virtual reality is clearly distinguished from the real physical world and brings consumers to an artificially constructed virtual realm (Rauschnabel et al. 2022). Mixed reality combines elements of digital reality and the real world (Milgram et al. 1995). Augmented reality, virtual reality, and mixed reality belong, in addition to voice assistants and chatbots, to the technologies that shape how the experiences of consumers will be built (Torres and Doherty Áine 2022).
Experiencing mixed reality is already possible today with the recent launch of the Apple Vision Pro glasses. The high demand for these glasses, a technology that expands reality through digital content (Schesswendter 2024), provides initial indications of future voice-marketing possibilities. According to Metaverse expert Philipp A. Rauschnabel, such glasses have the potential to disrupt the landscape of digital technologies (Horizont 2023). Furthermore, an implementation of voice technology, and thus voice marketing, into these glasses in the near future is conceivable. Through the Apple Vision Pro glasses, for example, brands could communicate with consumers in ways that create innovative and enhanced brand experiences. Doing so could arouse similar effects as augmented-reality interactions, which increase perceived physical closeness to brands and result in brand love (Rauschnabel et al. 2024b). The 4C framework (consisting of the orchestration of content, consumer, context, and computer device) developed by Rauschnabel et al. (2024a) for the context of augmented reality could serve as a theoretical frame to understand and investigate possible future implementations of voice marketing in new realities. Moreover, a study by Bigne, Ruiz, and Curras-Perez (2024) initiated research on voice assistants in the virtual-reality context. Altogether, the outlined technological developments would allow voice-marketing activities even in extended new realities, revealing further promising potential.

As the possible extension of voice marketing into new realities shows, AI has become increasingly integrated into customer experiences to enhance the customer journey (Zendesk 2024, p. 2). As such, AI increases the possibilities of personalized experiences (Puntoni et al. 2021; Zendesk 2024, p. 18). However, consumers feel unsecure when there is a lack of transparency in how and when information about them is captured and processed (Puntoni et al. 2021). Moreover, the study by Bilika et al. (2024) reports that, in the context of voice technology, successful attacks on audio synthesis systems occurred in about a third of the cases. Therefore, addressing data-security and privacy issues is becoming increasingly important to prevent personal and reputational damage for consumers and companies (Siau and Wang 2020; Zendesk 2024, p. 21). In this context, it is key to understand AI issues from consumers' perspectives, including their concerns (Siau and Wang 2020). Since AI technology is continuously evolving, it is likely that new data-security and privacy issues will arise. Therefore, if companies deal with data-security issues in a timely and, from now on, continuous manner, they will not only prevent wasted investments in AI-based technologies but also gain the continued trust of consumers (Siau and Wang 2020). This trust is especially important in the context of voice marketing because consumers are already concerned about their privacy when interacting with voice assistants (Kowalczuk 2018; McLean and Osei-Frimpong 2019). More specifically, consumers are, for example, worried about being listened to through their microphones (Lau, Zimmerman, and Schaub 2018). As voice marketing is based on AI technology, further advancements of this technology will also influence this marketing form. Therefore, the increasing importance of data security and privacy also applies to further developments in voice marketing.

Ultimately, there are inspiring and interesting means for possible developments in voice marketing, including the extension of voice marketing to new touchpoints and realities under consideration of growing data challenges. These developments once again confirm that "nothing is as constant as change" (Heraklit of Ephesus 535–475 B.C.). Therefore, it remains exciting to observe the upcoming developments in voice marketing in practice and research as well as the resulting challenges and opportunities such technology presents for the marketing discipline.

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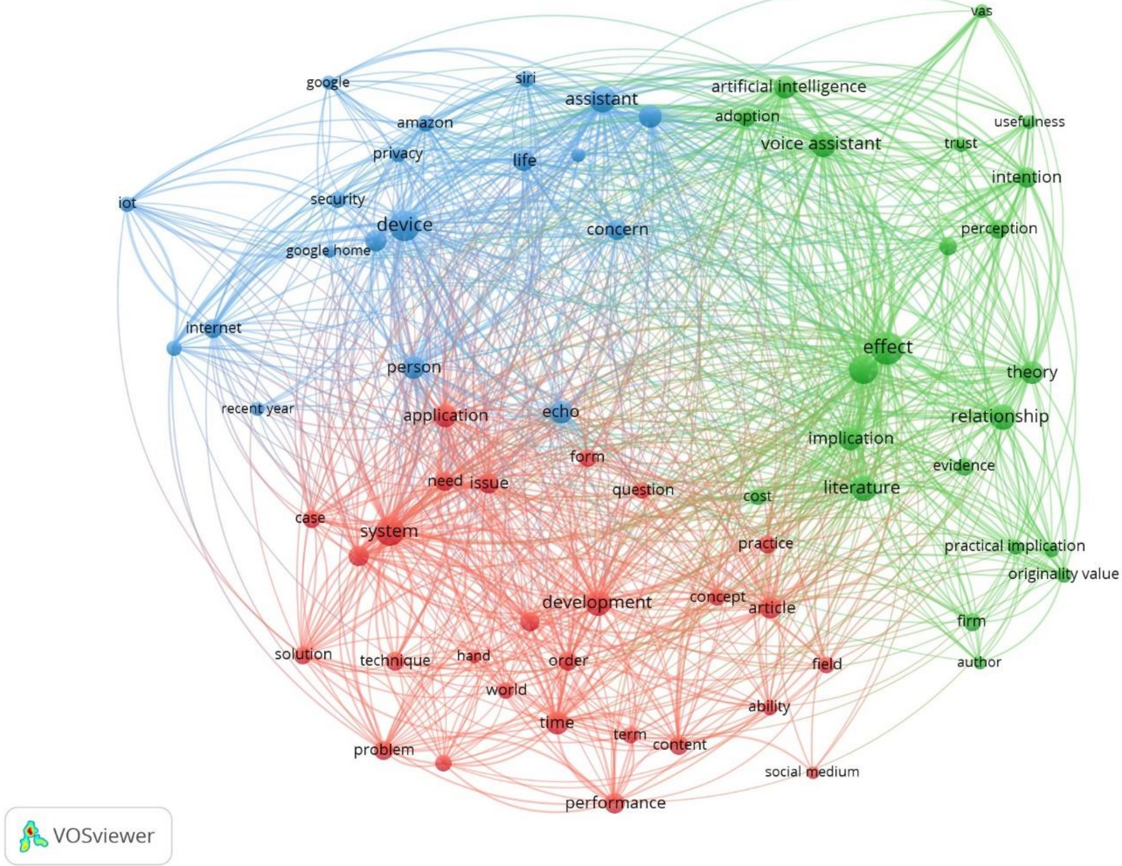
Appendix 1: Term co-occurrence analysis based on the Web of Science literature



Appendix 2: Constructs and items used in the study presented in Chapter 3

Constructs	Items
Attitude toward the brand	Please describe your overall feelings about the brand you just communicated with… … Unappealing / appealing … Bad / good … Unpleasant / pleasant … Unfavorable / favorable … Unlikable / likable
Cognitive decision effort	To complete the task, using the chatbot / voice assistant was very frustrating. To complete the task, using the chatbot / voice assistant took too much time. To complete the task, using the chatbot / voice assistant required too much effort. To complete the task, using the chatbot / voice assistant was too complex. I easily found the information I was looking for. (R) To complete the task, using the voice assistant / chatbot was easy. (R)
Customer satisfaction	How dissatisfied or satisfied are you with the communication via chatbot / voice assistant? To what extent did the communication via chatbot / voice assistant meet your expectations? Imagine a communication via chatbot / voice assistant that is perfect in every respect. How near or far from this ideal did you find the communication via chatbot / voice assistant?
Hedonic attitudes	The communication with the chatbot / voice assistant was… … Not fun / fun … Dull / exciting … Not delightful / delightful … Not thrilling / thrilling … Unenjoyable / Enjoyable
Perceived brand competence	To what extend do you believe that the brand is competent? To what extend do you believe that the brand is effective? To what extend do you believe that the brand is efficient?
Perceived brand warmth	To what extend do you believe that the brand is warm? To what extend do you believe that the brand is kind? To what extend do you believe that the brand is generous?
Social presence	There was a sense of human contact in the communication via chatbot / voice assistant. There was a sense of personalness in the communication via chatbot / voice assistant. There was a sense of sociability in the communication via chatbot / voice assistant. There was a sense of human warmth in the communication via chatbot / voice assistant. There was a sense of human sensitivity in the communication via chatbot / voice assistant.
Task-technology fit	In helping complete my task, the functions of the chatbot / voice assistant are enough. In helping complete my task, the functions of the chatbot / voice assistant are appropriate. In general, the functions of the chatbot / voice assistant fully meet my needs.
Trust	I trust the voice assistant / chatbot. I rely on the voice assistant / chatbot. It is an honest voice assistant / chatbot. The voice assistant / chatbot is safe.
Usage Experience	The voice assistant / chatbot that I have used provide the results I am looking for. The voice assistant / chatbot usually meet my expectations. I am extremely satisfied with using the voice assistant / chatbot when I trying to complete a simple task.
Utilitarian attitudes	The communication with the chatbot / voice assistant was… … Effective / ineffective … Helpful / unhelpful … Functional / not functional … Necessary / not necessary … Practical / impractical
Word-of-mouth	Given the experience communicating with the brand chatbot / voice assistant, how likely are you to recommend the brand to others?

Note: (R) are reverse coded items.

Appendix 3: Authors' keywords of studies based on the value-based adoption model

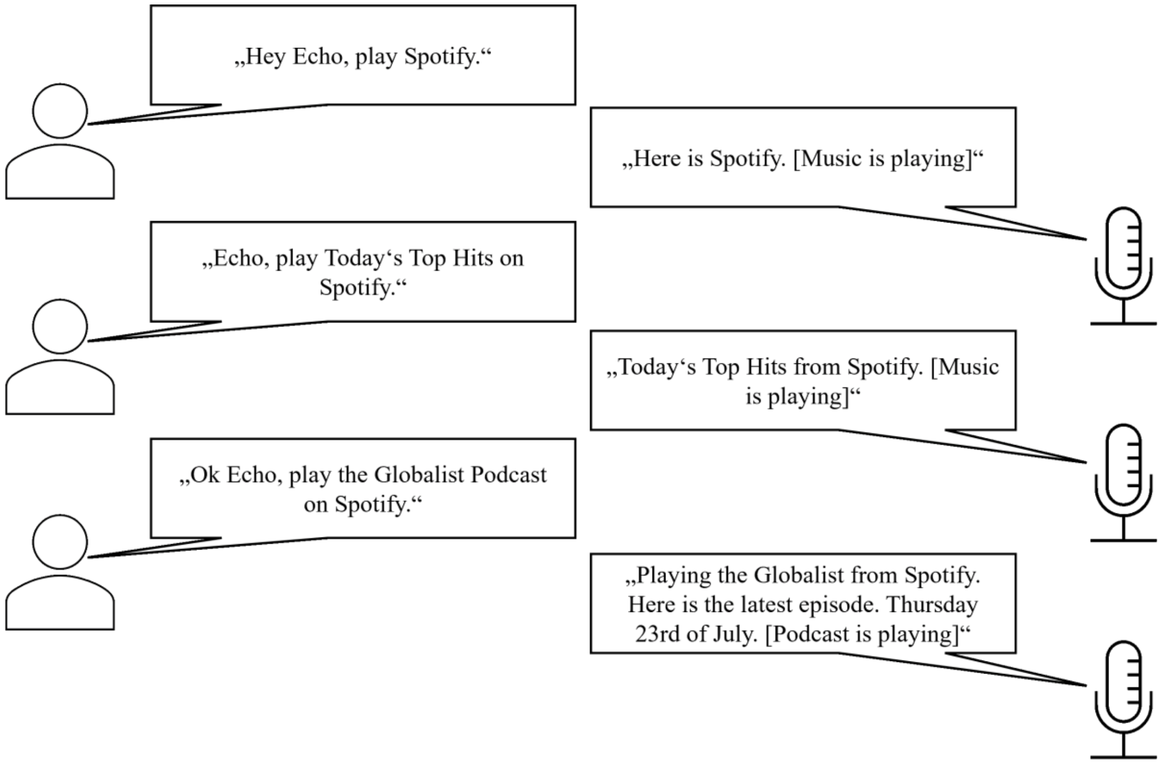
Area	Keywords
Keywords about the model	Adoption, adoption intention, artificial intelligence, behavioral intention, china, consumer, consumer behavior, consumer behaviour, customer value, expectation-confirmation model, extrinsic motivation, functional value, habit, hedonic value, inertia, innovation, intention, intention to use, internet of things, intrinsic motivation, iot, is success model, motivation theory, perceived benefit, perceived benefits, perceived enjoyment, perceived risk, perceived usefulness, perceived value, privacy calculus, sem, structural equation model, structural equation modelling, tam, technology acceptance, technology acceptance model, technology acceptance model (tam), technology adoption, theory of planned behaviour, tpb, unified theory of acceptance and use of technology, utaut, utaut2, utilitarian value, value, value-based adoption model
Investigated model variables	Acceptance, attitude, continuance intention, customer satisfaction, gender, information quality, loyalty, purchase intention, satisfaction, self-efficacy, service quality, social influence, social value, trust, user satisfaction, well-being
Investigated research contexts	Augmented reality, big data, covid-19, e-commerce, e-learning, electric vehicle, facebook, m-commerce, mobile, mobile advertising, mobile application, mobile applications, mobile banking, mobile commerce, mobile communication, mobile communications, mobile data services, mobile internet, mobile marketing, mobile payment, mobile services, mobile shopping, mobile technology, mobile tv, network externalities, neural network, online learning, service robots, sharing economy, smartphone, social commerce, social media, social networking sites

Appendix 4: Constructs and items used in the study presented in Chapter 4

Constructs	Items
Behavioral adoption intention	I plan to use [the brand's voice assistant application]in the future. I intend to use [the brand's voice assistant application]in the future. I predict that I would use [the brand's voice assistant application]in the future.
Attitude toward the brand use	Overall, I find using [the brand] positive. Overall, I feel favourable toward [the brand]. Overall, I am satisfied with the offers provided by [the brand]. Using [the brand] is a good idea. Using [the brand] is a wise idea.
Attitude toward the voice assistant provider use	Overall, I find using [the voice assistant provider] positive. Overall, I feel favourable toward [the voice assistant provider]. Overall, I am satisfied with [the voice assistant provider]. Using the [the voice assistant provider] is a good idea. Using the [the voice assistant provider] is a wise idea.
Brand experience	Audible makes a strong impression on my visual sense or other senses. I find [the brand] interesting in a sensory way. [The brand] does not appeal to my senses. (R) [The brand] induces feelings and sentiments. I do not have strong emotions for [the brand]. (R) [The brand] is an emotional brand. I engage in physical actions and behaviors when I use [the brand]. [The brand] results in bodily experiences (e.g., smiling). [The brand] is not action oriented. (R) I engage in a lot of thinking when I encounter [the brand]. [The brand] does not make me think. (R) [The brand] stimulates my curiosity and problem solving.
Brand innovativeness	[The brand] provides effective solutions to customer needs. Customers can rely on [the brand] to offer novel solutions to their needs. [The brand] always sells the same product offerings regardless of current customer needs. (R) [The brand] is not able to provide new solutions to customer needs. (R)
Brand loyalty	I encourage friends and relatives to use [the brand]. I say positive things about [the brand] to other people. I intend to use [the brand] in the next few years. I would recommend [the brand] to someone who seeks my advice.
Customer satisfaction	I was satisfied with the service provided by [the brand]. I was delighted with the service provided by [the brand]. I was unhappy with the service provided by [the brand]. (R)
Enjoyment	Using [the brand's voice assistant application] would provide me with a lot of enjoyment. I would enjoy using [the brand's voice assistant application]. Using [the brand's voice assistant application] would bore me. (R)
Perceived fee	The price that I would have to pay for using [the brand's voice assistant application] is too high. The price that I would have to pay for using [the brand's voice assistant application] is reasonable. (R) I am pleased with the cost that I have to incur for using [the brand's voice assistant application]. (R)
Perceived technicality	It would not be easy to use [the brand's voice assistant application]. It would take quite some time to get familiar with [the brand's voice assistant application]. It looks a little difficult to use [the brand's voice assistant application].
Perceived usefulness	Using [the brand's voice assistant application] in my daily work would enable me to accomplish tasks more quickly. Using [the brand's voice assistant application] would improve my work performance. Using [the brand's voice assistant application] would help in my daily work. Using [the brand's voice assistant application] in my daily life would increase my productivity. Using [the brand's voice assistant application] would enhance my effectiveness in my daily work.
Perceived value	Compared to the price that I would have to pay, [the brand's voice assistant application] would offer value for money. Compared to the effort I would need to put in, the use of [the brand's voice assistant application] would be beneficial to me. Compared to the time I would need to spend; the use of [the brand's voice assistant application] would be worthwhile to me. Overall, [the brand's voice assistant application] would deliver a good value.

Note: (R) are reverse coded items.

Appendix 5: Example of a third-party-skill audio recording as stimulus



Appendix 6: Cronbach's alpha (α) of each industry sector

Construct	Cronbach's α: financials industry sector	Cronbach's α: consumer-discretionary industry sector	Cronbach's α: consumer-staples industry sector
Adoption intention	0.961	0.971	0.968
Attitude toward the brand use	0.936	0.927	0.907
Attitude toward the voice assistant	0.976	0.969	0.949
Brand experience	0.926	0.782	0.879
Brand loyalty	0.929	0.906	0.899
Customer satisfaction	0.943	0.873	0.825
Enjoyment	0.936	0.910	0.955
Perceived fee	0.872	0.930	0.899
Perceived technicality	0.885	0.859	0.826
Perceived usefulness	0.968	0.944	0.974
Perceived value	0.904	0.885	0.922

Note: α = alpha.

Appendix 7: Average variance extracted (AVE) of each industry sector

Construct	AVE: financials industry sector	AVE: consumer-discretionary industry sector	AVE: consumer-staples industry sector
Adoption intention	0.889	0.899	0.900
Attitude toward the brand use	0.742	0.721	0.688
Attitude toward the voice assistant	0.891	0.864	0.796
Brand experience	0.650	0.292	0.528
Brand loyalty	0.772	0.706	0.707
Customer satisfaction	0.889	0.776	0.707
Enjoyment	0.880	0.840	0.915
Perceived fee	0.778	0.877	0.868
Perceived technicality	0.798	0.763	0.789
Perceived usefulness	0.858	0.775	0.886
Perceived value	0.643	0.684	0.801

Note: AVE = average variance extracted.

Appendix 8: Composite reliability (CR) of each industry sector

Construct	CR: financials industry sector	CR: consumer-discretionary industry sector	CR: consumer-staples industry sector
Adoption intention	0.96	0.96	0.96
Attitude toward the brand use	0.93	0.93	0.92
Attitude toward the voice assistant	0.98	0.97	0.95
Brand experience	0.92	0.71	0.87
Brand loyalty	0.93	0.91	0.91
Customer satisfaction	0.94	0.87	0.83
Enjoyment	0.94	0.91	0.96
Perceived fee	0.88	0.93	0.93
Perceived technicality	0.89	0.86	0.88
Perceived usefulness	0.97	0.95	0.97
Perceived value	0.84	0.87	0.92

Note: CR = composite reliability.

Appendix 9: Inter-item correlation matrix for the financials industry sector

	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.
1. Adoption intention	**0.898**										
2. Perceived value	0.419	**0.733**									
3. Perceived usefulness	0.543	0.458	**0.855**								
4. Enjoyment	0.621	0.508	0.608	**0.875**							
5. Perceived technicality	0.002	0.007	0.026	0.008	**0.749**						
6. Perceived fee	0.001	0.124	0.014	0.026	0.041	**0.840**					
7. Customer satisfaction	0.272	0.223	0.314	0.233	0.000	0.031	**0.796**				
8. Brand experience	0.417	0.166	0.397	0.283	0.172	0.006	0.244	**0.491**			
9. Brand loyalty	0.253	0.151	0.237	0.149	0.012	0.000	0.569	0.323	**0.734**		
10. Attitude toward the brand use	0.249	0.237	0.342	0.208	0.018	0.029	0.634	0.339	0.626	**0.718**	
11. Attitude toward the voice assistant	0.176	0.327	0.176	0.257	0.006	0.032	0.102	0.138	0.029	0.077	**0.863**

Note: The bolded elements are the AVEs.

Appendix 10: Inter-item correlation matrix for the consumer-discretionary industry sector

	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.
1. Adoption intention	**0.898**										
2. Perceived value	0.585	**0.733**									
3. Perceived usefulness	0.327	0.514	**0.855**								
4. Enjoyment	0.582	0.632	0.349	**0.875**							
5. Perceived technicality	0.045	0.082	0.045	0.045	**0.749**						
6. Perceived fee	0.108	0.168	0.052	0.100	0.047	**0.840**					
7. Customer satisfaction	0.032	0.008	0.011	0.049	0.008	0.070	**0.796**				
8. Brand experience	0.038	0.037	0.025	0.100	0.037	0.029	0.211	**0.491**			
9. Brand loyalty	0.073	0.012	0.021	0.040	0.018	0.045	0.345	0.370	**0.734**		
10. Attitude toward the brand use	0.081	0.019	0.015	0.082	0.002	0.042	0.500	0.295	0.604	**0.718**	
11. Attitude toward the voice assistant	0.500	0.469	0.316	0.452	0.118	0.045	0.033	0.023	0.035	0.066	**0.863**

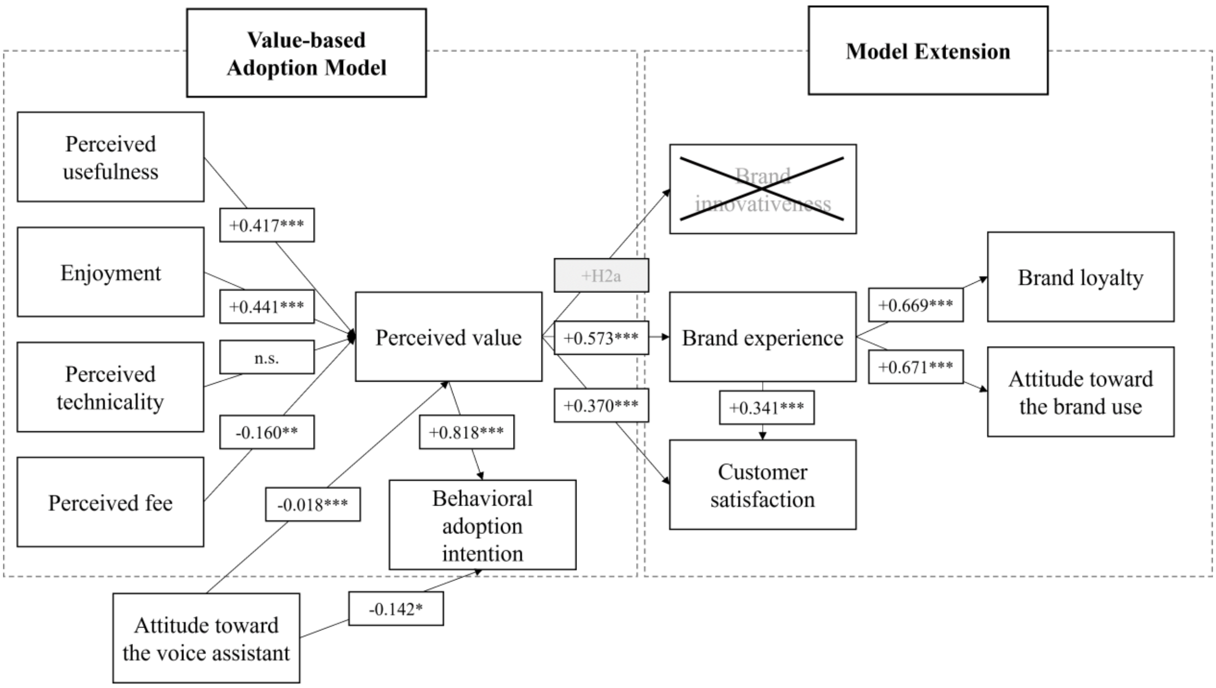
Note: The bolded elements are the AVEs.

Appendix 11: Inter-item correlation matrix for the consumer-staples industry sector

	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.
1. Adoption intention	**0.898**										
2. Perceived value	0.585	**0.733**									
3. Perceived usefulness	0.590	0.701	**0.855**								
4. Enjoyment	0.598	0.699	0.629	**0.875**							
5. Perceived technicality	0.000	0.004	0.003	0.003	**0.749**						
6. Perceived fee	0.017	0.100	0.043	0.102	0.027	**0.840**					
7. Customer satisfaction	0.221	0.211	0.157	0.222	0.000	0.043	**0.796**				
8. Brand experience	0.365	0.384	0.378	0.403	0.025	0.063	0.274	**0.491**			
9. Brand loyalty	0.457	0.381	0.280	0.437	0.001	0.081	0.356	0.339	**0.734**		
10. Attitude toward the brand use	0.339	0.336	0.257	0.368	0.011	0.101	0.457	0.320	0.558	**0.718**	
11. Attitude toward the voice assistant	0.274	0.152	0.230	0.178	0.003	0.018	0.192	0.184	0.258	0.271	**0.863**

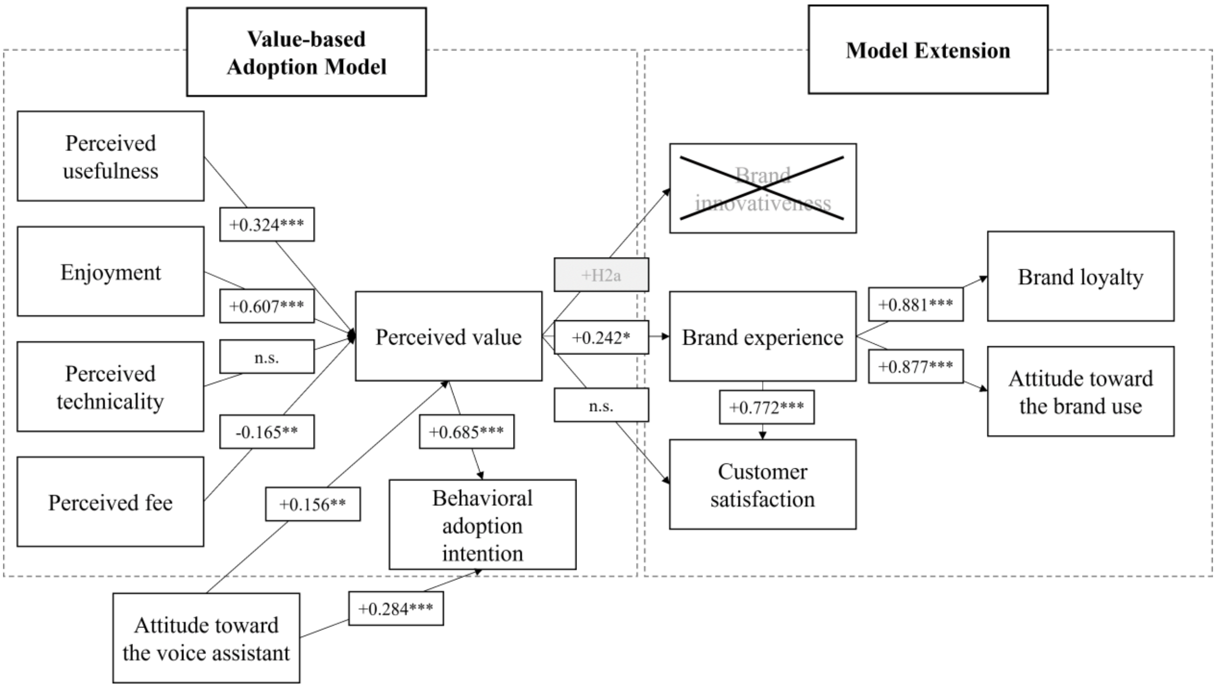
Note: The bolded elements are the AVEs.

Appendix 12: Data analysis results for financials industry sector



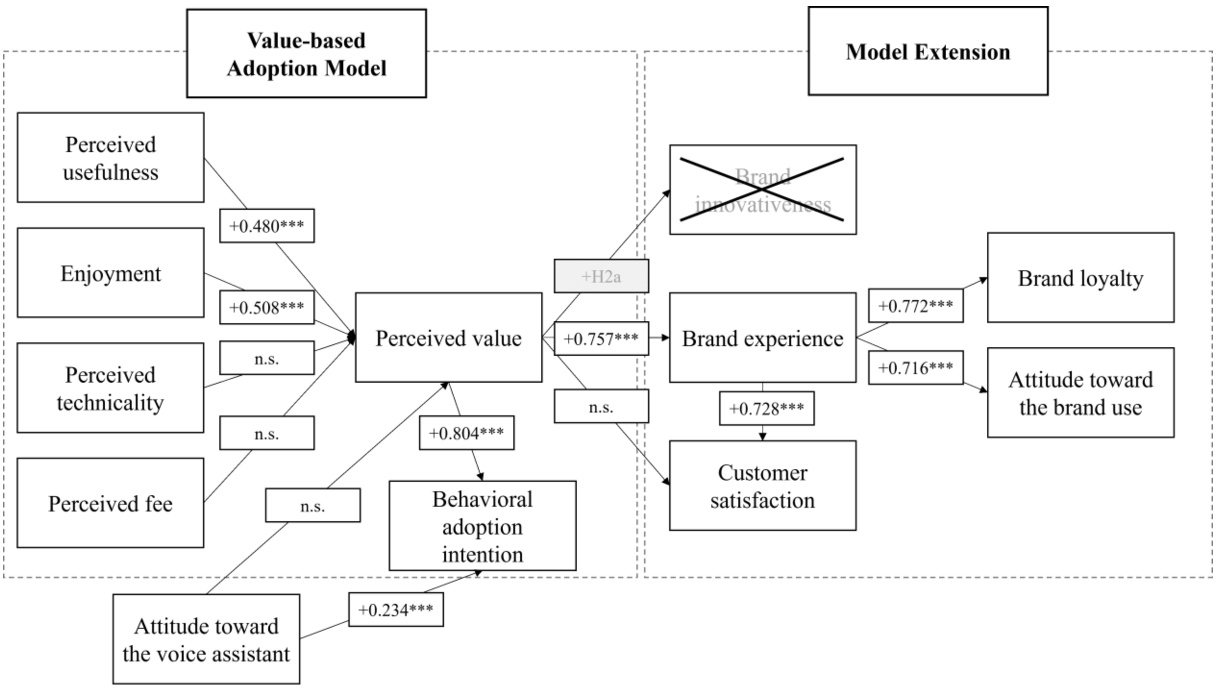
*Note: * = p < 0.05, ** = p < 0.01, *** p < 0.001, and n.s. = not significant.*

Appendix 13: Data analysis results for the consumer-discretionary industry sector



*Note: * = p < 0.05, ** = p < 0.01, *** p < 0.001, and n.s. = not significant.*

Appendix 14: Data analysis results for the consumer-staples industry sector



*Note: * = p < 0.05, ** = p < 0.01, *** p < 0.001, and n.s. = not significant.*

Appendix 15: Culturally specific constructs and items used in the study presented in Chapter 4

Constructs	Items
Affinity for technology	I like to occupy myself in greater detail with technical systems.
	I like testing the functions of new technical systems.
	I predominantly deal with technical systems because I have to. (R)
	When I have a new technical system in front of me, I try it out intensively.
	I enjoy spending time becoming acquainted with a new technical system.
	It is enough for me that a technical system works; I don't care how or why. (R)
	I try to understand how a technical system exactly works.
	It is enough for me to know the basic functions of a technical system. (R)
	I try to make full use of the capabilities of a technical system.
Long-term orientation	Respect for tradition is important to me.
	I plan for the long term.
	Family heritage is important to me.
	I value a strong link to my past.
	I work hard for success in the future.
	I don't mind giving up today's fun for success in the future.
	Traditional values are important to me.
	Persistence is important to me.
Privacy control	I was completely satisfied in my ability to control the level of privacy during the communication.
	I had little reason to be concerned about my privacy during the communication.
	I controlled my level of privacy during the communication.
	I had control over the communication.
Trust	I trust voice assistants.
	I rely on voice assistants.
	Voice assistants are honest.
	Voice assistants are safe.

Note: (R) are reverse coded items.

Appendix 16: Country comparison results (own illustration based on Hofstede Insights Oy 2024)