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New Trends in E-WOM: Effectiveness and Perceived Value of Artificial Intelligence-Based Recommendation Systems

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NEW TRENDS IN E-WOM: EFFECTIVENESS AND PERCEIVED VALUE OF ARTIFICIAL INTELLIGENCE-BASED RECOMMENDATION SYSTEMS

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New Trends in E-WOM: Effectiveness and Perceived Value of Artificial Intelligence-Based Recommendation Systems

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Departamento de
Dirección de Marketing e
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Universidad Zaragoza

Tesis Doctoral

Nuevas tendencias en E-WOM: Efectividad y valor percibido de los sistemas de recomendación basados en Inteligencia Artificial

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Directores

Dr. Carlos Flavián Blanco

Dr. Luis V. Casaló Ariño

2022

metodo research group

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ABSTRACT

The research on E-WOM has been extensively studied over the past two decades, with broad consensus on its importance in the consumer decision-making process. However, an updated view of the current state of knowledge in the booming field of E-WOM is required. Thus, this doctoral dissertation comes, through the second chapter, to provide a holistic understanding of the influence of the characteristics of the key E-WOM elements (i.e., sender, message and receiver) on consumer decision-making processes (in terms of perceptions, evaluations and behaviors), as well as, to identify emerging future research lines in E–WOM field.

As the result of conducting an extensive literature review on E-WOM, the current thesis highlights the growing importance of the recommendation systems based on artificial intelligence (AI) (e.g., voice assistants), as a novel trend in E-WOM. Thus, the third chapter of this thesis, moves forward with the analysis of the effectiveness of such AI-based recommendation systems by comparing the influence of AI-WOM (i.e., AI-based recommendations) provided by voice assistants, with the effect of traditional E-WOM received by written reviews, on consumer behavior. In parallel, this effectiveness has been studied according to the content type of the recommendations (commercial vs. non-commercial), as well as to the type of the product recommended (product vs. service).

After confirming that AI-WOM provided by voice assistants, generates better behavioral intentions than traditional E-WOM, the fourth chapter comes to explain how this AI-WOM generates value. Specifically, the dissertation identifies the main benefits (convenience, compatibility and personalization) and costs (cognitive effort and intrusiveness) associated with the perceived value of the voice assistants' recommendations, the relevant role of automated social presence in determining this

value, as well as the main consequences of the perceived value on consumer engagement with voice assistants.

Finally, the thesis relates the research goals with the main results and implications for both theory and practice derived from these interesting findings.

RESUMEN

La investigación sobre el E-WOM ha sido ampliamente debatida durante las dos últimas décadas, constatándose con gran consenso su relevante papel en el proceso de toma de decisiones del consumidor. Sin embargo, es necesaria una visión actualizada del estado actual del conocimiento en el prolífico campo del E-WOM, por lo tanto esta tesis doctoral viene a proporcionar, a través del segundo capítulo, una comprensión holística de la influencia de las características de los elementos clave del E-WOM (es decir, emisor, mensaje y receptor) en el proceso de toma de decisiones del consumidor (en términos de percepciones, evaluaciones y comportamientos), así como a identificar las líneas futuras emergentes de investigación.

Como resultado de realizar una extensa revisión bibliográfica sobre el E-WOM, la presente tesis destaca la creciente importancia de los sistemas de recomendación basados en inteligencia artificial (IA) (por ejemplo, asistentes de voz), como una tendencia novedosa en E-WOM. Así, el tercer capítulo avanza en el análisis de la efectividad de esos sistemas de recomendación basados en IA, comparando la influencia del IA-WOM (i.e., las recomendaciones basadas en IA) proporcionadas por los asistentes de voz, con el efecto del E-WOM tradicional recibido por reseñas escritas, sobre el comportamiento del consumidor. Paralelamente, se ha estudiado esta eficacia en función del tipo de contenido de las recomendaciones (comercial frente a no comercial), así como del tipo de producto recomendado (producto frente a servicio).

Tras confirmar que el AI-WOM proporcionado por los asistentes de voz genera mejores intenciones de comportamiento que el E-WOM tradicional, el cuarto capítulo viene a explicar cómo este AI-WOM genera valor. Específicamente, la capitulo identifica los principales beneficios (conveniencia, compatibilidad y personalización) y costes (esfuerzo cognitivo y intrusividad) asociados con el valor percibido las recomendaciones

realizadas por los asistentes de voz, el papel relevante de la presencia social automatizada en la determinación de este valor, así como las principales consecuencias del valor percibido en el compromiso del consumidor con los asistentes de voz.

Finalmente, la tesis relaciona los objetivos de la investigación con los principales resultados e implicaciones teóricas y prácticas derivadas de estos interesantes hallazgos.

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AI:	Artificial Intelligence
AR:	Augmented Reality
AVE:	Average Variance Extracted
CBF:	Content-Based Filtering
CF:	Collaborative Filtering
CMV:	Common Method Variance
CR:	Composite Reliability
E-WOM:	Electronic Word of Mouth
IDT:	Innovation Diffusion Theory
IoT:	Internet of Things
ML:	Machine Learning
MRT:	Media Richness Theory
NTTS:	Neural Text-to Speech technology
PLS:	Partial Least Squares
SEM:	Structural Equation Modeling
SIT:	Social Identity Theory
SPT:	Self-Perception Theory
TAM:	Technology Acceptance Model
TPB:	Theory of Planned Behavior
TRA:	Theory of Reasoned Action
VA:	Voice Assistant
VR:	Virtual Reality
WOM:	Word of Mouth

CHAPTER I. INTRODUCTION

1.1 INTRODUCTION

Consumers started to be exposed to an excessive amount of information through the advent of mass media, making the purchase decision more and more difficult. This led consumers to increasingly rely on Word of Mouth (WOM), "*interpersonal communication between a perceived non-commercial communicator and a receiver concerning a product or service*" when approaching the purchase process (Webster et al., 1970, p. 165). This social influence among consumers is explained by the fact that WOM conversations usually do not have a selling intent as it is in advertisements (Schlosser, 2011; Sen and Lerman, 2007).

Later, with the advent of the Internet and the emerging online platforms, the WOM has gained a new perspective called Electronic Word of Mouth (E-WOM) (Hennig-Thurau et al., 2004). According to these authors, E-WOM is defined as "*any positive or negative statement made by potential, actual, or former customers about a product or company, which is made available to a multitude of people and institutions via the Interne*t" (Hennig-Thurau et al., 2004, p. 39). E-WOM can emerge in several contexts such as blogs (Chu and Kamal, 2008; Lin et al., 2012), consumer review websites (Cheung et al., 2008; Gauri et al., 2008), discussion forums (Chiou and Cheng, 2003; Huang and Chen, 2006), shopping websites (Li and Zhan, 2011; Park et al., 2007) or social networking sites (See-To and Ho, 2014; Wang et al., 2012). As a result, E-WOM has been argued to be an effective marketing instrument (Bickart and Schindler, 2001; Kumar and Benbasat, 2006; Zhang et al., 2010). However, the current technological advances have led to the emergence of innovative technologies named "*smart technologies*", which might provide new opportunities for the development of E-WOM.

The remaining of the present chapter introduces first the E-WOM phenomena as a social influence process from a theoretical perspective, by highlighting the main theories considering this social influence. Then, the chapter continues with a brief analysis of WOM and E-WOM, outlining their main similarities and differences. Afterwards, the chapter gives a theoretical insight about the current technological advances, particularly, artificial intelligence (AI) and its effect on consumer behavior. Thereafter, the chapter highlights the relevance of E-WOM in services industries specifically in hospitality sector, which is the research context of this doctoral thesis. Finally, the chapter presents the research gaps, the research objectives as well as the thesis structure.

1.2 E-WOM AS A SOCIAL INFLUENCE PROCESS

Individuals behave following a social influence paradigm, and more importantly, they talk to each other following the same path (Hawkins et al., 2004). Social influence is described as the degree to which a person can influence other people behaviors or attitudes (Park, 2000) and it may occur in face to face environments but can be extended to the online context (Ridings and Gefen, 2004). Thus, E-WOM may be characterized as a social influence process.

Deutsh and Gerard (1955) suggested two mechanisms in which individuals may be influenced. First, informational influence (operating through internalization processes), which posits that individuals seek to gain information from others as evidences of reality. Internalization processes occur when individuals seek to enhance or support one's self-concept. Second, normative influence (operating through compliance processes), which suggests that individuals seek to gain positive outcomes and avoid negative outcomes from others. These processes occur when individuals conform to the expectations of another because of rewards or punishments (Kleman, 1961).

In addition, tie strength and homophily increases social influence. Specifically, tie strength and homophily refers to the degree to which individuals in the social groups regard each other as close and similar, respectively (Brown et al., 2007). Strong ties are more likely to lead to active information seeking behaviors than weak ones (Brown and Reingen, 1987). Besides, information from homophilic sources is more likely to be used and trusted (Steffes and Burgee, 2009).

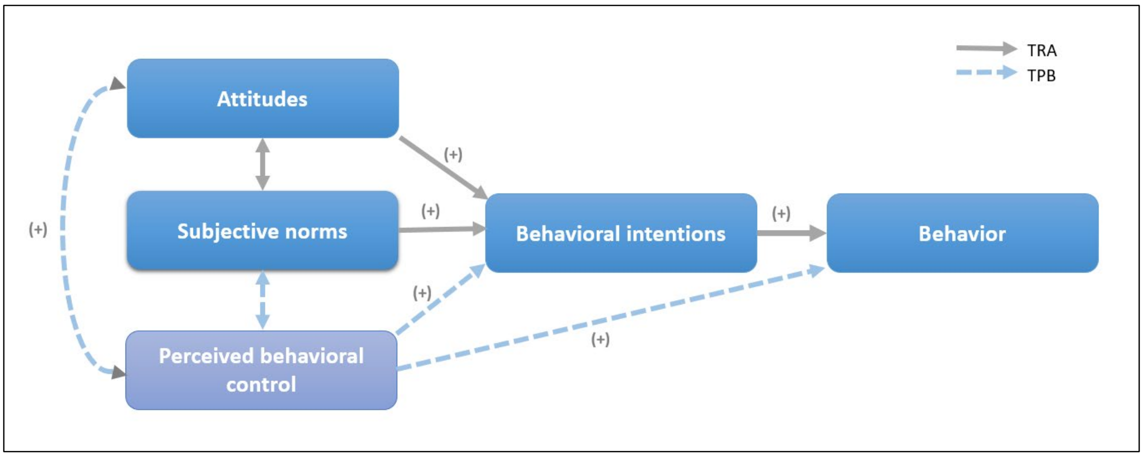
Due to its great relevance, many theories have included social influence in their models in order to explain the individuals' behaviors (e.g., Theory of Reasoned Action [Fishbein and Ajzen, 1975], Theory of Planned Behavior [Ajzen, 1991], Social Identity Theory [Tajfel, 1982], Diffusion of Innovation Theory [1985] and auto-perception theory [1972]). These theories are briefly presented in the next section.

1.2.1 Theory of Reasoned Action and Theory of Planned Behavior

The Theory of Reasoned Action (TRA) proposed by Fishbein and Ajzen (1975) is one of the theories that seek to explain human behavior. The TRA believes that people's behaviors are the result of their intentions to engage in such behaviors. Thus, intentions describe how hard individuals are willing to attempt or how much effort they intend to exert in order to complete an activity (Ajzen, 1991). Moreover, behavioral intentions are the result of two important factors: attitudes and subjective norms (Fishbein and Ajzen, 1975). Attitudes refer to "*the degree to which a person has a favorable or unfavorable evaluation or appraisal of the behavior in question*" (Fishbein and Ajzen, 1975). Subjective norms refer to the perceived social influence to perform or not a behavior (Ajzen, 1991). This influence could come from relevant people, such as relatives or friends (Park, 2000).

The Theory of Planned Behavior (TPB; Ajzen, [1991]) is an extension of the TRA (Figure 1.1) that attempts to overcome the TRA's limitations, which arise when people engage in behaviors over which they do not have complete volitional control (Ajzen, 1991). The key distinction between TRA and TPB is that TPB adds the perceived behavioral control as a factor. Perceived behavioral control is defined as "*the perceived difficulty or ease of performing a behavior*" (Ajzen, 1991, p. 188). Thus, people's intentions to perform a behavior are affected by both personal (attitudes and perceived behavioral control) and social influences (subjective norms). In both theories, subjective norms may represent the social influence exerted by E-WOM. Figure 1.1 shows the relationships proposed in both theories.

Figure 1.1 The Theory of Reasoned Action and Theory of Planned Behavior



Source: Ajzen (1991)

1.2.2 Social Identity Theory

The Social Identity Theory (SIT [Tajfel 1982]) describes how a consumer identifies with the other consumers. People derive a sense of self from the entities to which they belong and/or participate and this identity affects how they respond and act (Hogg and Terry 2000). Social identity refers to "*the individual's knowledge that he/she belongs to certain social groups together with some emotional and value significance to him of this group membership*" (Tajfel and Billig, 1974, p.292).

Social identity is generated through self-categorization. People categorize each other into "*in-group*" and "*out-group*" based on perceived similarities and differences.

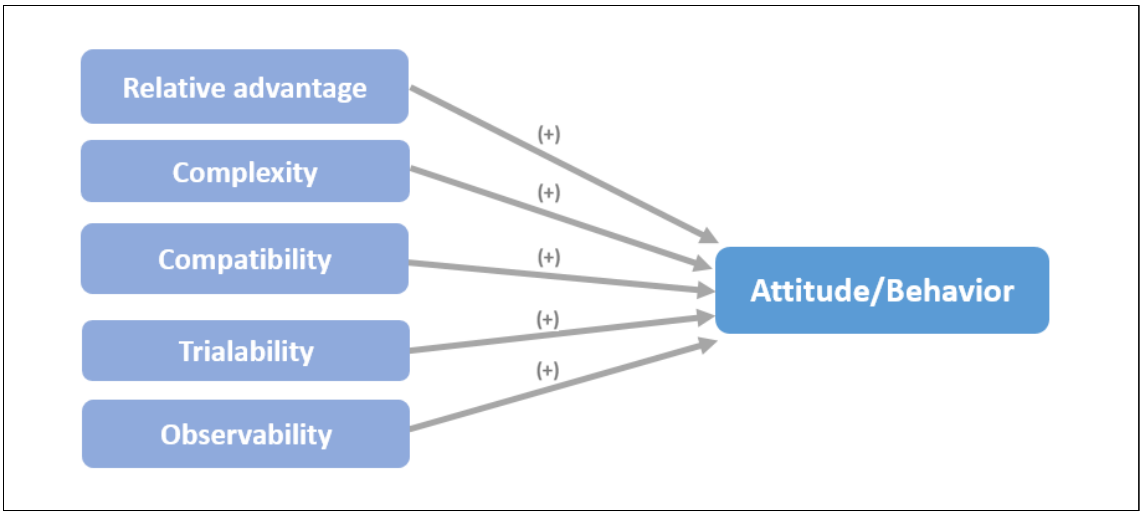
Self-categorization generates group-like thinking and behavior. Those who are in the same in-group category are treated favorably, and those in a different category, or in an out-group, are less likely to receive favorable treatment.

SIT argues that social influence within groups is exerted to the extent that individuals categorize themselves as group members and perceive themselves (and others) in terms of the shared stereotype that defines the in-group, in contrast to relevant outgroups (Turner, 1982). As a consequence, group members may be influenced by group norms, believes and opinions (e.g., E-WOM) because they stereotype themselves in terms of group membership.

1.2.3 Diffusion of Innovation Theory

The innovation diffusion theory (IDT [Rogers, 1995]), is one of the major theories that have sought to examine the elements that influence an individual’s attitudes and/or behaviors towards a new technology (Ibrahim and Sadiq, 2012). The IDT implies that technology adoption behavior is the consequence of a communication process and social influence, in which later adopters are informed by early adopters within their social network about the availability and usability of a new technology (Bhattacherjee and Sanford, 2006).

Figure 1.2 Innovation Diffusion Model



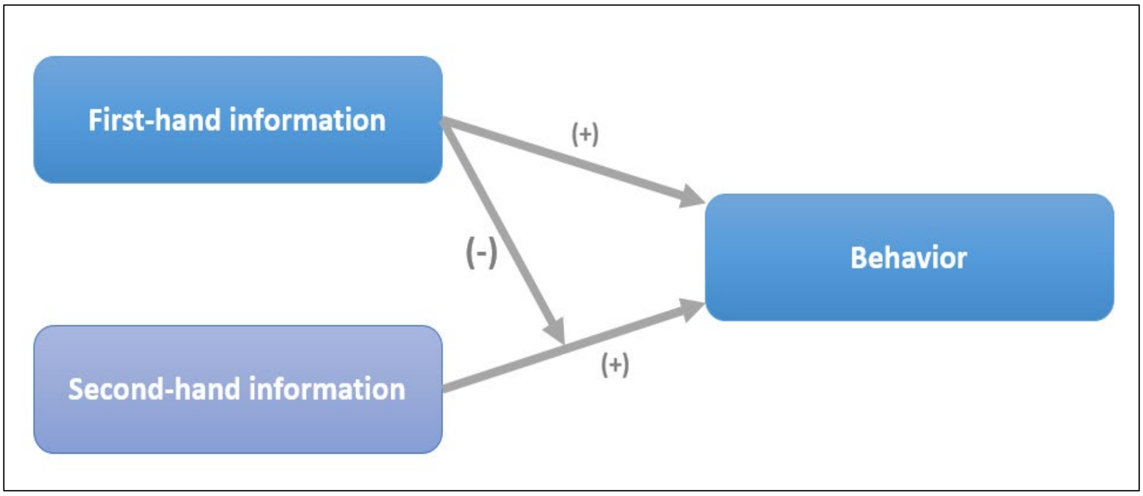
Source: Rogers (1995)

The most influential factors on attitudes or behavioral intentions adoption are relative advantage, complexity, compatibility, trialability, and observability ([Figure 1.3] Rogers, 1995). Relative advantage is defined as to the degree to which an innovation is perceived as more useful than its predecessor. Complexity relates to how difficult an invention is to comprehend and use. Compatibility relates to how well an innovation aligns with the user's values, beliefs, and habits. Trialability refers to the ability for consumers to test out an innovation prior to its widespread adoption. Finally, observability refers to the degree to which the outcomes of using an innovation are apparent to others. The E-WOM communication may be structured using IDT because E-WOM includes a product or service user exchanging information with numerous prospective users to influence future consumer behavior.

1.2.4 Self-Perception Theory

According to Self-Perception Theory ([SPT] Bem, 1972), individuals develop their attitudes, emotions, and interior states based on first-hand knowledge, such as their past acts and experiences. However, when first-hand information is vague or unobservable, individuals will rely on second-hand information, such as other people's actions or their own experiences, to determine their own behaviors (Figure 1.4).

Figure 1.3 Self-Perception Model



Source: Bem (1972)

The E-WOM communication process is connected to the SPT because, in the absence of prior experience with a product or service, individuals often rely on online information such as online reviews to determine their behavior (REF.). In this context, second-hand information, such as E-WOM, may be enough to predict consumer reactions.

1.3 FROM WOM TO E-WOM

Over the years, researchers have proposed different definitions of WOM. According to Arndt (1967, p. 379), "*WOM can be any oral and personal communication, positive or negative, about a brand, product, service, or organization, in which the receiver of the message perceives the sender to have a non-commercial intention*". Westbrook (1987) defined WOM as "*all informal communications directed at other consumer about the ownership, usage, or characteristics of particular good and service or their sellers*" (p. 261). More recently, Ismagilova et al. (2017) defined WOM as an "*oral person-to-person communication between a receiver and a communicator, where the receiver perceives the sender as non-commercial, concerning a brand, product,* *service, or organization*" (p.7). All the three definitions discussed have treated WOM as an informal communication between subjects (e.g., sender and receiver) concerning an object (e.g., products, brands, organizations, or sellers) or an experience (such as ownership, service or usage) for sharing and acquiring information with non-commercial intent.

With the emergence of Web 2.0 and new media channels, consumers' remarks concerning a product or company on the Internet are called E-WOM communication. According to Hennig-Thurau and Walsh (2003) whenever any good or bad comments are made to a significant amount of individuals or organizations on the Internet, it is known as E-WOM. Whereas, Godes and Mazylin (2004) and Park et al. (2007) added that differences exists between E-WOM and traditional advertisements because E-WOM is an independent statement generated by consumers regarding their experience which influences the buying decision of other customers. Compared to WOM, E-WOM is visible to a wider range of direct or indirect consumers, as it may be hosted in public settings (Erickson and Kellogg, 2000).

On the influence front, Godes and Mayzlin (2004) states that E-WOM have greater influence as compared to other influential sources. Besides, several studies have shown that consumer's places more trust towards E-WOM (Lee, 2014; Xu, 2014). In addition, Huang and Chen (2006) state that consumers seeking information online believe that online consumer recommendations are more trustworthy as compared to information generated by experts. Furthermore, E-WOM was also proven to be an important reference within the travel industry for consumers when they are making travel decisions and also other choices of hospitality products such as hotels and restaurants (Viglia et al., 2016; Litvin et al., 2008).

In sum, early research works argued that WOM is a significant influencer along with traditional mass communication (Kimmel and Kitchen, 2014). Later, along with online platforms, the same has been argued for E-WOM (i.e., its significant role in influencing the various stages of the consumer decision-making) (Davis and Khazanchi, 2008; Park et al., 2007). Due to the significance impact of both WOM and E-WOM in changing marketing environment, it is a fascinating to continuously study this construct, particularly, within the context of the current technological advances such as AI.

1.4 DIFFERENCES BETWEEN WOM AND E-WOM

Despite that E-WOM and WOM are similar processes, they differ in several dimensions, which make E-WOM a unique process (Table 1.1). First, the communication form in terms of time duration is the primary distinction between WOM and E-WOM. WOM mainly comprises face-to-face synchronous messages (Bickart and Schindler, 2001). Whereas E-WOM often consists of textual statements sent asynchronously through online channels, like consumer online reviews in both social and brand online communities. However, E-WOM can also be generated synchronously via instant messaging exchanged in certain social media networks (e.g., Facebook or Instagram instant messages). Second, the primary common characteristic of WOM and E-WOM is their origin or source. Generally speaking, neither form of communication is initiated by commercial entities (Lin and Heng, 2015). Third, WOM and E-WOM differs in their content valence. The valence refers to the nature of the message content, which could be positive, negative or neutral (Neelamegham and Jain, 1999). WOM content is hardly measurable as it is an oral message while E-WOM is typically made by a written message (e.g., reviews) and a rating usually ranging from "1" as extremely negative to "5" as extremely positive. Fourth, WOM and E-WOM have different scopes. While WOM communication is typically limited to smLueall groups (Steffes and Burgee, 2009), E-

WOM reaches a large number of individuals in a short period of time (Ismagilova et al., 2017). Because E-WOM is not constrained by time and space barriers (King et al., 2014) and because of the inherent bidirectional communication of online processes, these differences in reach are primarily triggered (Dellarocas, 2003). Lastly, consumer ties may vary between WOM and E-WOM communication. While most WOM communication is conducted by friends and relatives (strong ties) (Bansal and Voyer, 2000), the majority of E-WOM communications are generated by anonymous reviewers (weak ties), as Internet is primarily considered an anonymous place (Rains, 2007). Nevertheless, sometimes E-WOM could be posted by friends and relatives (strong ties) as well.

The table 1.1 summarizes the main differences and similarities between WOM and E-WOM communication.

Table 1.1 Key features of WOM, and E-WOM

Feature	WOM	E-WOM
Platform/Context	Face to face	Online
Timing	Synchronous	Synchronous, asynchronous
Origin	Consumer-initiated	Consumer-initiated
Valence	Positive, negative, neutral (hardly measurable)	Positive, negative, neutral (easily measurable)
Form	Oral	Mainly written
Audience	One-to-one	One-to-one/one-to-many
Ties strength	Often strong	Strong/weak

Source: own elaboration

1.5 SMART TECHNOLOGIES, AI AND CONSUMER BEHAVIOR

The increasing use of digital technologies has significantly reshaped marketing and consumer behavior with the emerging cutting-edge innovations such as smart technologies. Smart technologies are those physical devices or processes complemented by the smart properties of digital technologies (Yoo, 2010). Gretzel et al. (2015) describe smart technology as technology that supports a new form of value creation and collaboration that leads to competitiveness, entrepreneurship and innovation. Höjer and Wangel (2015) explain that what is new is not so much the individual technologies, products or services, but how interconnected and synchronized, and the systems they include to work in harmony. Although these advances are evolving in a constant cycle of growth and innovation, it has become clear that technological trends at the macro level, such as AI, big data, and the Internet of things (IoT), are facilitating and having an impact on smart technologies in various ways. With the growing penetration of technology in all industries, smart technologies have become the main focus of attention. In particular, smart technologies have created a new space for business opportunities in hospitality sector (Cao et al., 2022; Shen et al., 2020).

The concept of 'smart technologies' encompasses new forms of cooperation and value creation technologies (Femenia-Serra and Neuhofer, 2018). It is worth noticing that 'smart' is not the advance of a single technology, but the interconnection and collaborative advance of various technologies simultaneously. Smart technologies include a variety of computing and information technologies, as depicted in Table 1.2

Table 1.2 Summary of the different smart technologies

Form of smart technology	Short description	References
Internet of Things (IOT)	A network capable to process identification, location, tracking, monitoring, and management through RFID, infrared sensor, GPS, laser scanning, and other information sensing equipment, and connect the goods with the network for information exchange and communication.	Yun and Yuxin (2010); Kim et al., (2017).
Cloud computing technology	This technology has two meanings: (1) It refers to the system platform used to construct applications, whose status is equivalent to the operating system on a personal computer, (called cloud platform); and (2) it describes the cloud computing application built on this platform (cloud application).	Shroff (2010); Attaran, and Woods (2019); Srivastava and Khan (2018).
Artificial Intelligence (AI)	Technology allowing the use of computer software and hardware to simulate intelligent human behaviors to effectively process and analyze data and information, and to support decision-making and problem-solving.	Tsaih and Hsu (2018); Popesku (2019).
Mobile communication technology	The technology used for wireless communication allowing wireless real-time connection between systems and remote devices. 5G is the fifth-generation mobile communication technology, much faster and reliable than the previous 4G.	Castells et al. (2009); Rau et al. (2008)
Mobile devices and applications	Electronic equipment, such as mobile phones and tablets, and the technology connected with them. The mobile internet comprises various different devices and platforms; i.e., smartphones, tablets, in-car systems, and wireless home devices. It includes personal and business applications.	Benbunan-Fich and Benbunan, (2007);
Big Data	Big data is a term that describes the large volume of data—both structured and unstructured—that inundates a business on a day-to-day basis. Big data can be analyzed for insights that lead to better decision-making. It is worth noticing that this is exclusively used by businesses, not consumers.	Agrawal et al. (2014); Wang et al. (2020)
Virtual Reality (VR)	A form of information technology which enables users to navigate in computer-simulated environments. VR is a computer-generated environment in which people can experience places and situations as if they were actually present.	Flavián et al. (2021); Shin (2017)
Augmented Reality (AR)	An enhanced version of reality by which people see the real world with a digital display superimposed technology. AR enhances people's current perception of reality and enhances and leverages visitor experience through additional digital content.	Flavián et al. (2021); Tsai and Huang (2018); Javornik (2016).
Intelligent chat robot (Chatbot)	A robot able to understand and talk using human language with users.	Thomaz et al. (2020); Frankenfield (2018).
Wearable devices	A portable device that can be worn directly on the body or integrated into the user's clothes or accessories. For example, smart watch, smart bracelet, etc.	Park (2020); Chang et al, (2016).

Source: own elaboration

The research focus of this thesis is AI-based technologies because, first, AI has an influence on marketing operations and will have a greater impact in the future (e.g., Boddu et al., 2022; Jain et al., 2019). Second, AI involves consumer in the process since it relies on consumer knowledge to replicate new knowledge for product and service improvement. Therefore, these AI-based technologies advance consumer behavior which is our main context research.

Researchers propose that AI "*refers to programs, algorithms, systems that demonstrate intelligence*" (Shankar 2018, p. 6), "*manifested by machines that exhibit aspects of human intelligence*" (Huang and Rust 2018, p. 155), and "*involves machines mimicking intelligent human behavior*" (Syam and Sharma 2018, p. 136). It relies on several key technologies, such as machine learning (ML), natural language processing (NLP), neural networks, deep learning, physical robots, and robotic process automation (Davenport 2018). By employing these tools, AI provides a mean to "*interpret external data correctly, learn from such data, and exhibit flexible adaptation*" (Kaplan and Haenlein 2019, p. 17).

Another way to describe AI, depends not on its underlying technology but rather its marketing and business applications, such as automating business processes, gaining insights from data, or engaging customers (Davenport and Ronanki 2018). Also, these AI algorithms, can create language outcomes and offer future opportunities for new E-WOM communications shaped by non-human AI-based devices, that provide consumers with AI-based recommendations about products/services (Maedche et al., 2019, Williams et al., 2020). These communications can be disseminated by AI-based digital assistant like voice assistants (VAs [Bustard et al., 2019]). Such a function is particularly useful for consumers, especially because VAs are more efficient, personalized and objective than human beings in quality information, potentially leading to better matching the recommendations with consumers needs and preferences (Abrardi et al., 2022). Indeed, they can shift the decision-making process by allowing consumers to outsource purchasing decisions to algorithms (Gal and Elkin-Koren, 2017).

1.6 THE RELEVANCE OF E-WOM IN HOSPITALITY SERVICES

E-WOM has been shown to cause great changes in consumer behaviors for several products and services. For instance, products such as books (Chevalier and; Mayzlin, 2006); electronic devices (Lee et al., 2008; Zhu and Zhang, 2010; Chen et al., 2016), automobiles (Jalilvand and Samiei, 2012), or services such as movies (Hennig-thurau et al., 2015), restaurants (Kuo and Nakhata, 2019; Zhang et al., 2010) or health care (Chen et al., 2020).

Among these service industries, it has been argued that E-WOM has a relevant influence for hospitality services in particular (Casaló et al., 2015; Cantallops and Salvi, 2014). This effect is especially important due to the nature of hospitality-related products. First, hospitality services are considered as intangible, so they can only be evaluated after the consumption, elevating the importance of customers' previous information by their past consumption experiences. Second, hospitality industry is highly seasonal and perishable, hotels are exposed to great stress. E-WOM could possibly leverage the low season stress (Kościółek 2017). Lastly, hospitality industry is intensely competitive, indicating that the promotion of E-WOM influence may provide important competitive advantage for early customers (Litvin et al., 2008). All these evidences indicate the importance of examining the E-WOM influence in hospitality industry.

Online consumer reviews are the most common type of E-WOM (Chatterjee, 2001). Online reviews are considered by consumers more credible and useful than information provided by managers (Dickinger, 2011). In this regard, most research carried out in hospitality context has focused on the impact of online reviews on hotel room bookings (Ye et al., 2009), hotel performance (e.g. Cantallops and Salvi, 2014; Yang et al., 2018), hotel booking intentions (Sparks and Browning, 2011) and hotel choice (Vermeulen and Seegers, 2009). For instance, Dickinger and Mazanec (2008) found that reviews can significantly increase the consumer's booking intentions and the number of bookings in hotels. Vermeulen and Seegers (2009) found that online reviews improved consumers' awareness of hotels and honed their consideration sets. Ye et al. (2009) concluded that review ratings are important elements in the prediction of online room sales. In a nutshell, E-WOM influences the overall consumers' responses such as perceptions, attitudes and behavioral intentions in the hospitality context (e.g., Casaló et al., 2015; Nieto-García et al., 2017; Sparks and Browning, 2011; Vermeulen and Seegers, 2009).

1.7 RESEARCH GAPS AND OBJECTIVES

The importance of comprehending E-WOM process evolution and its effect on consumer behavior is outlined along this introduction chapter, showing that it is an important topic for both practitioners and academics. Previous research has made an enormous effort to advance the understanding of the E-WOM phenomenon in different contexts. However, due the vast amount of literature on this topic, there is a need to offer a framework able to explain the influence of E-WOM on consumer behavior, as well as to identify and better understand of new trends on E-WOM, especially, those due to the development of new technologies. Therefore, the main objective of this doctoral thesis is to understand how E-WOM influences consumer behavior based on the characteristics of the key elements involved in this communication process, identify the main new trends in E-WOM, and delve into the new recommendation systems based on AI. Focusing, as aforementioned, on the hospitality sector (e.g., hotels and restaurants) due to the importance of E-WOM phenomenon for these services (Casaló et al., 2015; Nicolau and

Sellers, 2010), this thesis addresses the following research gaps and aims to give answer to the following objectives:

Research gap 1. The research on E-WOM has been widely discussed during the two last decades. Various authors have carried out a meta-analysis (e.g., Ismagilova et al., 2020; 2020b; Yang et al., 2018; You et al., 2015; Babić Rosario et al., 2016) and extended literature reviews on this topic (e.g., Cheung and Thadani, 2012; Cantallops and Salvi, 2014; Babić Rosario et al., 2020; Donthu et al, 2021), noticing with great consensus its relevant role on the consumer's decision-making process. However, there is a need for an updated view of the current status of knowledge in the prolific domain of E-WOM to provide a holistic understanding of the influence of the characteristics of the key E-WOM elements (i.e., sender, message and receiver) on consumer decision-making processes (in terms of perceptions, evaluations and behaviors), and identifies emerging future research lines. Therefore, we aim to:

Objective 1. Offer a holistic framework explaining how key E-WOM elements' characteristics (i.e., sender, message and receiver) affects consumers' perceptions, evaluation and behaviors.

Objective 2. Identify new trends and research opportunities in E-WOM, specifically those due to the technological applications based on AI (e.g., voice recommendation systems).

Research gap 2. The voice technology is quickly becoming a focal point in academic research. As a main result, recent research has identified a high relevance of the application of VAs in marketing service (Klaus and Zaichkowsky, 2020; Hernandez-Ortega and Ferreira, 2021), which are able to offer personalized recommendations to consumers (Rhee and Choi, 2020; Pal et al., 2020). Indeed, VAs have been found to have a strong effect on consumer choices, capable of altering preferences based on the algorithms system and the voice features (e.g., Klaus and Zaichkowsky, 2020; Mariani et al., 2021). Thus, using a VA for recommendations may create a unique experience that is distinct from other recommendation systems. Therefore, there is a need to determine a new form of E-WOM based on AI, named AI-WOM, and analyze its effectiveness compared to E-WOM in different types of products (e.g., search vs. experience [Nelson, 1970]). To do so, we intend to:

Objective 3. Compare the influence of the traditional E-WOM received through written online reviews to the AI-WOM received through VAs, on consumer behavior.

Objective 4. Examine whether the effectiveness of AI-WOM differs when focusing on search vs. experience products.

Research gap 3. VAs are expected to create value for consumers as they help them make faster decisions, save time, and access more personalized services and products (Chopra, 2019; Eeuwen, 2017; Vassinen, 2018), consequently affecting consumers' decision-making process (Ameen et al., 2021; Grewal et al., 2018; Teller et al., 2019). Existing research on perceived value, however, offers little guidance in this context and the understanding of the antecedents of value perceptions remains equivocal (e.g., Rzepka, 2019). In addition, previous studies have mainly focused on perceived value of adopting VAs in general context (e.g., Rzepka, 2019; Kowalczuk et al., 2018; Park et al., 2018; Jain et al., 2021; Pal et al., 2021), but none prior study has dealt with the consumer perceived value when getting a product or service recommendation from a VA, how this value is developed and which consequences arise from it. On the one hand, there is thus a need to identify the main costs and benefits associated with VAs, how they determine the recommendation's value perception, and which is the role of the main characteristics of VAs (e.g. social presence [Chattaraman et al., 2019]) in this process. On the other hand, we aim to discover whether perceived value of VAs' recommendations may serve to engage the consumer with these devices. Therefore, this research also aims to:

Objective 5. Define the relevant costs and benefits associated to VAs and their role in developing the perceived value of VAs' recommendations.

Objective 6. Analyze how social presence may influence the formation of perceived value of VAs' recommendations.

Objective 7. Evaluate the effect of perceived value of VAs' recommendations on consumer engagement.

1.8 THESIS STRUCTURE

The structure of this doctoral thesis is shown in the Figure 1.5 Specifically, it is structured in five chapters organized as follow. The present chapter introduces the research topic, gaps and objectives. Chapter II aims to respond to our first and second research objectives. First, the chapter analyzes the existing literature on E-WOM in hospitality field by reviewing 97 academic articles. Grounded on communication theory, the chapter summarizes previous studies and explains how E-WOM influences consumers' behavior, focusing on the central elements of communication (i.e., message, sender and receiver). Second, drawn from the literature review, the chapter identifies some future research opportunities related to E-WOM. The remaining of the thesis will focus on one of these lines: the application of AI-based technologies to offer recommendation services (specifically, the case of VAs).

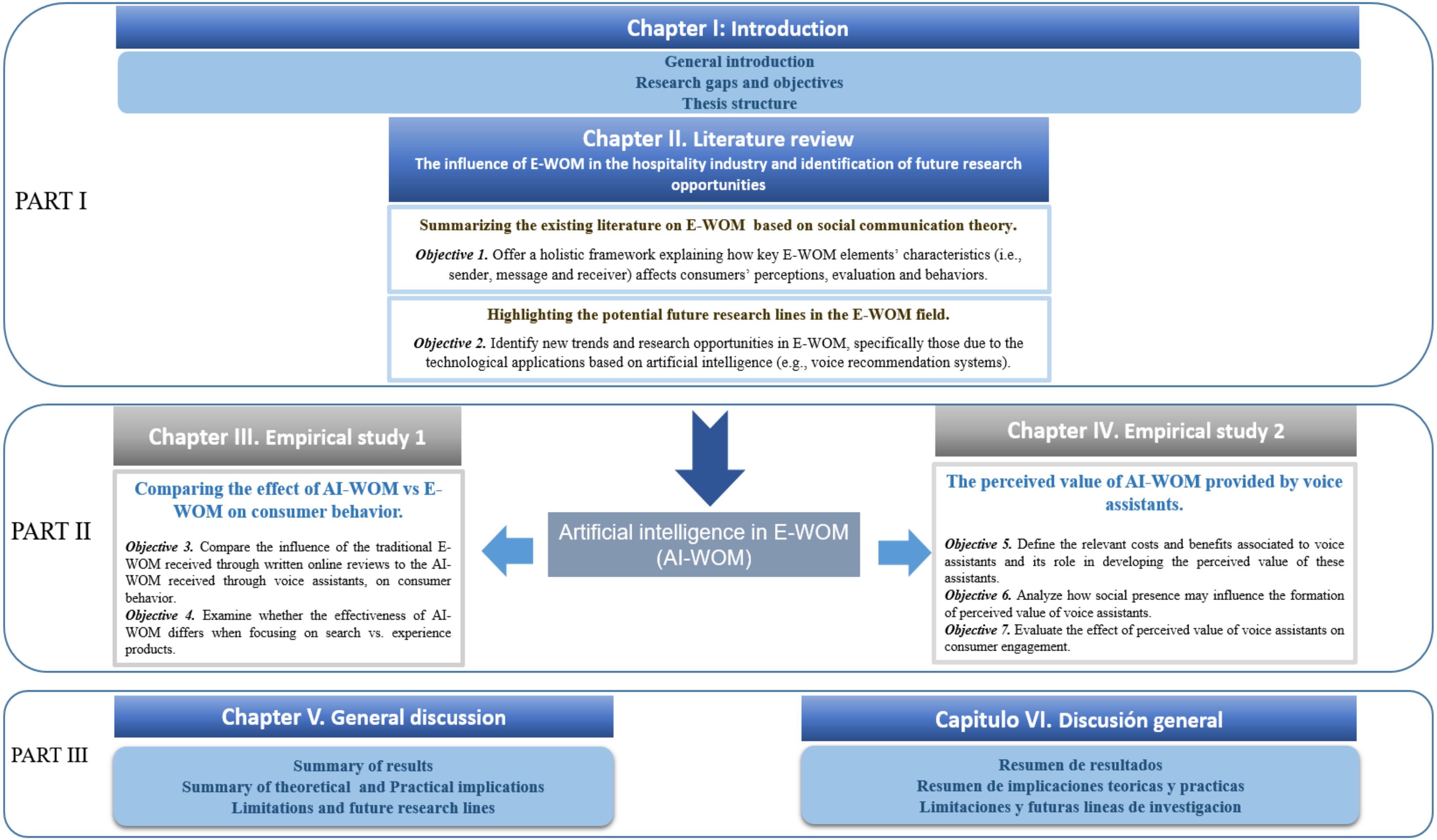
Chapter III comes to respond to the research objectives 3 and 4. The chapter is an empirical study based on between-subjects experiment design that compares the influence of written consumer online reviews (traditional E-WOM) with recommendations provided by AI-based VAs (AI-WOM) on consumer behavior. Specifically, based on

Media Richness Theory and Attribution Theory, the research model investigates how the recommendation modality (Voice vs. Text) and the content of the recommendation (Non-commercial vs. Commercial) influence consumer perceptions (credibility and usefulness) and, subsequently, their behavioral intentions. Additionally, the chapter analyzes if these relationships could vary according to the type of the recommended product (search vs. experience product).

Chapter IV aims to respond to objectives 5, 6 and 7 by analyzing a second empirical model that examines the antecedents and consequences of perceived value of VAs' recommendations, based on the cost-benefit paradigm (e.g., Kleijnen et al., 2007). Following previous literature (e.g., Kleijnen et al., 2007; Cherif and Lemoine, 2019), convenience, compatibility and personalization are considered as the main benefits associated to these VAs. On the other hand, the cognitive effort and intrusiveness were selected as costs. In addition, the chapter explores whether social presence - the most prominently cited feature of VAs (Chattaraman et al., 2019) - has an effect as a predictor of the benefits and the costs of the perceived value of VAs' recommendations. Furthermore, the chapter examines how this perceived value influences consumer behavior related to the VAs. Specifically, analyzing whether this perceived value may serve to develop consumer engagement with VAs.

Chapter V includes a general discussion, summarizes the findings from the previous chapters and presents the main theoretical and managerial implications, as well as recognizes the research limitations and offers insights for further research. Finally, chapter VI displays a spanish summary of the main conclusions obtained throughout this doctoral thesis.

Figure 1.4 Structure of the doctoral thesis



CHAPTER II. LITERATURE REVIEW ON THE INFLUENCE OF E-WOM IN THE HOSPITALITY INDUSTRY AND IDENTIFICATION OF FUTURE RESEARCH OPPORTUNITIES

2.1 INTRODUCTION

The previous chapter introduced the research topic of this doctoral thesis by giving a global overview of E-WOM and the importance of studying this phenomenon from both theoretical and practical perspectives. In this regard, the present chapter, as an extension to the previous one, analyzes extensively the existing literature on E-WOM in hospitality sector in order to give answer to research objectives 1 (better understanding the influence of E-WOM on consumer behavior in a holistic way) and 2 (identifying future research opportunities in this field).

As already noted in the previous chapter, various authors have suggested that hospitality is one of the sectors most influenced by E-WOM (e.g., Cantallops and Salvi, 2014) in terms of hotel room bookings (Ye et al., 2009), hotel performance (e.g., reputation, overall performance, booking intentions [Cantallops and Salvi, 2014; Yang et al., 2018]), hotel booking intentions (Sparks and Browning, 2011) and hotel choice (Vermeulen and Seegers, 2009). Most of these studies focused on some characteristics of the key elements of E-WOM (i.e., message, and/or sender and/or receiver [Chandler, 1994]), but there is no holistic understanding of the influence of the characteristics of E-WOM elements on consumer decision-making processes in the hospitality sector. Indeed, the only study that has reviewed the elements of E-WOM communication followed a general approach (Cheung and Thadani, 2012), without taking into account the characteristics of specific contexts.

An updated view of the current status of knowledge in the prolific domain of E-WOM would help hospitality managers better understand this phenomenon. Thus, this chapter aims to map the current state of research in the E-WOM field and identify emerging future research lines. To address this need we integrate – grounded on communication theory– results from previous studies into the central elements of communication (message, sender, receiver) and discuss the main E-WOM trends in the hospitality realm. In addition, we propose some elements of E-WOM communications that might be further researched; fake and negative reviews as message-related elements, companies' strategies in dealing with negative reviews as receiver-related elements, artificial intelligence (AI) as a sender-related element, and the platform as a medium-related element which determines how senders and receivers relate to each other.

The remainder of the present chapter is organized as follows. First, we present the methodology used to conduct the literature review. Second, we present the literature review, focusing on the determinants of the impact of E-WOM from the perspective of communication theory. Then, we use the results of our analysis of the academic literature to identify research gaps that we recommend being addressed in the future. Thereafter, we discuss the main findings of the chapter, their theoretical and practical implications and, finally, the possible research limitations.

2.2 METHODOLOGY

The present study is based on an analysis of a collection of academic articles retrieved from Web of Science and SCOPUS. The works were selected based on the following criteria: (1) E-WOM is the main focus of the investigation; (2) publications addressing elements of social communication; (3) publications dealing with E-WOM in hospitality; and (4) publications about new trends in the E-WOM realm were also considered.

The articles were scanned based on words included in their titles, keywords and abstracts; terms searched for included E-WOM, social communication, online reviews, online recommendation, communication theory, fake reviews, negative reviews, online travel communities and AI. The articles were taken from scientific journals selected based on their importance, research focus, academic rating and the number of related papers they had published. The main journals from which papers were selected were (see the full list of papers in appendix A): *Tourism management, Computers in Human Behavior, International Journal of Contemporary Hospitality Management* and *International Journal of Hospitality Management*. 97 articles were found to be related in various ways, to the research topic.

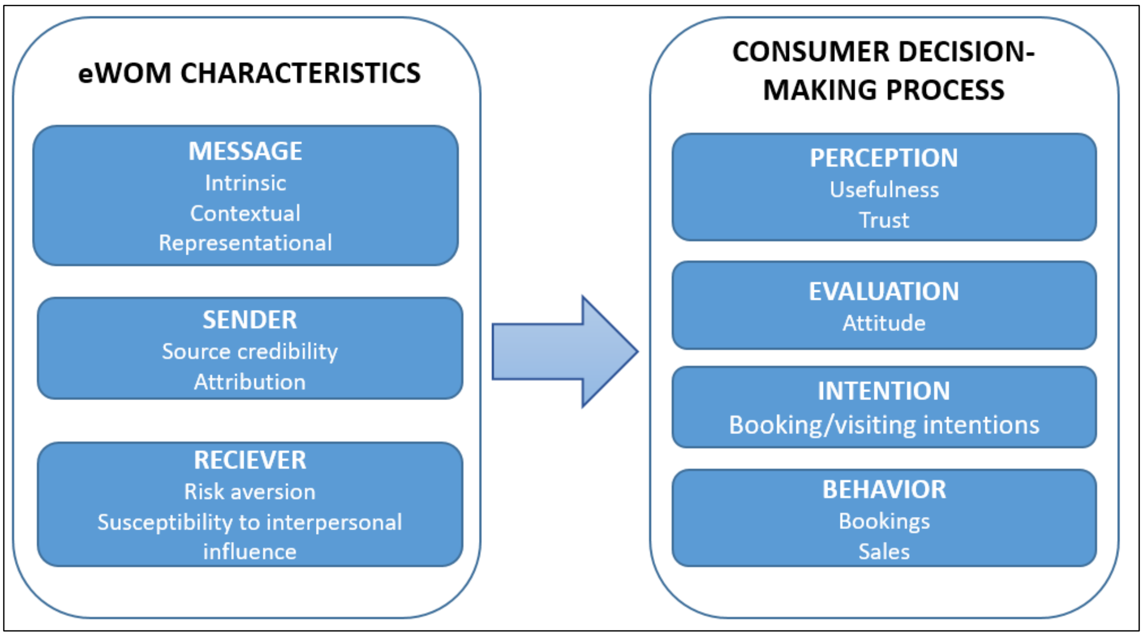
2.3 DETERMINANTS OF THE IMPACT OF E-WOM FROM THE PERSPECTIVE OF COMMUNICATION THEORY

Hovland (1948), one of the founding fathers of social communication theory, defined social communication as "*the process by which an individual (the communicator) transmits stimuli (usually verbal symbols) to modify the behavior of other individuals (communicates)*" (p. 317). Based on this theory, our work analyzes E-WOM communications as a new form of social communication.

In the hospitality sector E-WOM characteristics have been found to influence several consumer perception-related variables (e.g., usefulness [Casaló et al., 2015], trust [Sparks and Browning, 2011]), evaluations (e.g., attitude [Vermeulen and Seegers, 2009]), intentions and behaviors (e.g., Sparks and Browning, 2011). For instance, both reviewer (e.g., expert vs. non-expert) and review characteristics (e.g., review valence) may affect the usefulness of reviews (Casaló et al., 2015), which in turn determine intention to follow the review advice/recommendation (Casaló et al., 2011b). Similarly, focusing on hotels, review valence (positive vs. negative) and/or reviewer expertise may affect the customer's attitude toward the reviewed service (Vermeulen and Seegers, 2009). Several works have confirmed that review characteristics such as valence and numerical ratings may, in combination, increase booking intentions (e.g., Sparks and

Browning, 2011). Figure 2.1 displays the variables analyzed based on the characteristics of the message, the sender and the receiver (Chandler, 1994).

Figure 2.1 Holistic framework of the influence of E-WOM characteristics on the consumer's decision-making processes in hospitality sector



Source: own elaboration

2.3.1 Online consumer reviews

Online consumer reviews are the most common type of E-WOM (Chatterjee, 2001). They serve, first, to provide information about products/services and, second, as recommendations (Park et al., 2007). According to Casaló et al. (2008; 2009), online reviews are an important information source that provide consumers with detailed and reliable information by sharing past consumption experiences. Thus, they are perceived as more credible than information provided by managers. In particular, consumers tend to rely more on other consumers' reviews when purchasing high involvement products (Park et al., 2007); since hospitality-related products are high involvement, we expect hospitality-related reviews will be extensively consulted in hospitality-related decisions.

Various researchers have examined the impact of online reviews on customers' behaviors such as booking trips (Xiang and Gretzel, 2010) and hotels and restaurants (Sparks and Browning, 2011), and even on the consumer's emotional state (Flavián-Blanco et al., 2011). For instance, Dickinger and Mazanec (2008) found that reviews can significantly increase the consumer's booking intentions and the number of bookings in hotels. In addition, Vermeulen and Seegers (2009) found that online reviews improved consumers' awareness of hotels and honed their consideration sets. Ye et al. (2009) concluded that review ratings are important elements in the prediction of online room sales. Flavián-Blanco et al. (2011) found that online reviews influence the emotional state of consumers because of the effort they must make in their searches. This can affect their behavioral intentions. In summary, the analysis of online reviews can help improve the quality of products/services, the identification of customer needs, and to implement new marketing strategies (Yacouel and Fleischer, 2012).

2.3.2 E-WOM communication elements

E-WOM is a relatively new form of social communication that involves both information seeking and information sharing customers. Working within this framework, and following our review of the previous related works, we conclude that there are three major communication elements (Chandler, 1994): 1) the message is the communication (positive, negative or neutral) transmitted by a sender to a receiver; 2) the sender is the person who transmits the communication; and 3) the receiver is the individual who receives the communication. In addition, we identify the different variables related to each element and their interrelationships.

2.3.2.1 Message characteristics

- Intrinsic characteristics

The intrinsic characteristics of the message are based on the concept that information has quality in its own right (Wang and Strong, 1996). Nelson et al. (2005) defined intrinsic characteristics as properties of information independent from any specific user, task or application. Accuracy, objectivity and valence have been proposed as the dimensions of intrinsic characteristics (Wang and Strong, 1996; Mudambi and Schuff, 2010). Information accuracy is the extent to which information is correct and believable (Wand and Wang, 1996). Information objectivity refers to rational and concrete content and valid argumentation (Park and Lee, 2008). Message valence is the positive, negative or neutral direction of information (Mudambi and Schuff, 2010). In the online context, positive messages highlight the strengths of products/services and encourage people to acquire them, while negative E-WOM emphasizes the weaknesses of products/services and, thus, discourages acquisition (Dellarocas et al, 2007; Flavián et al. 2021).

Prior studies into online consumer reviews have suggested that information accuracy has, in general, a positive influence on perceptions of the usefulness of online reviews (Cheung et al., 2008) and on customers' intentions to adopt the information (Filleri and McLeay, 2013); in particular, in hotel reviews (Zhang et al., 2016). Media richness theory proposes that the more accurate is the message, the higher will be the receiver's perceptions of its usefulness. In addition, it has been found that perceptions of the objectivity of information positively affects attitudes toward the information (Park and Lee, 2008). Negative reviews are perceived as more useful than positive reviews, and generate negative attitudes (Lee et al., 2008). This finding is in line with Cacioppo and Bernston (1994), who suggested that negative input has a greater effect on attitudes and behaviors than has positive input. Nonetheless, positive online reviews have been found to enhance consumers' assessments of hotels (Vermeulen and Seegers, 2009), booking intentions and sales (Ye et al., 2009).

- Contextual characteristics

Contextual characteristics are based on the concept that information must relate to the context of the task at hand; that is, to add value information must be relevant, timely and complete (Wang and Strong, 1996). Filieri and Mcleay (2014) argued that information relevance refers to the extent to which it is applicable and helpful for a task. Information timeliness refers to its status as up to date (Nelson et al., 2005). Completeness refers to the extent to which information has sufficient depth and scope to address the task at hand (Wang and Strong, 1996).

Previous research in the hospitality sector has demonstrated that information relevance has a significant impact on perceptions of information usefulness and is an important antecedent of behavioral intentions (Filieri and Mcleay, 2014). In addition, as consumers seek quick and effortless information, the timelier is the message, the more it is of use (Cheung et al., 2008). Regarding information completeness, reviews which include detailed information (e.g., information about the product/service, pictures) can alleviate customers' uncertainty about a product/service, and allow them to develop more confidence in their decision-making processes (Cheung et al., 2008).

- Representational characteristics

Representational characteristics are related to how information is presented, that is, is it understandable, easy to read and easy to interpret (Wang and Strong, 1996)? Representational characteristics are language, semantic, lexical expressions and visual cues that increase the understandability and the ease of interpretation of a review (Davis and Khazanchi, 2008).

In the context of online travel communities, some works have shown that a significant relationship exists between ease of reading and customers' perceptions of the usefulness of reviews (Liu and Park, 2015), and that customers tend to search for reviews that help them obtain the specific information they need. In addition, understandability has been shown to be a positive influence on information adoption in online reviews (Cheung et al., 2008). Visual cues, such as videos, have been found to improve the usefulness of reviews and increase intention to follow their advice (Casaló et al., 2015; Orús et al., 2017; Flavián et al., 2009; 2017). Moreover, semantic content and style properties, such as affective content and figurative language, may reinforce the impact of the online reviews on intention to follow their advice (Ludwig et al., 2013).

2.3.2.2 Sender characteristics

- Source credibility

Various studies have noted that source credibility is the most investigated message sender-related factor (Sussman and Siegal, 2003). Petty and Cacioppo (1981) described source credibility as the extent to which an information source is perceived to be believable and trustworthy. Hovland and Weiss (1953) argued that credibility has two dimensions, expertise and trustworthiness. In online environments users often seek out others who offer trustworthy advice (Boush and Kahle, 2002). In the hospitality context, credibility has been found to be important due to the intangible nature of hospitality products and the psychological risks associated with hospitality-related decision-making (Loda et al., 2009). Casaló et al. (2011b) argued that source credibility enhances the usefulness of online reviews, and that customers consider that reviews are useful if they provide sufficient, good information that is likely to help them predict how an experience will turn out. Ayeh et al. (2013) showed the positive influence of source credibility on customers' attitudes toward using user-generated content in their travel planning. In addition, Filieri (2015), Sussman and Siegal (2003) and Ayeh et al. (2013) showed that hospitality information messages perceived to have higher source credibility are associated with higher levels of adoption.

- Attribution

Attribution theory proposes that individuals make causal inferences as to why communicators advocate certain positions or behave in certain ways (Mizerski et al. 1979). Specifically, the theory proposes that the more the customer attributes a review about a product to the product's actual performance, the more the customer will perceive that the communicator is credible, the stronger will be the customer's belief that the product is as described in the review, and the more the customer will be persuaded by the review (Mizerski et al. 1979). Thus, in the hospitality industry, for instance, if a customer feels that a reviewer has positively reviewed a hotel because of its actual performance, and the review relates to the core services of hotels, then (s)he will attribute the review to the quality of the hotel.

The attribution process has been shown to play a significant role in consumers' evaluations, attitudes, behaviors (Weber and Sparks, 2010) and decision-making (Mizerski et al., 1979). In the context of online travel communities, Browning et al. (2013) reported that consumer reviews that customers associate with hotels' services and characteristics are more likely to affect their perceptions, and be seen as more useful, and generate more positive attitudes, than reviews that the customers associate with the characteristics of the reviewer.

2.3.2.3 Receiver characteristics

- Consumer susceptibility to interpersonal influence

The consumer's susceptibility to interpersonal influence is his/her general tendency to accept information from others as true (Deutsch and Gerard, 1955). Consumers highly susceptible to interpersonal influence have been shown to be more influenced by the opinions of others when making purchase decisions (Schroeder, 1996). In the E-WOM context, an individual with greater propensity to be influenced by others is likely to attach more weight to E-WOM information than one who is less susceptible to interpersonal influence (Sparks and Browning, 2011). It has been found that consumer susceptibility to interpersonal influence positively impacts on their attitudes and behavioral intentions (Lee et al., 2011). Park and Lee (2008) found that consumers with greater susceptibility to interpersonal influence perceive reviews as being more useful than do consumers with less susceptibility to interpersonal influence. Sharma and Klein (2020) argued that, in forming their behavioral intentions, it is likely that individuals more easily influenced by information provided by others will give more weight to their perceptions of the advice offered.

- Risk aversion

Risk aversion has been defined as "*the extent to which people feel threatened by ambiguous situations, and have created beliefs and institutions that try to avoid them*" (Hofstede and Bond, 1984, p. 419). In the WOM communication context, previous research has shown that people who perceive higher risk will seek out WOM communication more actively than people who perceive lower risk (Arndt, 1967). Therefore, WOM is a credible source of information to draw on to assess risk and reduce uncertainty about behavioral decisions (Murray, 1991).

Previous research has revealed that the individual's level of risk aversion can impact on his/her decision-making processes and general attitudes and behaviors (Mandrik and Bao, 2005). In the online travel context, consumers' levels of risk aversion may make them sensitive to safety issues when choosing travel-related products (Mandrik and Bao, 2005). As a result, those with high levels of risk aversion may rely heavily on online travel communities for trustworthy information to use in their purchasing decisions.

Table 2.1 summarizes some characteristics –not previously discussed– related to the communication elements of E-WOM. The table displays, for each characteristic, the definition, the associated E-WOM element, the main consequences and some related previous studies.

Table 2.1 Other characteristics related to E-WOM elements

Characteristics	Definitions	E-WOM element	Consequences	Previous works
Identity disclosure	The social identity that an individual establishes in an online community. A way of presenting oneself thathelps others find one's personal profile/geographic location (Nbeth, 2005).	Sender	Perceived usefulness, credibility	Kruglanski et al. (2005); Susan and Siegal (2003); Liu and Park (2015)
Enjoyment	The extent to which the reading and understanding of reviews is perceived to be enjoyable in its own right, irrespective of any performance consequences (Davis et al.,1992).	Message	Perceived usefulness	Liu and Park (2015); Venkatesh et al. (2002)
Review type	The orientation of a review e.g., recommendation vs attribute value information (Park and Lee, 2008).	Message	Purchase intention, perceived informativeness, persuasiveness (moderated by the consumer's expertise)	Park and Kim (2008); Park and Lee (2008); Xia and Bechwati (2008)
Review rating	The rating given by the reviewer to a product/service (Lee and Lee, 2009).	Message	Perceived usefulness, attitude	Lee and Lee (2009)
Recommen dation consistency	Whether the E-WOM recommendation is consistent with other contributors' experiences of the same product/service (Cheung et al., 2009).	Message	Perceived usefulness, reviewcredibility (moderated by consumers' involvement level)	Cheung et al. (2009)
Source type	The information source of a recommendation (e.g., consumer reports, friends, sales assistants) (Huang et al., 2009).	Sender, platform (medium)	Perceived informativeness, perceived usefulness	Huang et al. (2009)
Homophily	The degree to which pairs of individualsare similar in age, education and social status (Steffes and Burgee, 2009).	Sender, receiver	Behavior, trust, attitude	Steffes and Burgee (2009)
Involvement	Degree of psychological identificationand affective, emotional ties the consumer has with a message (Park and Lee, 2008).	Receiver	Attitude, purchase intentions	Cheung et al. (2009); Doh and Hwang (2009); Lee et al. (2008); Park and Lee (2008);
Gender	Gender of the reviewers: male/female. (Awad and Ragowsky, 2008).	Sender, receiver	Trust, perceived usefulness, purchase intentions	Awad and Ragowsky (2008); Dellarocas et al. (2007)

Source: own source

2.4 FUTURE RESEARCH OPPORTUNITIES

Although E-WOM has been studied only over the last 15-20 years, the phenomenon has attracted scholars from diverse fields, such as marketing (Park and Kim, 2008), communications (Cheung et al., 2009) and psychology (Park and Lee, 2008). However, there are controversies and research gaps in the hospitality-related E-WOM literature that remain to be addressed. In this section we discuss some potential future research avenues related to the aforementioned E-WOM elements: fake reviews as message-related elements, strategies for dealing with negative reviews as receiver-related elements, platforms as medium-related elements determining how senders and receivers relate to each other, and AI systems as sender-related elements.

2.4.1 Fake online reviews

Recently, social media and consumer review sites have come to seem quite unreliable and fake (Luca and Zervas, 2016), which is an obvious concern for users. Fake reviews have been described as "*the intentional control of information in a technologically mediated message to create a false belief in the receiver of the message*" (Hancock, 2007, pp. 290). A natural consequence of the existence of fake online reviews is that, in general, the credibility of all reviews will decline (Lappas et al., 2016).

One of the main findings of a study by the UK's Competition and Markets Authority (2015) was that fake positive reviews are more common than fake negative reviews. The study suggested that this may be because it is easier and less risky for business owners to post positive reviews about their own entities than to post negative reviews. As an example, one study found that around 20% of hospitality industry reviews were potentially fake (Wu et al., 2020). In practice, these percentages are likely to vary across platforms (Lappas et al., 2016). Recently, some researchers have examined reviewers' motivations to post fake reviews. Choi et al. (2017) and Rixom and Mishra (2015) suggested that powerless individuals are more likely to write fake reviews when offered money than when incentivized by charitable motives.

The growing concern over fake online reviews has motivated online communities to implement various types of defense mechanism. For instance, reviews that TripAdvisor regards as suspicious can be placed on hold, and even be eliminated, if the website's proprietary filtering process finds enough evidence (TripAdvisor, 2019). In addition, Mayzlin et al. (2014), in the context of TripAdvisor, discussed the "*verified buyer*" badge, which allows only those who have actually purchased a product/service to post reviews. In any case, little is still known about the motivations of those who post fake reviews, their consequences for companies (e.g., reputational loss) and their influence on consumers' decision-making processes.

2.4.2 The main companies' strategies for dealing with negative reviews

While conventional wisdom suggests that any publicity is good publicity, existing research (e.g., Zhang et al., 2016) has shown the many downsides of negative reviews, such as reputational harm, reduced sales and decrease in consumer trust. Despite the potential harm, only limited research has examined strategies for handling negative reviews. This section examines the main strategies followed by companies for dealing with negative reviews, and discusses their advantages and disadvantages. Future research might use this examination as a basis for exploring the effectiveness of each strategy in more detail.

- <u>Response</u>

Response strategy involves listening to, acknowledging and addressing the negative feedback generated by online communities (Rajan, 2016). Web specialists have attained near consensus on the most appropriate method of handling unfavorable reviews: respond as positively as possible (Kiesow, 2010). Response strategy recognizes that marketing communication is interactive and consumers' reactions to messages deployed must be considered in the process. In addition, response strategy provides an opportunity to quickly and politely correct inaccurate information (Barone, 2009).

Response strategy has the potential to increase customer loyalty and build stronger consumer-company relationships (RightNow, 2011). Sparks et al. (2016) showed that, when compared to the no-response baseline, responses from hotels created significantly more trust and positive consumer attitudes. Nieto and Hernandez-Maestro (2014) found, in the context of Spanish rural lodging establishments, that when companies responded appropriately to negative reviews their average ratings improved. These results are consistent with the findings of Lee and Song (2010), who found that individuals evaluate companies positively when they respond to online complaints. Despite the advantages of response strategy, it has some significant downsides. For instance, managers must be careful to advocate without angering entire communities of consumers who will see the message, and they should understand at what point they need to respond (Thomas et al., 2012).

- <u>Delay or ignoring</u>

Delay strategy is based on the concept that if a company does not respond to a negative review the issue will eventually die down (Vogt, 2009). Although delay/ignore strategy appears to be a less viable option in today's socially mediated world, there are reasons why companies may choose to adopt it. For example, by ignoring a negative attack management avoids engaging in a tug-of-war with consumers attacking their brand image (Thomas et al., 2012). However, a delay strategy can create the belief that the company is being unresponsive and is unwilling to listen to its customers. When companies are unresponsive, or slow to respond, they are perceived as uncaring, and/or guilty of the actions/inactions complained of by their accusers (Thomas et al., 2012).

- Partnership

A partnership strategy engages the consumer in the process, indeed, may involve turning over control of the process to the consumer. The strategy involves the company working in partnership with consumers (fans), thereby creating constructive and committed relationships (Thomas et al., 2012). By collaborating with fans - potential customers - companies can come to understand their preferences and, thereby, respond appropriately to their needs and reduce complaints and negative comments.

For example, Coca Cola's Facebook page was created by two fans, helped by the company's marketing team. Using this strategy, in which the consumer controls its social media reviews, Coca Cola has built an effective partnership with its fans (Graham, 2011). Consequently, the company is perceived to have a high level of authenticity and transparency. In addition, partnership strategies enable companies to benefit from their fans (Safko and Brake, 2010). In fact, according to Graham (2011), fans are twice as likely to consume, and ten times more likely to purchase, the product than non-fans. However, while partnering with fans can help the company deal with negative online attacks, it does involve giving up control. Simply put, if the company and its partners fall out, the partners have insider knowledge that gives them a great deal of power to do damage.

- Censorship

Censorship is a strategy through which companies attempt to take control over consumer reviews by removing unwanted information (Dekay, 2012). Giving up control of the message is difficult for companies accustomed to operating within the one-way communication model (Thomas et al., 2012), and adopting censorship as a strategy can create negative publicity which can quickly spread among online communities (Jackson, 2008). Although this strategy allows companies to maintain greater control over reviews, the nature of online communities is such that negative perceptions may continue to exist, and the companies' tactics may be seen as aggressive and hostile (Thomas et al., 2012).

2.4.3 The moderating effect of the platform on E-WOM influence

The internet has facilitated E-WOM communication between customers on a variety of platforms (Cheung and Thadani 2012). For example, E-WOM is exchanged on personal blogs, social networking sites such as Facebook and on online travel communities such as TripAdvisor; academics need to analyze whether these platforms reinforce or diminish the influence of E-WOM. Previous studies have mainly tested the effects of E-WOM posted on social media (See-To and Ho, 2014) and on online travel communities (Belanche el al., 2019; Casaló et al., 2011b; Casaló et al., 2010; Liu et al., 2019) separately. In both cases, E-WOM was found to influence consumers' purchase intentions. However, the effects of E-WOM posted on these two different platforms have not hitherto been compared, although there are three major differences between them that may increase or decrease the influence of E-WOM.

- Tie strength

Tie strength is the level of intensity of the social relationship between individuals; it varies greatly across consumer social networks (Steffes and Burgee, 2009). There are two types of tie strength, strong ties and weak ties. People with whom one has strong ties are regarded as more credible and reliable than people with whom one has weak ties. Liviatan et al. (2008) proposed that people have more detailed and concrete knowledge about individuals with whom they share close relationships, because this closeness involves more intimate interactions and exposure to privileged information about the other person's personality (Koo, 2016). Information derived from strong ties is perceived as more useful, and information derived from weak ties is considered less valuable, even questionable (Wang and Chang, 2013). In the online context, it has been found that the strength of the tie between the sender and the customer positively impacts on E-WOM adoption (Kim and Bae, 2016).

- Social cues

Social information cues include information about personal identities, and spatial and environmental contexts. Social networks usually provide richer social cues than do online travel communities (Baym, 2015). Previous research has shown that a lack of social cues - source information - negatively impacts on perceptions of the credibility of online reviews (Dellarocas, 2003). Similarly, Park et al. (2014) argued that personal profile information is an important social cue which significantly impacts on E-WOM source credibility. More specifically, Lee and Youn (2009) found that, because there are more social cues in personal blogs than there are on other platforms, customers perceive reviews posted on personal blogs as more useful.

- Expertise and objectivity

Customers engage in information exchange in online travel communities because they provide the opportunity to share knowledge gained from previous trips (Lee and Yang, 2015). Previous research (Liu et al., 2019) has shown that customers with past experiences who engage in E-WOM communication are most likely to be the more preferred sources of information, and the most influential, in the pre-trip stage of travel decision-making. In this respect, the distinctiveness of online travel communities, compared to social networking sites, is the customers' expertise (Wang and Fesenmaier, 2004). Previous studies have highlighted some unique roles of online travel communities. First, they permit individuals to access other customers' knowledge and feelings about specific destinations (Chalkiti and Sigala, 2008; Chang and Chuang, 2011); and they are utilized as collaborative decision-making platforms that offer unbiased information about emotional experiences regarding given destinations and hospitality products (Casaló et al., 2011a).

2.4.4 Artificial Intelligence in E-WOM (AI-WOM)

2.4.4.1 Definition

Because of increased human–machine interactions, development in robotics and AI has permitted machines to perform increasingly multifaceted functions (Borghi and Mariani, 2021). AI-based devices (e.g., robots) can emulate human behavior attentively and perform the same tasks as they do (Vrontis et al., 2021). Because of this, even though individuals frequently collect information from others, the advent of "big data" results in the accessibility and efficacy of a novel source of information known as algorithms (Logg et al., 2019). These AI algorithms, which can separately create language outcomes and offer future opportunities for new communications shaped by non-human AI tools, can aid consumer decision-making (Mendes and Mattiuzzo, 2022, Williams et al., 2020). We call these communications "*AI-WOM*".

In this article, AI-WOM is referred to AI-based recommendations given by automated devices based on AI systems, interacting with consumers without human intervention, in order to support consumer decision-making process about products/services.

The AI-WOM process relies basically on two main systems; content-based filtering (CBF) (Zenebea and Norciob, 2009) and user-collaborative filtering (CF) (Herlocker et al., 2002). CBF identifies consumer shopping preferences according to products' features that the consumer has purchased in the past to recommend similar products to the consumer (Mishra et al., 2015). To overcome the limit of recommendation nurtured by consumers' past experiences, CF, which is used by companies such as Amazon, guesses the customer's preferences by recommending products that are most likely to be purchased by a similar group (Thorat et al., 2015).

Kozubska (2018) found that recommendations are a common application of AI in the hospitality industry. For instance, AI is used to make recommendations for flights, hotels, restaurants and clubs based on the user's preferences, past booking history and search results. This application can reduce the many challenges that customers face when organizing trips. The following section briefly reviews some examples of AI applications in the hospitality sector. AI-based recommendation systems in hospitality, mainly include Chatbots and voice assistants (VAs) such as Alexa (Prasad, 2019), simplifying customer's purchase decisions and product sales (Soo Kim, 2013).

2.4.4.2 AI-WOM applications

- Chatbots

Chatbot is a natural language computer program designed to approximate human speech and interact with people via a digital interface (Thomaz et al., 2020). Chatbots are configured to self-learn in response to users' requests instead of using pre-programmed answers. When a Chatbot gets a new text input, its keywords are saved for future data processing. Hence, the number of questions/situations that it can handle continue to grow, and the correctness of each reply it makes may increase (Frankenfield, 2018). Chatbots have multiple applications in various industries, growing particularly strongly in the hospitality industry (Faggella, 2019). For example, Expedia and Skyscanner took advantage of Facebook's technologies to launch a basic bot that helps customers book hotel rooms. Marriott Hotels also features a Chatbot on its website that offers basic services, such as booking a room.

Chatbots are an alternative way for customers to search for tips and information; they simply ask questions using keywords and receive appropriate answers (Faggella, 2019). Ambawat and Wadera (2019) found that Chatbots improve the customer's experience; in particular, they can enrich the pre-arrival experience. In addition, this technology can help maintain relationships between consumers and companies.

- Voice assistants (VAs)

AI-powered VAs that engage in natural conversational interactions with humans have been integrated into various devices (e.g., smartphones, cars). Individuals can interact with devices using their voice as the input mechanism in order to receive oral advice/recommendations about products/services (Kozubska, 2018). The AI-WOM process relies on a ranking algorithm (Ursu, 2018) combined with voice command navigation through a recommender system (Baizal et al., 2020) where the consumer specifies a more or less precise query to the VA. Based on this query input, the algorithm-based VA calculates recommendations with ranked product proposals that may satisfy the user's personal needs (Baizal et al., 2016).

Most related studies have demonstrated that VAs reduce search effort and increase cross-selling by providing product/services recommendations. Thus, they can affect the consumer's decision-making processes (Tam and Ho, 2006). Also, it has been argued that VAs create a more intimate experience, humanize interactions, simulate social presence and enhance trust (Cherif and Lemoine, 2017). Simms (2019) found that VAs learn the consumer's preferences, and consequently increase their influence on his/her behavioral intentions. Nevertheless, some studies have suggested that these technologies raise privacy concerns (Simms, 2019).

2.4.4.3 E-WOM vs. AI-WOM – Similarities and differences

The concepts of E-WOM and AI-WOM share certain important similarities. Arguably, the key common characteristic relates to the origin or source of E-WOM and AI-WOM. E-WOM is usually giving by a consumer statement/image or video posted in online platforms. Whereas AI-WOMI is provided by AI systems that ca be disseminated by automated devices based on AI systems ((Longoni and Cian, 2020). Another important feature of E-WOM and AI-WOM is related to the content valence. Specifically, in this regards, research often distinguishes between positive, negative and neutral E-WOM. As it is usually made by written statements, E-WOM is easily measurable by ratings function (Hoffman and Daugherty, 2013; Pfeffer et al., 2014; Ladhari and Michaud, 2015) as aforementioned in the section 1.4. Similar criterion is applied to AI-WOM (Tikhonov and Yamshchikov, 2018; Williams et al., 2019), however, it is expected that AI-WOM could be hardly measurable, when it is provided by voice messages (e.g., voice assistants' recommendations), or easily when it is provided by text message (e.g., Chatbots' recommendations). The matter of valence is often associated with the impact of recommendations on consumers, and there are conflicting views on the issue. In fact, whereas a stream of research argues for the stronger effect of negative E-WOM and AI-WOM on individuals (Williams et al., 2019; Lim and Chung, 2011), other scholars provide evidence to the contrary (East et al., 2008). In any case, both E-WOM and AI-WOM have proven to have a strong influence on consumers (Garnefeld et al., 2011; Ursu, 2018). The two types of communication are often preferred to, and more trusted by individuals than company-initiated marketing initiatives (Chatterjee, 2011 Cherif and Lemoine, 2017).

Nonetheless, despite the identified similarities, there are also significant differences between the two concepts. Traditional E-WOM and AI-WOM differ in the strength of social ties, or the degree of closeness between the communicator and receiver of information (Groeger and Buttle, 2014; Baker et al., 2016). E-WOM could have strong or weak strength ties conversely to AI-WOM which often characterized by weak strength ties, since the recommendations are given by automated autonomous device. This difference is important, as the strength of social ties can moderate the impact of E-WOM on consumers (Baker et al., 2016). The closeness between the communicator and the receiver of the message can affect E-WOM persuasiveness (Teng et al., 2014), and influence consumers' decisions (Steffes and Burgee, 2009), as well as motivate the individual to spread the message further to one's social network (Chu and Kim, 2011).

Additionally, the context communication is another key distinction between the E-WOM and AI-WOM. Whereas traditional E-WOM refers to the computer-mediated interactions that appear across various Internet and social media platforms, AI-WOM captures autonomous AI-based devices. These can include an extensive list of devices, such as VAs (Baizal et al., 2020), Chatbots (Ambawat and Wadera, 2019) and personal virtual assistants (Voorveld and Araujo, 2020).

E-WOM and AI-WOM, further differ in the temporal aspect. In AI-WOM, interactivity is one of the main characteristics of smart products (Hoffman and Novak, 2015). The production and consumption of information happen simultaneously, in two-way communication flow (Hood et al., 2015), making it synchronous. Consumers enter in conversations with VAs or Chatbots through voice input or text input respectively, and receive an instant feedback (Berger, 2014). By contrast, E-WOM can take on both synchronous and asynchronous characteristics (Chu and Kim, 2011). Synchronous E-WOM can take a form of a conversation in a forum, where the information is sent and received at the same time. Examples of asynchronous E-WOM are comments on review websites, which are usually not consumed at the same time as they are produced, and are consequently characterized by a lower level of interactivity (Lovett et al., 2013).

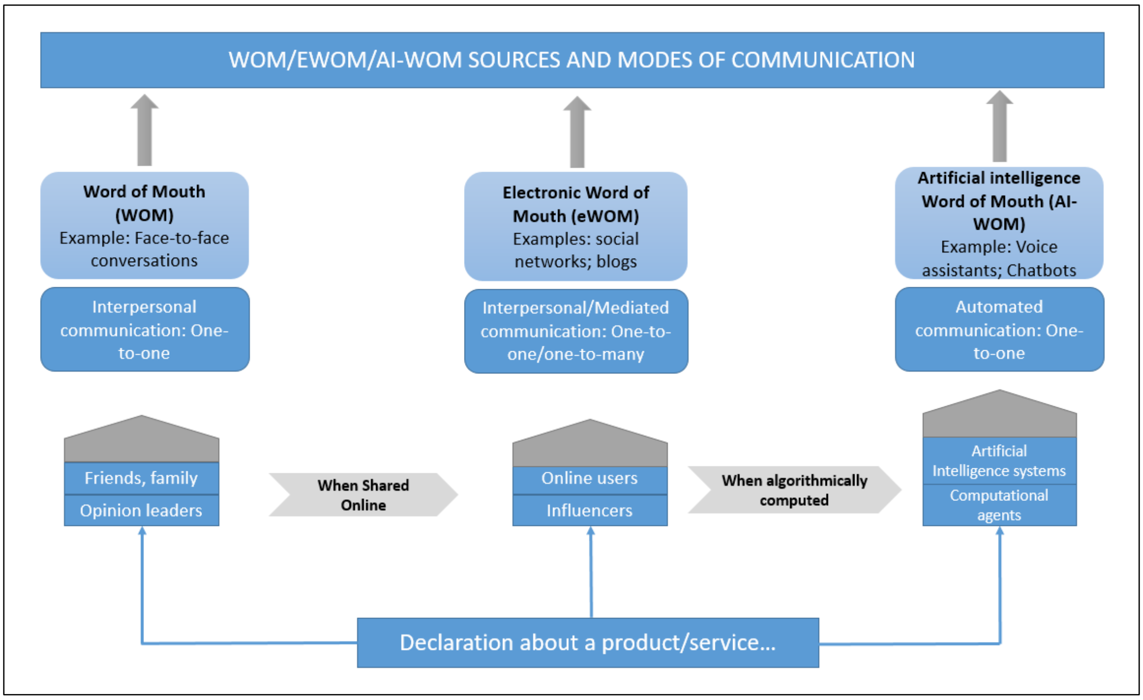
Depending on the dissemination channel, AI-WOM is a message directed at a specific individual and not at many individual (Rabassa et al., 2022). Therefore, perceiving the communication as personalized. Accordingly, due to the one-to-one communication, consumers would perceive the AI-WOM as a real person recommendation. Whereas, E-WOM messages can be directed at one or multiple individuals (Barasch and Berger, 2014), and can potentially encompass a considerably larger audience than AI-WOM. In this instance, E-WOM can be regarded as a less personal communication (Lovett et al., 2013). Table 2.2 extends previous Table 1.1 to compare the key features of WOM, E-WOM and AI-WOM. In addition, Figure 2.2 summarizes WOM, E-WOM and AI-WOM modes of communication.

Table 2.2 Key features of WOM, E-WOM and AI-WOM

Feature	WOM	E-WOM	AI-WOM
Platform / Context	Face to face	Online	AI-based devices
Origin	Consumer-initiated	Consumer-initiated	AI systems
Valence	Positive, negative, neutral (hardly measurable)	Positive, negative, neutral (easily measurable)	Positive, negative, neutral (easily /hardly measurable)
Form	Oral	Mainly written	Oral/written
Audience	One-to-one	One-to-one/one-to-many	One-to-one
Ties strength	Often strong	Strong/weak	Often weak
Timing	Synchronous	Synchronous, asynchronous	Synchronous

Source: own elaboration

Figure 2.2 WOM, E-WOM and AI-WOM characteristics and modes of communications



Source: own elaboration

2.5 DISCUSSION

The present study differs from previous works that have focused on the effects of E-WOM on customers' behaviors, the factors that generate E-WOM and its impact on hotel performance (Cheung and Thadani, 2012; Cantallops and Salvi, 2014); this work provides- based on social communication theory- a holistic understanding of the influence of the elements of E-WOM on the customer's decision-making processes in hospitality context, and identifies emerging hospitality-related E-WOM trends for possible future research.

The present study examines three essential components of E-WOM communication - message, sender and receiver - and its impacts on the customer's decision-making processes (perceptions, evaluations, intentions and behaviors). It has been found that message valence is the variable that has been most examined in terms of message usefulness and intention to adopt the message (Lee et al., 2008). Similarly, previous studies have shown that the message's relevance, understandability and visual cues are important antecedents of the customer's behavioral intentions (Filieri and Mcleay, 2014; Wang and Strong, 1996). Regarding the sender element, it has been argued that source credibility is the most important feature of customers' decision-making processes, due to the intangible nature and economic and psychological risks associated with hospitality-related products. In turn, the customers' susceptibility to interpersonal influence is – among the other receiver characteristics previously discussed – the variable that has been most examined in terms of influencing the attitudes and behavioral intentions.

In addition, as the result of conducting an extensive literature review on E-WOM, it has been identified the main new trends and research possibilities in the area of E-WOM. First, the need for more research into online fake reviews to better understand E-WOM sender motivations; second, the importance of managing negative reviews by hospitality companies (e.g., responding appropriately, developing a partnership with consumers); fourth, the moderating role of the E-WOM platform for the relationships previously suggested; and finally, the increasing significance of various technologies/applications based on AI (e.g., voice assistants), might increase the effectiveness of the E-WOM communication.

2.5.1 Theoretical implications

The present study makes several important contributions to the emerging E-WOM literature. To the best of the authors' knowledge, this is the first study built on the social communication framework to classify E-WOM research papers in the hospitality field, and to propose specific elements of E-WOM for future research. In fact, the lone research that has examined the aspects of E-WOM communication used a broad approach (e.g., Cheung and Thadani, 2012), without taking into consideration the characteristics of specific contexts (i.e., hospitality). In addition, most previous studies focused only on one or two consumer response variables, and did not examine the interrelationships among E-WOM's key elements. Therefore, the present study explores theoretically how the characteristics of each key element (message, sender, receiver) affects the consumer's response variables (usefulness, trust, attitude, behavioral intentions and actual behaviors) in hospitality context.

In addition, this chapter identifies four relevant aspects as potential future research lines in E-WOM field. First, the online fake reviews are an issue that has not been extensively researched and is fundamental to the credibility and reliability of E-WOM. With regard to this point, further research may investigate how the veracity and credibility of published reviews can be identified, as well as the main sender motivations to post fake reviews. Second, although some prior research has explored the management response in online context, the investigation of the E-WOM management response from the perspective of hospitality companies still remain inchoate. Therefore, further research can extensively and intensively examine how hospitality managers process, handle, and manage negative E-WOM, particularly how they could turn challenges and difficulties into customer-driven opportunities. Third, the chapter suggests more research on the nature of the E-WOM platforms, particularly, on how the persuasiveness of E-WOM could vary according to the type of platforms where E-WOM is posted, thereby providing a complement to existing research. Last, AI and its applications, have emerged recently marketing services. Thus, future research may focus on the role of AI-based technology in increasing the effectiveness of E-WOM in the hospitality field. The application of AI may develop recommendation systems that understand consumer preferences which lead to personalized and accurate recommendations about products/services, and consequently increase the E-WOM effectiveness.

2.5.2 Practical implications

In addition to the above theoretical implications and contributions, this study presents a number of practical insights to practitioners. First, the study makes hospitality managers aware that user-generated E-WOM messages are a rich source of data that may influence consumers' behavioral intentions. Therefore, improving E-WOM message features, by updating the information and making it more visual and attractive, can contribute to the effective management of businesses. Second, lack of source credibility causes psychological discomfort and, consequently, weak purchase intentions. Therefore, managers should take actions to foster credible reviews, such as offering awards and/or privileged status to those users who provide pictures and/or videos to support their reviews, and those with higher expertise, etc. Third, individuals highly susceptible to interpersonal influence are more likely to purchase products/services that they perceive will improve their reputations in the eyes of others. Thus, practitioners should adopt strategies to employ celebrities and/or opinion leaders to promote their products/services, and reward loyal consumers by casting them as role models.

As aforementioned, the present study makes several proposals for future research. First, identifying the motivations, especially the psychological mechanisms that lead individuals to post fake reviews without external financial incentives, might help managers design suitable defense strategies to improve relationships between companies and consumers. In addition, based on the principle of "*bad is stronger than good*", consumers tend to value negative E-WOM more than they do for positive E-WOM, therefore, it is beneficial for practitioners to manage negative reviews. In this vein, managers should respond effectively to negative reviews and/or collaborate with consumers to understand their needs; in this way they can turn unsatisfied customers into loyal customers and create committed relationships. Moreover, the important effect of the E-WOM platform on the receiver's behavioral intentions towards the products/services has been demonstrated. Managers should focus more on involving members of social networks with strong ties in interpersonal communications (for example, micro-influencers are proposed to have greater influence on their followers than macro-influencers due to a closer relationship with them). Companies should also introduce some social media features (e.g., self-disclosure, commenting, sharing, chatting) onto their websites to encourage consumers to generate E-WOM. Finally, this research suggests managers to apply AI technologies in their traditional marketing method in such AI-based recommendation systems. These systems can create extra context-based information from the consumers' earlier communications (i.e., patterns, sensor data from private devices), which personalizes content to a more superior scale than the traditional E-WOM. Thus, firms could offer suitable brand/product-related content to engage their consumers and strengthen their product/brands among E-WOM communications.

2.5.3 Limitations and future research lines

While the findings of the present study are valuable, they need to be viewed in the light of its limitations. The E-WOM literature is very extensive, and this study has not taken it all into account. For instance, this study focused on E-WOM from the perspectives of communication theory and consumer behavior, and did not analyze other potential consequences of E-WOM on brand equity or reputation. Future studies should extend the literature review, and increase the number of papers analyzed, based on different perspectives. In addition, the keywords used to undertake the searches might have influenced the findings. However, it is reasonable to believe that the journal papers used are representative of the main E-WOM communication-related research efforts in hospitality sector. Finally, research into the impact of E-WOM communication is continuously developing. It is strongly recommended that a systematic literature review be undertaken to improve our understanding of the impacts of the three elements (message, sender, and receiver) on the consumer's decision-making processes.

CHAPTER III. EFFECTS OF VOICE ASSISTANT RECOMMENDATIONS ON CONSUMER BEHAVIORAL INTENTIONS

3.1 INTRODUCTION

The previous chapter reviewed the existing literature on E-WOM and examined its impact on consumers' decision-making processes in hospitality services. Through this literature review, the chapter concluded that one of the main trends in hospitality-related E-WOM is the use of recommendation systems based on artificial intelligence (AI). In this regard, the present chapter aims to analyze the effect of AI-based recommendation systems, specifically the case of voice assistants (VA).

VA are devices powered by AI, being usually integrated as software into diverse devices (e.g., smartphones, TVs) or as Bluetooth speakers (e.g., Amazon Echo Alexa), which continually listen for a keyword to activate their functionality (i.e., 'Alexa…' or 'Hey Google…'). Once it hears the keyword, the device consumes the user's voice, interprets the language, and processes a response all in real-time (Grover et al., 2020). VA gives advice based on consumer preferences and habits, to which this agent has access (Ling et al., 2021). These features help and guide consumers during their online experience by obtaining product/service recommendations.

Although the market is still young, penetration levels for voice-enabled technologies have been growing exponentially. The growth of the VA industry is expected to average 28% per year between 2021 and 2023 (Statista, 2021). In addition, forecasts suggest that by 2023, the number of VA s (including integrated software and Bluetooth speakers) will reach 8.4 billion units – a number higher than the world's global population (Statista, 2021). More than one-third of the US population use voice assistants (115.2 million users in 2019, with a predicted 135.6 million users by the end of 2022), millennials being the heaviest users, but use is rising among all age groups (Petrock, 2020). Additionally, 70% of Google Assistant requests are expressed by voice, and 43%

of these requests are for seeking products recommendations when ordering items (ComScore, 2021). In the hospitality context, a recent research that surveyed 16,000 travelers from 25 countries suggests that half of the respondents use voice search for some part of their trip (Iribarren, 2021).

The voice technology is quickly becoming a convergence point in academic research because of its interdisciplinary nature, and research on VAs is highly fragmented with contributions from a variety of disciplines. As a main result, previous research has identified a high relevance of VAs for the future of E-WOM and its crucial application for marketing service (Klaus and Zaichkowsky, 2020; Hernandez-Ortega and Ferreira, 2021). Other studies have produced insights into the design and the functional characteristics of VAs (eg., Sciuto et al., 2018; Gollnhofer and Schuller, 2018), their anthropomorphism and social roles (eg., Han and Yang, 2018; Schweitzer et al., 2019), customers' attitudes towards VAs (eg., Nasirian el al., 2017; Brill, 2018), or personalization-privacy paradox (eg., Lau et al., 2018; Manikonda et al.; 2018). In addition, there are existing comparative studies on VAs field, such as synthetic vs. human voice (Cherif and Lemoine., 2019); customers' satisfaction in voice commerce vs. e-commerce (Kraus, 2019) and voice mail vs. e-email (Keil and Johnson, 2002).

Prior literature has also shown that VAs have a strong effect on consumer choices, capable of altering preference based on the AI interaction and voice feature (e.g., Klaus and Zaichkowsky, 2020; Mariani et al., 2021). Using a VA may create a unique experience that is distinct from other recommendation technology (Lieberman and Schroeder 2020). VA's ability to signal warmth (e.g., feelings of control with voice; positive emotions with voice) and competence (e.g., natural language process, immediate answers) enhance the quality of its recommendations (Dellaert et al., 2020). Nevertheless, according to Bjork (1970), people have difficulties to retain information in short term memory when it comes to listen to it. More specifically, when asking a VA for a product/service recommendation, and rejecting the first recommendation, the assistant would make a second and a third and so on. However, people are unlikely to ask for the fourth option, and if they do, they will have difficultly comparing it to the first option, which they have already started to forget. Accepting the first recommendation that the VA made is thus usual. Therefore, Dellaert et al. (2020) suggest that the VA indirectly limit the amount of information that can be provided to consumer. Whereas, screens based technology (e.g., traditional E-WOM) provide several alternatives which can be presented at once and remain frozen there for a span of time. Therefore, the fact of receiving information from screen channel, leads consumers to retain their role as decision-makers (Klaus and Zaichkowsky, 2020). However, extant studies seem insufficient to understand the influence of VA recommendations on consumer perceptions and intentions, or compare its influence with other recommendation sources such as E-WOM.

Consumer online reviews are the most accessible form of E-WOM (Chatterjee, 2001), and the most influential online information in shaping consumer behavioral intentions (Plummer, 2007). Consumers tend to perceive the E-WOM as more reliable due to the communicator's independence from a marketer's persuasive intent (Casaló et al., 2010; Park et al., 2007). Prior research highlighted the vital role of credibility and usefulness in the persuasiveness of the E-WOM (Yan and Hua, 2021; Racherla and Friske 2012). Credibility is connected to the expertise and the trustworthiness concepts (Ohanian, 1990), and, in this context, refers to the extent to which the review is perceived as an objective opinion that can be trusted. Besides, usefulness of online reviews refers to "*the degree to which consumers believe that online reviews would facilitate their purchase decision-making process*" (Park and Lee, 2009, p. 334).

Communication channels have different affordances that influence consumer perception and intention. That is what exactly confirms Media Richness Theory (MRT). This theory was introduced by Daft and Lengel in 1986, and was subsequently applied to new media that emerged in the 1990s (e.g., emails) and then 2000s (e.g., social media). The concept of media richness (Daft and Lengel, 1986) provides a theoretical framework for understanding the potential benefits that consumers gain from different types of media and how much a specific medium is able to deliver an information and non-verbal cues. Additionally, when exposed to a given information, consumers often infer why a person posts that particular information about a certain product/service (Campbell and Kirmani, 2000; Sen and Lerman, 2007). The process by which consumers infer the information source's motives behind sharing product information can be explained by Attribution Theory (Kelley, 1973). Therefore, the current study contributes to the literature on VAs and E-WOM by applying both the MRT and Attribution Theory to compare the influence of traditional E-WOM received through written online reviews, to the recommendation made by VAs, on consumer behavior. In this vein, we analyze user perceptions (credibility, usefulness) and behavioral intentions related to the recommendation (i.e., intention to follow the recommendation, intention to recommend, and intention to purchase) depending on: 1) the modality of the recommendation (text vs. voice) and 2) the content of the recommendation (commercial vs. non-commercial). Additionally, the product type (search vs. experience product) is taken into account as a moderating factor in order to better understand if these relationships vary depending on whether a product or service is recommended (Figure 3.1).

3.2 THEORETICAL FRAMEWORK AND HYPOTHESES DEVELOPMENT

3.2.1 Media Richness Theory and the influence of recommendation modality on perceived credibility and usefulness

Communication channels have different affordances that influence consumer perception and intention. The most important one to consider is the modality (Berger and Iyengar, 2013). MRT was originally proposed to explain the effects of different types of media on task performance. The theory's core proposition is the more cues a communication channel has –the *"richer"* a medium is–, the more satisfying and effective that medium is perceived (Daft and Lengel, 1986; Caplan et al., 2014). Face-to-face interaction has been classified as the "*richest*" way to communicate because it can transmit verbal and non-verbal cues, which mitigates misunderstandings (Campbell, 2006), whereas the unaddressed documents (e.g., standard reports) have been considered as the poorest medium in communication richness (Kahai and Cooper, 2003). Below we apply MRT to compare the influence of VAs' recommendations and E-WOM (in the form of written online reviews) on consumer perceptions and intentions.

The VA uses voice to relay information. This ability to talk lead customers to have a kind of interaction that can create the perception of a personal relationship (Rhee and Choi, 2020; Moriuchi, 2019). Prior studies have shown the voice feature lead users to personify the VA (Tassiello et al., 2021; Branham et al., 2019), and even considering it as a friend, or a family member (Purington et al., 2017; Zhao and Rau, 2020). Similarly, several research suggested that the VA makes the experience more intimate, humanizes the interactions, simulates a social presence during the recommendation process, and enhances trust between the consumer and the service (Qiu and Benbasat, 2009). More specifically, Kontogiorgos et al. (2019) studied the effects of invitational rhetoric in VA's messages. Invitational rhetoric refers to the extent to which the communication style stimulates people to engage in a conversation and creates mutual understanding (Klein et al., 2020, Liu and Sundar, 2018). Indeed, the authors found that VA's message contains invitational rhetoric which positively affects users' perceptions and behavioral outcomes. These findings align with the main proposition of MRT, which suggests that, when a technology possesses a set of characteristics that are similar to people (e.g., voice), a person's reaction to the technology will reflect as a social behavior and will respond to it with social rules as in person interaction (Moon and Nass, 1996). Therefore, VAs may be considered as a rich communication channel (De Greeff and Belpaeme, 2015; Rudovic et al.; 2018).

On the other hand, focusing on E-WOM, various scholars argued that many online reviews via screens currently fail to meet users' needs. People are particularly attentive and receptive to devices with high non-verbal contingency (Breazeal et al., 2016) with an expressive narrative style (Kory Westlund et al., 2017). Written online reviews (e.g., text recommendations) has limited number of cues compared to voice recommendations, that can convey the information with different non-verbal cues such as voice tone, speed, pitch, volume and emphasis (Kontogiorgos et al., 2019). For example, Spence et al. (2019) and Stoll et al. (2016) found that consumers face greater uncertainty and expect a less favorable experience when they are facing written recommendation.

Taking into account all above and based on MRT, voice feature, natural-language processing, and immediate feedback make VAs a richer communication channel, leading consumers to consider it as a friend or a conversation partner. As a result, a personal acquaintance and trustful relationship will be derived (Pitardi and Marriott, 2021). The more highly the message sender is identified (e.g., friend), the more credible the receiver perceives the information to be (Keller, 2007; Bampo et al., 2008). On the other hand, the multiple cues that convey VAs, make the information more accurate (including detailed information about the product/service), which can alleviate the uncertainty, resolve the ambiguity and help to acquire the needed information. Hence, a higher usefulness may be perceived (Filieri, 2015). Therefore, we hypothesize that:

> **H1.** Voice recommendation (vs. text recommendation) generates higher levels of (a) perceived credibility and (b) perceived usefulness of the recommendation.

3.2.2 Attribution theory and the influence of recommendation content on perceived credibility and usefulness

According to literature review, recommendations may be classified into non-commercial (or organic) and commercial (or sponsored) recommendations (Kim et al., 2019; Boerman et al., 2017). The non-commercial recommendation provides product/service information created by consumers based on their personal usage experience (Chen and Xie, 2008). These recommendations occur naturally when people become advocates because they are satisfied with the product/service and have a natural desire to share their support and enthusiasm, and recommend it (Park et al., 2007). In this case, the recommendation is attributed to the product's actual features and/or performance. Whereas, commercial recommendation refers to any recommendation that includes information in order to promote a given product/service or brand, and not to provide the real consumer experience and evaluation (Chen and Xie, 2008). Commercial recommendations are strongly perceived as being biased because they provide information with some other implicit intentions than consumers' recommendations and experience (Lu et al., 2014). For example, companies sometimes provide (monetary and non-monetary) incentives to consumers in order to generate commercial recommendations, which would ultimately increase sales (Petrescu et al., 2018; Zhou and Duan, 2015). However, if readers notice that, their influence in consumer choices will be reduced as the recommendations will be attributed to the personal consumer reason (compensation) and not to the product/service reasons.

Commercial reviews can induce uncertainty in the reviewer's trustworthiness, leading the consumer to doubt the information in the review and consider it as less useful and credible. Such reasoning is in line with Kelley's discounting principle, which states that "*the role of a given cause in producing a given effect is discounted if other plausible causes are also present*" (Kelley, 1973, p. 8). Following this principle, when a reviewer writes about how much he enjoys using a given product/service, consumers will attribute the reviewer's behavior to the qualities of the product itself. However, when consumers learn that the reviewer was rewarded for writing the review, another possible cause (i.e., the desire to receive the incentive) is present, so that consumers may therefore discount the product qualities as a cause. Therefore, previous research has found that commercial recommendations, compared to non-commercial ones, decreases perceived credibility (Kim et al., 2019) and usefulness (Colliander and Erlandsson, 2015). In sum, based on all above, we propose the following hypothesis:

> **H2.** Non-commercial recommendation (vs. commercial recommendation) generates higher levels of (a) perceived credibility and (b) perceived usefulness of the recommendation.

3.2.3 The influence of credibility on perceived usefulness of recommendation

Several works examining online reviews have stressed the importance of source credibility (e.g., Filieri, 2015; Lo and Yao, 2019) over message credibility. However, message credibility may also have a crucial role in the evaluation of reviews; it has been defined as "the consumers' perception that the information contained in a review is believable, true, or factual" (Cheung et al., 2009, p. 12). In this respect, scholars usually agree that perceived credibility enhances the perceived helpfulness and effectiveness of information (Filieri et al., 2018b, Kamins et al., 1989). When a recommendation is considered credible, the information it contains is perceived as accurate and reliable and, thus, useful for the consumer's decision-making. Indeed, online reviews that consumers perceive to be useful provide them with diagnostic information pre-purchase that enable them to better assess the quality of products and how they are likely to perform; that is, perceptions of usefulness make the message more effective (Filieri, 2015). Thus, we argue that if consumers regard a recommendation as credible, they are highly likely to consider the recommendation to be useful. The following hypothesis is proposed:

H3. Perceived credibility of the recommendation has a positive effect on its perceived usefulness.

3.2.4 The influence of perceived credibility and usefulness on behavioral intentions

Behavioural intentions reflect the strength of a person's willingness to perform a specific behaviour; the stronger the intention to conduct the behaviour, the more likely it is that the behaviour will be conducted (Ajzen, 1991). Intention to follow recommendations, intention to purchase and intention to recommend are the most important consumer behavioural intentions related to recommended products, as they provide solid explanations of how the consumer will behave in the future (Casaló et al., 2011; Cheung and Thadani, 2012).

Scholars have demonstrated that perceived message credibility is one of the most important antecedents of recommendation adoption (Cheung et al., 2009) and purchase intentions (Filieri, 2016). Credibility is determined early in the information persuasion process (Wathen and Burkell, 2002). When consumers establish that a recommendation has credibility, they regard the information it contains as clear and their confidence in accepting it increases (Petty et al., 2002; Sussman and Siegal, 2003). By contrast, if a recommendation is judged to be untrustworthy, consumers lose confidence in the source's intentions because of their distrust, and the message has reduced persuasiveness (Teng et al., 2014). Thus, credibility positively affects the consumer's intention to follow recommendations (Zhang et al., 2014) and the probability that the recommendation will be used in his/her purchase decision (Lis and Post, 2013). Finally, when consumers receive a credible product/service recommendation, they put trust in it, and perceive it to provide valid information about the product/service, which leads them to consider it important for their personal contacts, and to recommend it to them. This is consistent with previous research into consumers' behavioural intentions to share information on consumer online platforms (Filieri et al., 2020; Filieri 2015; Ma and Chan, 2014). In sum, perceived credibility is an important factor in making recommendations more persuasive and for increasing consumers' behavioural intentions. As a consequence, we propose:

> **H4.** Perceived credibility of the recommendation has a positive effect on consumer behavioral intentions: (a) to follow the recommendation; (b) to purchase the product/service; and (c) to recommend the product/service.

Similarly, consumers assign certain levels of usefulness to reviews by means of a screening process in which irrelevant information is excluded and only useful information is taken into consideration (Purnawirawan et al., 2012). Willemsen et al. (2011) suggested that the usefulness serves as the primary currency to gauge how consumers evaluate the reviews as well as an effective predictor of consumers' intentions (Cheung et al., 2008; Park and Lee, 2009). For example, information usefulness is strongly associated with consumer decision to adopt information (Cheung et al., 2008; Erkan and Evans; 2016) and with purchase intentions of the recommended product, because useful information helps the customer make a decision (Kowatsch and Maass, 2010). As well, the perceptions of review usefulness would positively influence individuals' willingness to share information with others (Park and Lee 2009; William and Cothrel, 2000). Consumers share information or intent to recommend a product/service with others because they have a genuine desire to help other people with their consumption decisions or to save others from negative experiences (Chiu et al. 2009). Based on all these, the following hypothesis is proposed:

> **H5.** Perceived usefulness of the recommendation has a positive effect on consumer behavioral intentions: (a) to follow the recommendation, (b) to purchase the product/service, and (c) to recommend the product/service.

3.2.5 The moderating effect of product type: search vs. experience product

Traditionally, Nelson (1970) reckoned that the primary distinction of search/experience products is based on whether consumers can evaluate products or their attributes prior to purchase. If product attributes can be acquired prior to purchase, the product belongs to search products (e.g. tangible products); whereas if product attributes cannot be known until or after consumers purchase and use the product, it is categorized into experience products (e.g., services) (Klein, 1998). Similarly, Weathers et al. (2007) classified search products and experience products based on the extent to which consumers feel they need to experience the product to evaluate its quality. The greater the need to employ one's senses to assess a product, the more experience characteristics the product possesses. By contrast, the more one thinks that information will be adequate to evaluate a product, the more search characteristics the product possesses. When investigating consumers' recommendations, many researchers have proposed that product type may exert a moderating role (e.g., Huang et al., 2013; Zhang et al., 2014).

As aforementioned, information about search product attributes is easy to acquire (Hsieh et al., 2005), objective, and easily compared (Mudambi and Schuff, 2010), as well as discoverable before purchase without interacting with the product (Huang et al., 2009). In contrast, attributes information for experience products is difficult and costly to obtain

(Mudambi and Schuff, 2010), and consumers have a greater need to use their senses to evaluate these products (Weathers et al., 2007). In addition, since consumers can fully judge experience products only after consuming them, the risk or uncertainty of the choice process is higher for experience than for search products. According to risk theory (Dowling and Staelin, 1994), consumers undertake greater information search when the choice context is associated with higher perceived risk. Consequently, in that case, information processing involves a higher cognitive effort (Huang et al., 2009). On the other hand, when the information is received through a rich media, it tends to be easier to process, interpret and assimilate, and consequently enables consumers to better evaluate the given information (Maity et al., 2018; Suh, 1999). Therefore, through a rich media, the recommendation for experience products may be easier to evaluate and, as a result, the influence of voice (vs. text) recommendation in developing credibility and usefulness will be greater for experience than for search products.

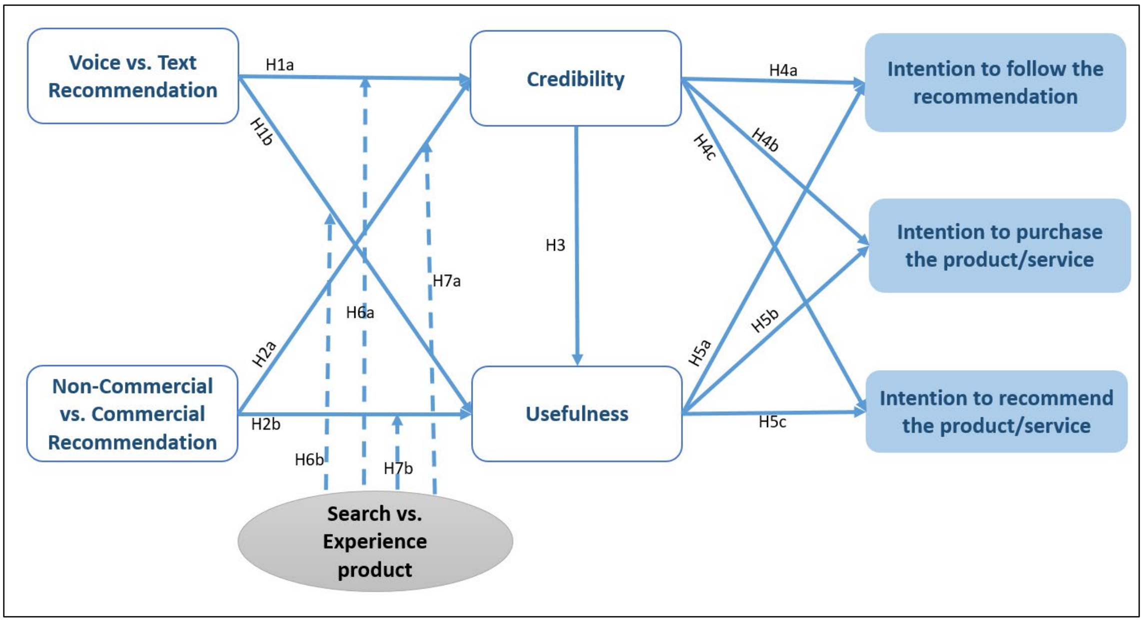
In turn, Weathers et al. (2007) indicated that consumers tend to believe more in recommendations about search products, because they may think the objective nature of these products will make it easy for the reviewer to write a useful recommendation. Additionally, Hsieh et al. (2005) and Weathers et al. (2007) stated that, compared to experience products, the features and attributes for search products are more stable and homogeneous, hence, the recommendation would be attribute to stable factors. Consequently, in that case, the consumer would believe that the reviewer has really experienced the products and reported their real evaluation (Bae and Lee, 2011). Therefore, recommendations for search products may be easier to evaluate and as a result, the influence of non-commercial (vs. commercial) recommendations in developing credibility and usefulness will be greater for search than for experience products.

Hence we propose our last hypotheses:

H6. The difference on (a) perceived credibility and (b) perceived usefulness between voice and text recommendations will be greater for experience products (vs. search products).

H7. The difference on (a) perceived credibility and (b) perceived usefulness between non-commercial and commercial recommendations will be greater for search products (vs. experience products).

Figure 3.1 Conceptual research model



Note: Solid lines represent direct effects; dashed lines represent moderating effects.

3.3 RESEARCH METHODOLOGY

3.3.1 Experiment design

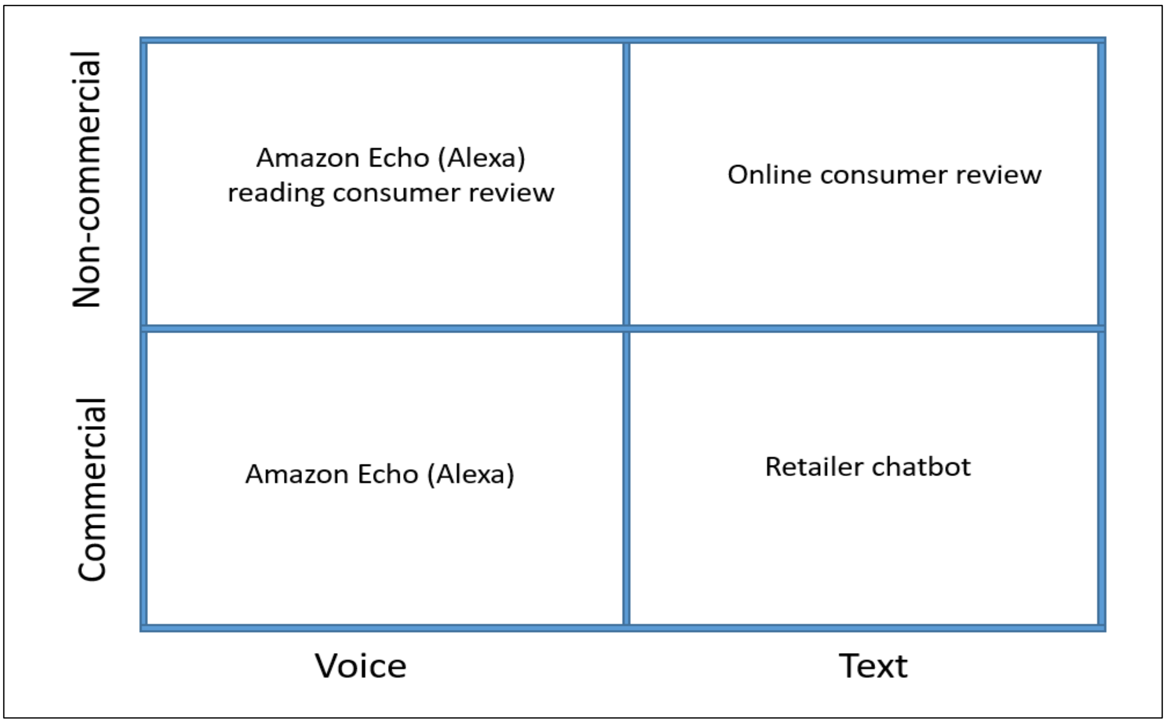
To test the proposed model, an experiment design was conducted using 2 (modality: voice vs. text) x 2 (recommendation content: commercial vs. non-commercial content) x 2 (product type: search vs. experience product) factorial, between-subjects design. Participants were randomly assigned to the eight scenarios.

In the current market, there exist several VAs as Bluetooth speakers such as Amazon Echo (Alexa) and software integrated in smart devices like Apple Siri. In our study, we focused on Amazon Echo (Alexa) because it is leading the global smart speaker market, having a market share of 30%, and 70% of the US market (Statista, 2022).

The combination of modality and recommendation content allow us to define a set of four recommendation situations that represent real world (see Figure 3.2):

- A VA of Amazon Echo making a commercial recommendation (e.g., this VA can recommend the amazon private label products);
- A VA of Amazon Echo reading a non-commercial consumer online review;
- A retailer's Chatbot making a text commercial recommendation;
- A non-commercial online consumer review posted in social media platform.

Figure 3.2 Recommendation typologies based on modality and content



Source: own elaboration

For the voice modality, we used a text-to-speech (TTS) demo version available online (https://ttsdemo.com/) to replicate the experience of having a voice recommendation. To control the possible effects of vocal characteristics (e.g., gender, pitch, speed), we used the same female voice character with the preset standard vocal effect for all voice recommendation conditions.

Hospitality is one of the sectors most heavily characterized by consumers' tendency to share online recommendations (Amatulli et al., 2019). Additionally, due to its intangible nature, it has been argued that, consumer online recommendations in hospitality sector, are more influential and impactful, on consumer decision making, than other online source information (Schuckert et al., 2015). Thus, two types of products were chosen within the context of hospitality related products; a suitcase was selected for a search product condition, and a dinner in a restaurant for experience product. The suitcase was used because it is an essential product that most people carry for their trips. Additionally, it is used for multiple years once purchased. People actively conduct searches and carefully compare models and features before purchasing it. By contrast, a dinner in a restaurant is an experience product, for which it is difficult to evaluate the quality before interacting with product (trying the restaurant). Additionally, the evaluation of its quality depends on personal preferences and tastes, thus it is difficult to compare one with another or evaluate its quality before going to the restaurant and having dinner there. Moreover, these two products have been considered because they may have a similar price.

For the commercial recommendation, following recommendations from previous studies (Skorupa and Dubovičienė, 2015), we used a lot of exclamation marks, short sentences such as « Don't wait anymore and buy it now!! », persuasive expressions, and empathic terms such as « amazing », « incredible », superlatives like « the best », and overwords that are repeated. Whereas, for the non-commercial recommendation, the words were commonly used in formal style and objective manner without persuasive language and with less exclamation marks. The length of recommendations was similar in all scenarios.

Table 3.1 Description of recommendations used in the research depending on content and product types

	Search product	**Experience product**
Commercial content	*"I recommend you C.K.L suitcase. With this suitcase you will be pleasantly surprised by the design and its easy handling. For other suitcases you will surely pay much more and receive much less. This suitcase is spacious and elegant. The size is perfect! If you love multi-compartments suitcases, you could not ask for more!! Also, you will surely enjoy its amazing innovative 360-degree spinner wheels! Most importantly, incredible price!! C.K.L suitcase is the best! Don't wait anymore and buy it now!! I rate it with 4.8 of stars!"*	*"I recommend you Summer House restaurant. In this restaurant, you will be pleasantly surprised by the local and the service you receive. For other restaurants, you will surely pay much more and receive much less. The local is very spacious and cozy. The location is perfect! If you like to walk with your partner in the downtown, you could not ask for more!! Also, you will surely enjoy its amazing dishes and cocktails! Most importantly, incredible price!! Summer House is the best! Don't wait anymore and book it now! I rate it with 4.8 of 5 stars!"*
Non-commercial content	*"Last week, I bought C.K.L suitcase. I can honestly say the design of C.K.L suitcase and its easy handling are great. The suitcase is very spacious and elegant. The size is perfect! With pockets and multi-compartments for socks, chargers…etc. Regarding the wheel maneuverability, this suitcase offers the innovative 360-degree spinner wheels and affordable price. I highly recommend it! I rate it with 4.8 of stars!"*	*"Last I went to summer House restaurant. I can honestly say the local of Summer House restaurant and the service you will receive are great. The local is very spacious and cozy. The location is perfect! Within walking distance to the downtown. Concerning the menu, Summer House restaurant offers a delicious dishes and tasty cocktails with very reasonable price. I highly recommend it! I rate it with 4.8 of 5 stars!"*

E-WOM has greater influence on consumer purchase decisions for high-involvement products (Gu et al., 2012) because consumers often spend considerable time searching for high involvement product information to make the right decision (Belk and Clarke, 1978). Therefore, in the current study, we set all the conditions as high involvement products. For search product, participants were instructed to imagine that they want to buy a suitcase for a trip to meet their partner's parents for the first time, and they want to impress their future in-laws as possible as they can. And they need to buy a new suitcase. For experience product, the participants were asked to imagine that they are looking for a restaurant to surprise their partner and invite her/him to a romantic dinner to celebrate their anniversary together. Thus, they need to book a table.

Afterwards, the participants were asked to fill out a questionnaire in order to evaluate their perceptions and intentions towards the received recommendation. The purpose of the research was mentioned clearly on top of the survey. The excluded responses were either filled in very short time or failed the screening questions, that indicated the participants have not paid attention to the questions. For text recommendation surveys, the participant has access to visualize and read the recommendation written in the survey (see appendix B). For the voice recommendation surveys, the questionnaire had a link to the audio file in which once the participant press play he/she listen the recommendation (see appendix C). The items of all the constructs were adapted from established scales (see table 3.3) using a seven-point Likert scale, where 1 represents "*strongly disagree*" and 7 "*strongly agree".* We also include some question to check our manipulations as well as to control the quality of the answers.

3.3.2 Pre-test

Before the main experiment, a pre-test was carried out to ensure the effectiveness of manipulations. We conducted the pre-test with 80 participants (10 per condition). All treatment conditions were confirmed as properly manipulated. The modality manipulation was successfully confirmed (99% of participants confirmed the text condition, 98% confirmed the voice condition), as well as the product type manipulation (100% of participants confirmed the search product condition and 96% confirmed the experience product condition [See appendix D1]). Finally, adapting measures for sponsorship of the recommendation from De Jans et al. (2019), results of a t-test showed a significant difference ($t = 4.16$, $p < 0.001$) between the group who received commercial recommendation ($M = 4.95$) and the group who received non-commercial recommendation ($M = 3.60$).

In addition, we control for realism, involvement and review characteristics (length, valence and quality). The measures for scenario realism were taken from Bagozzi el al. (2016), while the measures for product/service involvement were taken from Zaichkowsky (1985) (see appendix E). These measures were recorded on a seven-point Likert scale (1 = "*strongly disagree*"; 7 = "*strongly agree*"). Measures of the valence of the recommendation, the length of the recommendation, and the quality of the review were recorded on a five-point Likert scale (1 = "*Very low*"; 5 = "*Very high*"). Regarding realism scenario, user involvement, valence, length and the quality of the recommendations, there were no statistical difference in their means across scenarios (F_R=1.4, p>0.1; F_I=2.53, p>0.1; F_V=0.93, p>0.1; F_L=1.30, p>0.1; F_Q=1.17, p>0.1), indicating that all these variables are homogeneous among all the conditions (see appendix D2).

3.3.3 Main Study: Data Collection

Data were collected in November 2021. Participants are US residents that were recruited through an online survey; a market research company, Prolific, assisted us in the process. To take part, the participants had to be users of VAs at least once; a qualifier sentence was included for this aim ("*This* survey is exclusively addressed to VA users, so if you have used the VA at least once, please answer sincerely *this questionnaire*"). A total of 251 users of VAs were recruited to undertake the survey, having a minimum of 30 respondents in each scenario. Table 3.2 shows the main demographic characteristics of the sample.

Table 3.2 Demographic characteristics of the research sample

		Frequency	%
Gender	**Male**	126	50.2
	Female	122	48.6
	Prefer not to say	3	1.2
Age	**18-25**	81	32.3
	26-30	49	19.5
	31-35	39	15.5
	36-40	27	10.8
	41-45	17	6.8
	46-50	14	5.6
	51-55	10	4
	56-60	8	3.2
	61-65	6	2.4
Education level	**Primary school**	1	0.4
	High school degree	58	23.1
	Undergraduate degree	139	55.4
	Graduate degree	53	21.1
Citizenship	**American**	228	90.8
	Other	23	9.2

3.4 RESULTS

A confirmatory factor analysis was carried out to confirm the dimensional structure of the scales. Partial Least Squares- Structural Equation Modeling (PLS-SEM) method, which has been widely used in recent research (e.g., Hu et al., 2021), was applied using SMARTPLS 3.0 (Ringle and Sarstedt, 2016). We selected the PLS-SEM approach because it is especially useful when the cause-effect model is exploratory and presents novel relationships unexamined in previous empirical studies (Hair et al., 2014). This is the case in the present study, where we analyze consumer perceptions and behavioral intentions towards voice vs. text recommendations.

3.4.1 Measurement model

To evaluate the dimensional structure of the scales, we examined the factor loadings to make an initial assessment of the internal consistency of the constructs. The factor loadings exceeded the 0.7 threshold (Henseler et al., 2009) in their respective constructs (see Table 3.1). The reliability of the measures is analyzed using composite reliability (CR). The CR values are shown in Table 3.1; they exceeded the recommended value of 0.7 (Hair et al., 2014). Similarly, Cronbach's α surpassed the recommended 0.7 threshold for all reflective constructs (Nunnally and Bernstein, 1994), as can also be seen in Table 3.3. Convergent validity is also assessed using average variance extracted (AVE), which should be greater than 0.5 (Fornell and Larcker, 1981). The results shown in Table 3.1 meet this criterion. Finally, the results shown in Table 3.2 confirmed the discriminant validity of the measures, as the square roots of the AVEs of each construct are greater than their corresponding inter-construct correlations (Fornell and Larcker, 1981).

Table 3.3 Reliability and validity indices

Construct	Factor loadings	Cronbach's α	CR	AVE
Usefulness (Adapted from Venkatesh, 2003).		0.962	0.972	0.897
USF.1 I find the recommendation very helpful.	0.965			
USF. 2 I find the recommendation very useful.	0.959			
USF. 3 I find the recommendation very informative.	0.930			
USF.4 I acquired from the recommendation the information I need.	0.934			
Credibility (Adapted from Meyer, 1988 and Filieri, 2015).		0.962	0.959	0.853
CRD.1 I find the recommendation fair.	0.928			
CRD.2 I find the recommendation accurate.	0.895			
CRD.3 I find the recommendation credible.	0.947			
CRD.4 The arguments in the recommendation are convincing.	0.924			
Intention to follow (Adapted from Casaló et al., 2011b and Cheung et al., 2009).		0.950	0.964	0.870
IF.1 I feel comfortable behaving according to the recommendation I obtained from the VA/chatbot/online review.	0.938			
IF.2 I do NOT hesitate to take into account the recommendation obtained from the VA/chatbot/online review.	0.893			
IF.3 I feel secure in following the recommendation obtained from the VA/chatbot/online review.	0.961			
IF.4 I definitely follow the recommendation obtained from the VA/chatbot/online review .	0.938			
Non-commercial content	1.000	1.000	1.000	1.000
Intention to purchase (Adapted from Filieri et al., 2018).		0.927	0.954	0.873
IP.1 It is very likely that I would buy/choose the recommended suitcase/ restaurant	0.969			
IP.2 I would definitely purchase/choose the recommended suitcase/ restaurant	0.933			
IP.3 I would consider purchasing/choosing the recommended suitcase/ restaurant	0.900			
Intention to recommend (Adapted from Hosany and Witham, 2010).		0.917	0.948	0.859
IR.1 I would recommend the suitcase/restaurant to friends and relatives	0.968			
IR.2 I would say positive things about the suitcase/restaurant to other people	0.955			
IR.3 I would seldom miss an opportunity to tell others about the suitcase/restaurant	0.854			
Voice modality	1.000	1.000	1.000	1.000

Table 3.4 Discriminant validity

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Credibility (1)	**0.924**						
Intention to follow the recommendation (2)	0.809	**0.933**					
Intention to purchase the product/service (3)	0.772	0.858	**0.934**				
Intention to recommend the product/service (4)	0.666	0.797	0.811	**0.927**			
Non Commercial content (5)	0.281	0.276	0.253	0.206	**1.000**		
Usefulness (6)	0.843	0.786	0.779	0.669	0.256	**0.947**	
Voice modality (7)	0.131	0.032	0.032	-0.034	-0.019	0.114	**1.000**

Note: Diagonal elements (bold figures) are the squared roots of the AVEs (the variance shared between the constructs and their measures). Off-diagonal elements are the inter-construct correlations (Fornell and Larcker's test).

Finally, since we collected data using a questionnaire, common method variance (CMV) was assessed, as CMV may happen when the respondents fill out the questionnaires very quickly in a more or less automatic manner (Podsakoff et al., 2003). In addition to the recommended procedural steps applied during the survey design and administration process (e.g., participants were assured anonymity and confidentiality, etc.), single factor Harman's test was performed for CMV validity analysis. The results indicated that the majority of the variance is not accounted for by one general factor, as it accounts for less than 50% of the variance (Baumgartner et al., 2021).

3.4.2 Structural model

Before conducting the main experiment, we performed the same manipulation checks as in the pre-test to confirm the quality of the experiment design. Results were again satisfactory, so the scenarios were clear, and the items of the questionnaire were well understood. Having confirmed positively the pre-test results as well as the reliability and validity of the measurement scales, we next evaluated the direct effects proposed in the research model (H1-H5) through PLS. The path relationships and the R^2 levels of the endogenous latent variables were initially assessed, and a bootstrapping procedure method was conducted to calculate the statistical significance of the path relationships (Temme et al., 2006), using 5000 subsamples. Figure 3.2 shows a summary of results.

As to the explanatory power of the research model, we can partially explain the key study's endogenous variables: intention to follow the recommendation (R^2 =0.692), intention to purchase the recommended product/service (R^2 =0.653), intention to recommend the product/service (R^2 = 0.484). According to Chin (1998), these findings suggest that the R^2 values are moderate to substantial. In addition, the model explains more 70% of perceived usefulness and 9.8% of perceived credibility (see Figure 3.3).

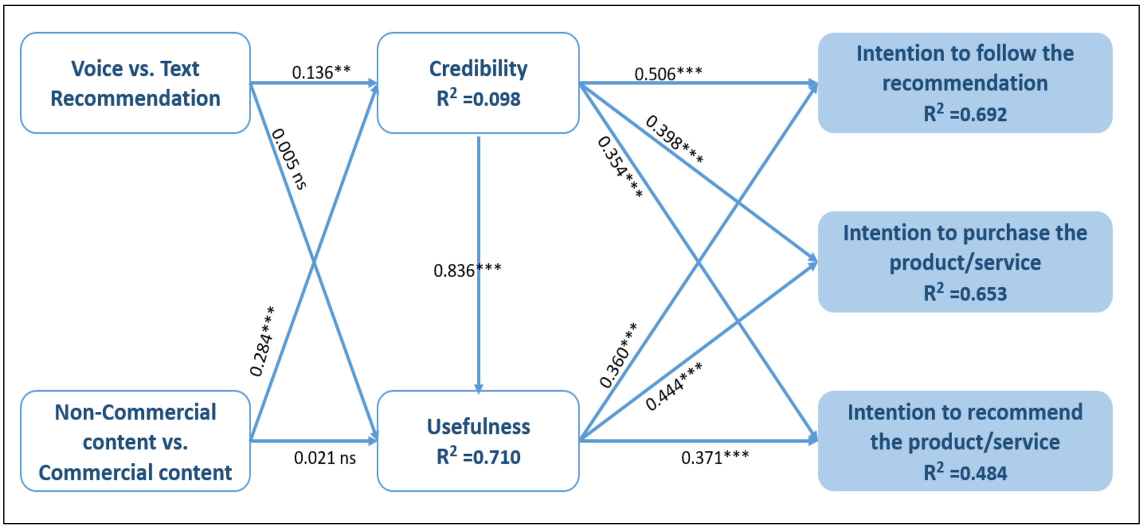
Regarding the modality, voice recommendation has a direct positive effect on credibility (β=0.136, p<0.01), whereas, there is no direct effect on usefulness (β=0.005, p>0.1). Therefore, we find support for H1a, but not for H1b. These findings are consistent with the prior studies suggesting that voice messages can transmit verbal, non-verbal and social cues which could convey effectiveness and credibility (Perloff, 1993; Sproull and Kiesler, 1986). Similar results are found for the recommendation content, the non-commercial recommendation has a significant direct effect on credibility (β=0.284, p<0.001), whereas the direct effect on usefulness is non-significant (β=0.021, p>0.1), which supports H2a but not H2b. This finding confirms first the proposals of attribution theory (Kelley, 1967) in this context. The more the consumer attributes the communicator's review to the product's actual performance, the more the consumer will have confidence in the accuracy of the review, the stronger the consumer's belief that the product has the attributes mentioned in the review, and the more the consumer will perceive the review is credible. Additionally, this result is consistent with the persuasion knowledge model (Cacioppo and Petty, 1984). When the recommendation is perceived non-commercial, the consumer often link this kind of recommendations to peer recommendation in which people express their real experiences and evaluations, being hence more credible.

In turn, perceived credibility has a positive effect on perceived usefulness (β=0.836, $p<0.001$), suggesting a mediating effect of credibility that is examined in Table 3.5. Specifically, we observe that the voice and non-commercial recommendations exert an indirect effect on usefulness via credibility. Following the indications of Nitzl et al. (2016), these results suggest that perceived credibility fully mediates these relationships. That is, when a consumer receives a voice recommendation or a non-commercial recommendation, he or she perceives them more credible, and subsequently develops a greater usefulness perception toward these recommendations. In other words, unless the recommendation is credible it will not be considered useful. These findings are in line with previous research supporting the mediated role of credibility in predicting usefulness (Saima and Khan, 2020; McKnight and Kacmar, 2007). When the recommendation is credible, it provides good information that is likely to help consumers to predict how an experience will turn out, enhancing the usefulness of the recommendation. This finding is in line with several previous works on consumer decision making (e.g., Filieri, 2015; Lopez and Sicilia, 2014; Teng et al., 2014; Serman and Sims, 2020).

In addition, perceived credibility exerts positive effects on behavioral intentions (to follow the recommendation [β=0.506, $p<0.001$]; to purchase the recommended product/service [β= 0.398, $p<0.001$]; to recommend the product/service [β=0354, $p<0.001$]). Thus, hypotheses, H4a, H4b and H4c are supported. These results highlight that credibility is a predictor of consumer behavioral intentions (e.g., Ayeh et al., 2013; Sussman and Siegal, 2003). When exposed to a credible recommendation, the information is considered trustworthy and consumers may accept and apply the recommendation as it posited.

Similarly, perceived usefulness positively influences intention to follow the recommendation (β=0.360, p<0.001), intention to purchase the recommended product/service (β=0.444, p<0.001), and intention to recommend the product/service (β=0.371, p<0.001), thus supporting H5a, H5b and H5c respectively. These effects confirm the relevance of usefulness as a strong determinant of behavioral intentions (Davis, 1989). In our context, usefulness of the review help consumers make the right purchase decision. In addition, when consumer found a useful information that he has been looking for about a given product/service, he tends to recommend that product/service to their contacts that could be interested in or simply to whom were looking for the same information. These results also suggest that voice (vs. text) and non-commercial (vs. commercial) recommendations exerts significant indirect effects on behavioral intentions via consumer perceptions (see Table 3.3).

Figure 3.3 Structural analysis of the research model: Direct effects



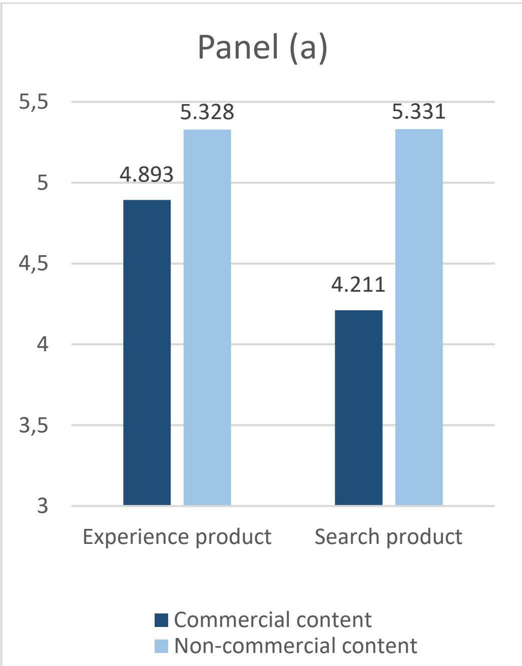
$^{**}p<0.01$ $^{***}p<0.001$ ns: non-significant

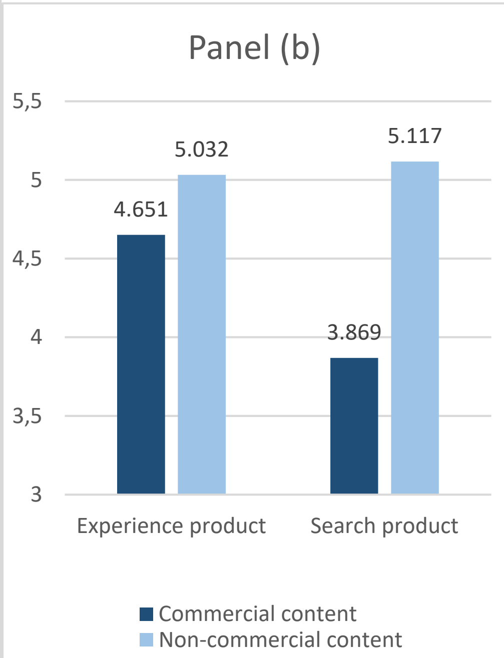
Table 3.5 Total indirect effects

	Mediator	Specific Indirect Effect	T statistics	P values
Voice (vs. Text) → Usefulness	Credibility	0.114	2.204	0.028
Non-commercial content (vs. commercial) → Usefulness	Credibility	0.237	5.068	0.000
Voice (vs. Text) → Intention to follow	Credibility & Usefulness	0.112	2.236	0.026
Voice (vs. Text) → Intention to purchase	Credibility & Usefulness	0.107	2.210	0.028
Voice (vs. Text) → Intention to recommend	Credibility & Usefulness	0.093	2.217	0.027
Non-commercial content (vs. commercial) → Intention to follow	Credibility & Usefulness	0.236	4.918	0.000
Non-commercial content (vs. commercial) → Intention to purchase	Credibility & Usefulness	0.228	4.837	0.000
Non-commercial content (vs. commercial) → Intention to recommend	Credibility & Usefulness	0.196	4.618	0.000

To test H6 and H7, we conducted a series of 3 way-ANOVAs, with perceived credibility and usefulness as dependent variables, and modality (voice vs. text), content (commercial vs. non-commercial) and type of product (search vs. experience) as independent variables. Results show that there is no interaction effect of recommendation modality and product type on perceived credibility ($F(1, 243) = 0{,}008$, $p>0.1$) nor usefulness ($F(1, 243) = 0.456$, $p>0.1$). Therefore, H6a and H6b are not supported. However, we observe significant interaction effects of content and product type on both credibility ($F(1, 243) = 7.153$, $p<0.01$) and usefulness ($F(1, 243) = 3.897$, $p<0.1$). Therefore, H7a and H7b are supported. Figure 3.4 shows these interaction effects in more detail; as can be seen, the effect of non-commercial content on perceived credibility and usefulness is higher for a search than for an experience product. No further interaction effects between modality and content were found. These findings provide interesting insights into the moderating role of the product type on the effect of the recommendation modality towards the credibility and the usefulness of the recommendation, confirming that whether a search or an experience product is recommended, the effect of voice modality on credibility and usefulness does not change. Whereas, greater differences on credibility and usefulness between non-commercial and commercial recommendations appear for search product. As aforementioned, these findings are explained by perceived stability. Search products attributes are more stable and homogeneous than experience products (Hsieh et al., 2005), so that the recommendation may be attributed to real and stable factors and, consequently, greater levels of credibility and usefulness are developed.

Figure 3.4 Panel (a): Interaction effect of recommendation content and product type on usefulness. Panel (b): Interaction effect of recommendation content and product type on credibility





3.5 DISCUSSION

To the best of the authors knowledge, this is the first empirical study investigating the effect of VA applied to the E-WOM context, by comparing both voice recommendations made by VAs and text recommendations through written online reviews. To do that, this study applies MRT (Daft and Lengel, 1986) and Attribution Theory (Kelley, 1973) to measure the influence of VA recommendations on consumer behavioral intentions. The major finding of the study is that VA recommendations are perceived as more credible and useful (exerting credibility a mediating role), and consequently generate higher consumer behavioral intentions. Similar results are found for the non-commercial recommendations, highlighting the higher effect of these recommendations on credibility, usefulness as well as on consumer behavioral intentions. More especially, these effects are stronger when the non-commercial recommendation is for search products than for experience products. Additionally, these findings provide rich understanding to practitioners to take advantage from VA technology and make appropriate actions in their business strategies.

3.5.1 Theoretical implications

This research has three main theoretical implications. First, this study contributes to the literature of VAs and E-WOM by making the first step into understanding the influence of voice recommendation made by VAs compared to text recommendation (traditional E-WOM) received through written online reviews, on consumer behavior. VAs are a relatively new phenomenon that currently receives great attention from academics and practitioners, but less is known about how VAs might influence consumers' decisions. Specifically, the current study extends this theory to VAs in consumer decision making process by empirically testing the causal connection between the voice recommendation and the consumer perceptions in terms of credibility and usefulness, which in turn influences the consumer behavioral intentions (to follow the recommendation, to purchase, and to recommend the product/service). The study results suggest that recommendation received through the VA is stronger in altering consumer decision, compared to the traditional E-WOM (e.g., written online review). By bridging

AI-based devices literature and E-WOM field, this study highlights the importance of voice technology in increasing the effectiveness of E-WOM. VAs can capture customer preferences and humanize interactions, making the recommendation more credible and useful, and leading to adopt the recommendation.

Second, while previous researchers have applied MRT to organizational information (Daft and Lengel, 1986), emails (Schmitz and Fulk, 1991), websites (Hopkins et al., 2004), online stores (Brunelles, 2009), mobile Apps (Anandarajan et al., 2010), or social media (Xiao et al., 2021), the current study contributes to existing theory of MRT by applying it within the field of AI-based technologies in general and VAs in particular. More specifically, the article suggests that VAs are an AI-based technology able to interact with the same human cues (Chi et al., 2022); thus, it is distinct from computer-mediated communication in that it is not simple computer system passing information between two people, but rather an autonomous source with intentions at the other side of the interaction (Miller el al., 2013; Spence, 2019). Therefore, VAs are considered a rich medium as an "*in person*" interaction.

Finally, the study contributes to the general body of knowledge in the moderating role of product type in E-WOM effect (Park and Lee, 2009). To be precise, this research advances the role of product type within the field of VA recommendations by distinguishing between search product and experience product recommendations.

3.5.2 Practical implications

As aforementioned, the main contribution of the study is that, compared to traditional E-WOM, VAs recommendations have a strong and influential effect on consumer decision making, thanks to their greater perceived credibility and usefulness. This finding highlights relevant points that need to be considered as a guidance for business managers (e.g., product managers, retail managers, digital communities' managers) as well as for VAs' designers.

The greater credibility level of VA recommendations and its crucial role in developing behavioral intentions may lead product and retail managers to take advantage from this point by boosting the implementation of voice technology in their customer services as well as in their marketing communication services (e.g., using VAs for launching and recommending a new product). Additionally, the research findings highlight the relevant role of perceived usefulness on consumer behavioral intentions. Even though VA recommendations are perceived as more useful, practitioners should focus on increasing the usefulness of the services provided by virtual assistants. For example, supermarket and shop managers could think beyond the traditional role of VAs - providing product recommendations - and offer value-added services, such as reciting recipes containing the supermarket brand products or even reading out lists of ingredients when people cook their dishes.

Lastly, as the use of VAs proliferates, it becomes important for VAs' designers to improve and innovate their voice technologies, to increase the richness of this medium. To this aim, it is first recommended to enhance the voice feature, by introducing, an innovative technology able to convey human quirks (e.g., laughing, sneezing, sobbing, etc.) and to carry fluctuations in tone when pronouncing words. Second, implementing a new technology that allows consumers to hold long-term conversations is also recommended. Designers should go beyond a simple assistance through a recommendation, to offer nearly human companionship throughout the purchase process. Also, consumers tend to personalize the VAs when they receive from them a useful recommendation (Capgemini, 2019). Therefore, it will become increasingly important for VAs to have a persona and become more life-like. Finally, designers should solve accent and language problems by building a voice-enabled technology that recognizes commands with greater ease.

3.5.3 Limitations and future research lines

This research has several limitations that open future research opportunities. First, this study has focused on situational involvement, which it is temporary in nature as it disappears when the purchase is completed (Bloch, 1981). Therefore, it would be interesting that future works take into consideration the product enduring involvement in order to examine if the consumers' long-term perceptions of the importance of the product influence the relationships proposed in this research. Additionally, we have considered a female voice in the design of the voice recommendations. Previous studies demonstrated that traits inferred from voice characteristics (e.g., gender) may affect the effectiveness of the information persuasion (Nass and Moon, 2000). Currently, Google Home and Siri offers diverse voice options. Future studies should examine how different voice characteristics (female vs. male) affect the way consumers perceive and behave toward the VAs' recommendations.

Moreover, data were collected from VAs' users in the United States market. However, several research works have noted the importance of incorporating cultural differences when dealing with AI-based technologies and consumer behavior (Huang and Zhang, 2020). In this line, further studies may compare the consumers' behaviors towards AI-based VA recommendations across cultures exploring, for example, potential differences between individualistic and collectivistic countries. Finally, according to traditional literature on psychology, personality traits may affect significantly people persuasion information process (e.g., McCrae and Costa, 1987). Therefore, further research should examine how consumers' personality traits (e.g., Big Five Model) may affect their behavioral intentions toward the VA's recommendations.

CHAPTER IV.

ANTECEDENTS AND CONSEQUENCES OF PERCEIVED VALUE OF AI-BASED RECOMMENDATIONS SERVICES: THE CASE OF VOICE ASSISTANTS

4.1 INTRODUCTION

Thus far, our thesis has delved into the validation of the effectiveness of the AI-based recommendations in altering consumer behaviors by comparing traditional E-WOM (online consumer reviews) with AI-based recommendations provided by voice assistants (VAs) on consumer behaviors, being the latter perceived as more credible and useful. The present chapter seeks to take one step further in the AI-based recommendations effectiveness by analyzing how product recommendations provided by voice assistants (VAs) creates value for consumers and which consequences this value may have.

VAs can help consumers to accomplish a variety of tasks (i.e., playing music; making or receiving calls [Chattaraman et al., 2019]), but, additionally, VAs can be used effectively to deliver value-added service recommendations (Rhee and Choi., 2020). It is reported that 70 % of Google's users use the phone's VA daily, and 43% of those consumers use VAs for products and brands recommendations (ComScore, 2021). The way VAs give recommendations to consumers makes an important departure from any other types of recommendation agents (e.g., peer consumers' online reviews, Chatbots). The speech-recognition system enables VAs to recognize a user's verbal commands and respond quickly using spoken language (Whang and Im, 2021). Also, artificial intelligence (AI) technology enables VAs to understand consumer's needs and generate the accurate answer. More specifically, product recommendations provided by VAs may create value for consumers as they help them make faster decisions, save time, and access more personalized services and products subsequently affecting consumers' decision-making process (Rhee and Choi, 2020).

However, extant research on VAs is mostly limited to existing frameworks of general technology adoption, such as Technology Acceptance Model (TAM; Davis, 1989;

Balakrishnan et al., 2021;) and Unified Theory of Acceptance and Use of Technology (UTAUT; Venkatesh and Davis, 2000; Vimalkumar et al., 2021). Hence, research on VAs need to look beyond the concepts examined using the traditional adoption models. More specifically, there are specific calls for research to explore the main elements that should be incorporated into AI devices like VAs to provide added value (Flavian and Casaló, 2021; Belanche et al., 2020). In this respect, recent studies have focused on analyzing VAs value either in general (e.g., Park et al., 2018) or in specific contexts (e.g., hospitality, Loureiro et al., 2021; voice commerce, Rzepka et al., 2020; smart home devices; Benlian et al., 2020). The current research contributes to previous studies on the emerging but limited body of research on consumer usage of VA's recommendations by addressing three relevant points:

First, we analyze the main drivers and barriers of the perceived value of VAs' recommendations. Consumer perceived value is the basis for all marketing decisions, and it is a vital construct that has helped scholars decipher consumer behavior over the past three decades (Zeithaml et al., 2020). Analysis performed by Lin and Lu (2015) revealed that perceived value is a complex and context specific phenomenon, and that it is based on the difference between what the customer gets (benefits) and what he/she gives (costs). Therefore, following a cost-benefit approach is usual when analyzing perceived value (e.g., kleijnen et al., 2007). According to this framework, when adopting a technology system, users consider the costs required in addition to the benefits of the system (Hernandez-Ortega and Ferreira, 2021). After comparing the costs and benefits, users can perceive value, which further affects their behavioral intentions (Lin and Lu, 2015). Specifically, recent studies suggest that the use of VAs generates positive consumer value perceptions (e.g., McLean et al., 2021). Among the specific benefits of VAs' recommendations, convenience via voice input and output and hands-free concept may be highlighted (Qiu and Benbasat, 2009), as well as compatibility, which is the benefit most considered in technology adoption literature (Chattaraman et al., 2019). In addition, personalization is suggested as another benefit of VAs due to the algorithm-based technology that identifies consumer preferences according to previous interactions with the consumer and what the consumer has purchased in the past (Mishra et al., 2015). However, various research highlighted the dark side of VAs, such as cognitive effort and intrusiveness (McLean et al., 2021), which may undermine consumer's value perceptions. While accuracy of speech recognition has improved over time, speech recognition errors still take significant cognitive effort to think about how to phrase queries. Also, it has been found that the intrusiveness of voice-enabled technologies can be considered potentially high, as they are constantly listening to users' wake up keyword or simple errors in the form of unintentional microphone activations, which can be an important source of monitoring and privacy concerns (Jeon et al., 2020).

Second, to provide a more comprehensive understanding of consumer perceived value, we analyze consumer reactions to the presence of VA as an entity. The most prominently cited feature of VAs is social presence, which reflects the subjective capacity of the technology to make people experience their interlocutor as psychologically present (Chattaraman et al., 2019). Indeed, the feeling of presence is at the heart of all simulated experiences and influences the value that users acquire from using a technology (Forgas-Coll et al., 2022). Van Doorn et al. (2017) distinguish between human social presence, evoked by the interaction with a human, and Automated Social Presence (ASP), evoked in an interaction with technology that engages customers socially. ASP is gaining in relevance, as companies increasingly replace human service personnel with automated service robots (Verhagen et al., 2014), being a crucial antecedent of several key service and customer outcomes (Van Doorn et al., 2017). Therefore, we combine the ASP concept

(Van Doorn et al., 2017) with the costs-benefits paradigm (Kleijnen et al., 2007) to explore whether social presence of the VA has an effect on the aforementioned benefits and costs that will determine perceived value of VA's recommendations.

Third, this study examines how this perceived value influences consumer behavior related to the VA's recommendations. Specifically, we analyze whether perceived value of VAs' recommendations may serve to develop consumer engagement with the VA. According to the reciprocity principle (Schmidtz, 2006), when one party benefits from relating or interacting with another party, it is at least a good thing, and perhaps a moral obligation, for the benefitting party to return some of that benefit to the other party. Starting from that point, our study considers engagement with VA as a return part of the value that consumers receive from VA recommendations. It is acknowledged in previous literature that consumer perceived value is the main antecedent of consumer engagement (e.g., Brodie et al., 2011). In this study, therefore, we intent to confirm that engagement is a consequence of perceived value in the context of VA recommendations. Specifically, we focus on the behavioral dimension of engagement, which refers to the "*level of energy, effort and/or time spent on a brand, in particular interactions*" (Hollebeek, 2011, p. 787) and includes proactive behaviors such as E-WOM related behaviors (i.e., spreading E-WOM [Brodie et al., 2011;], and E-WOM adoption [Phua et al., 2018]) and continuance usage (Pal et al., 2021). Consequently, and taking into account that behavioral intentions translate into actual behaviors (e.g. Venkatesh and Davis, 2000), consumer engagement is measured in this study by the following three behavioral intentions: (1) intention to recommend the VA, (2) intention to follow the recommendation of the VA, and (3) continuance intention to use the VA.

Thus, based on the cost-benefit paradigm (e.g., Kleijnen et al., 2007), social presence (e.g., Van Doorn et al., 2017) and engagement (e.g., Hollebeek et al., 2011), the current study develops a research model (see Figure 4.1) that investigates the main drivers of the perceived value of VA's recommendations. On the one hand, we consider, social presence as the main antecedent of the benefits (convenience, compatibility and personalization) and costs (cognitive effort and intrusiveness) of VAs, which in turn exert a direct influence on consumers' perceived value of VA's recommendations. On the other hand, we verify whether or not the generated value leads to consumer engagement with the VA, in terms of (1) intention to recommend, (2) intention to follow the recommendation, and (3) intention to continue to use. From a practical perspective, this research assisted service providers and VAs' designers in understanding how VAs should be designed in order to enhance their recommendations' perceived value and, subsequently, foster consumer engagement with the VA. Specifically, maximizing both social presence and personalization, as well as minimizing intrusiveness, are crucial to generate perceived value and engagement with VAs.

4.2 CONCEPTUAL BACKGROUD

4.2.1 Perceived value

The fundamental assumption in consumer behavior research, is value maximization (Kim et al., 2007), and it is essential to understand individual choices. According to prospect theory (Kahneman and Tversky, 1979), the value function is described in terms of perceived gain or loss compared to a baseline. It posits that individuals pick the conduct that results in the largest payout. Additionally, perceived value has been viewed as a compromise between the "*give*" and "*get*" components of a product (Dodds and Monroe, 1985). According to Zeithaml (1988), perceived value is the consumer's total evaluation of a product's usefulness based on their views of what is received and what is provided. From the standpoint of consumer choice, people assess the worth of a choice object by weighing all the advantages and costs (Kahneman and Tversky, 1979; Zeithaml, 1988).

Consumers determine their choice behavior based on this overall behavior. Thus, this study defines perceived value as a consumer's perception of the net benefits gained based on the trade-off between relevant benefits and costs derived from the VA use for receiving product or service recommendations. Among others, VAs may create value by providing personalized information and targeted recommendations (Huang et al., 2018), as they incorporate information from the end consumer (i.e., present and past choices, purchases, needs and preferences, localization) through algorithms and data processing analytics tools (Stucke and Ezrachi, 2018). In addition, VAs are hands-free control devices, helping them make faster decisions and save time and effort (Chopra, 2019; Vassinen, 2018). Next section presents the main benefits and costs associated to VAs.

4.2.2 Benefits and costs

To identify the antecedents of the perceived value of VAs' recommendations, we build on the benefit-cost paradigm (Kleijnen et al., 2007). Regarding the main benefits in the context of new technologies, systematic research first suggests that convenience and compatibility relate consistently to innovative technologies (Agarwal and Prasad 1998). For example, convenience is amongst the most common benefit for consumers' online services (Tan and Liao, 2021). Convenience represents consumers' time and effort perceptions about using a technology because they can save effort for routine tasks and time for very time-consuming tasks (Ukpabi and Karjaluoto, 2017). Several studies have explored time saving (Berry et al., 2002) and effort saving (Emrich et al., 2015) as aspects of convenience in online context. Similarly, in mobile services, convenience directly and positively influences perceived value (Lin and Lu, 2015). Second, according to the Technology Task Fit Theory, the technology's compatibility with users' existing beliefs and needs is an important component of perceived value (Goodhue, 1995). Compatibility is defined as the degree to which consumers perceive innovations as consistent with their needs, values, past experiences and routines (Wu and Wang, 2005). Research on mobile transaction services reveals that compatibility has been found as an antecedent of perceived value (Koenig-Lewis et al., 2010). Likewise, other research in robot services (Salm-Hoogstraeten and Müsseler, 2021) and smart speakers (Malodia et al., 2021) have highlighted that compatibility is the most significant benefit affecting technology adoption. Besides to convenience and compatibility, we incorporate personalization as our third VA's benefit. Personalization in new media communication refers to the extent to which a technology can facilitate interpersonal communication and interaction based on consumers' personal and preference information (Song et al., 2016). Findings from communication studies suggest that personalized communication attracts more attention and it is perceived as more beneficial than non-personalized communication (Tam and Ho, 2006). In social media context, it has been argued that personalized recommendation enhances the consumer perceived value of the platform. In the same vein, Kraus et al. (2019); Rhee and Choi (2020) and Pal et al. (2020) have found that personalization is the main advantage of VAs. By receiving a tailored recommendation, consumers perceive an accurate information which facilitates their purchase decision making process and consequently, increases their perceived value of the VAs' recommendations.

In forming value perceptions, consumers balance costs against benefits. Cognitive effort is considered as a first cost factor, similar to previous studies on mobile transactions (Kleijnen et al., 2007) or on online shopping (Hong et al., 2004). Cognitive effort refers to the total extent of cognitive resources, such as perception, memory and judgment, needed to complete a task (Cooper-Martin, 1994). Drawing on information search literature, Lynch and Ariely (2000) found that cognitive effort represents an information search cost. Similarly, in smart technology context, cognitive effort has been perceived as a barrier in spreading voice-enabled devices (De Barcelo Silva et al., 2020). Finally, following recent works on VAs (Cowan et al., 2017), we also include intrusiveness as a major cost for consumers, due to its "*always-on*" listening feature. Technology intrusiveness is the extent that the technology has the potential to monitor and surveille users by accessing to their personal information data (Sweeney and Davis, 2020) . Several studies have shown that intrusiveness can cause reactance and avoidance (e.g., Baek and Morimoto, 2012; Li, Edwards, et al., 2002) resulting in negative evaluations and behavioral intentions regarding the source that triggers the reactance (Ozcelik and Varnali, 2019). Also, it has been found that intrusiveness is also linked to personalized queries, as queries that become too personal (e.g., by using private information) can cause an uncomfortable feeling and raise feelings of intrusiveness (van Doorn and Hoekstra, 2013). In technology research, when a technology is perceived as intrusive, this can lead to a decrease in its perceived value (Benlian et al., 2020).

4.2.3 Social presence

Social presence is described as "*the degree to which another individual stands out in an engagement*" (Short et al., 1976, p. 65). Based on robotics study (Chattaraman et al., 2019), the amount of ASP in services is increasing. ASP can be described as the extent to which computerized machines give people the impression of being in the company of another social entity (Van Doorn et al., 2017). The ASP may supplement or replace human service personnel, particularly in responding to typical service requests. For instance, users can socially connect with their VA to receive product or service information rather than visiting a store. According to social response theory (Reeves and Nass, 1996), individuals respond with media similarly to how they interact with other humans. They accomplish this through the use of social rules, two-way interaction, discussion, and social roles. The language-based dialogues between people and AI devices serve as a key humanlike quality that evokes a sense of social presence in the consumer's consciousness, so influencing customers to interact with the artificial agent as they would with humans (Chattaraman et al., 2019). Humans are growing increasingly accustomed to participating in quasi-social relationships with AI 'beings' as a result of the technological advancements we have experienced in recent years (Van Doorn et al., 2017).

Prior research (e.g., Forgas-Coll et al., 2022; Rosenthalvon der Pütten et al., 2016) demonstrates that AI gadgets based on spoken language create a strong sensation of social presence. In addition, social response theory describes the idea of reciprocity in the interactions between people and machines. Consumers take turns speaking with VAs, pausing for a VA's response and providing extended responses (Cerekovic et al., 2017). In addition, as consumers become accustomed to conversing with a VA, like they would with other people, they begin to develop a rapport with the technology (Cerekovic et al., 2017).

Moving beyond text-based customer interactions, VA technologies take another step toward emulating human service interactions via voice communication, significantly decreasing the barriers for consumers to engage with product recommendations at a time that is convenient for them. Providing technology with a voice is an effective means of promoting social connection (Nass and Brave, 2005). In essence, voice-enabled interactions level the playing field between technology service providers and human service providers as social agents, as both are able to communicate social presence. In the same manner that consumers connect with human service professionals, they can develop a social rapport with their VAs, hence improving social cues and the engagement potential of such devices.

4.2.4 Engagement

The concept of engagement has received great attention in the last decade, but previous research has conceptualized engagement from two main perspectives. On the one hand, consumer engagement can be analyzed from a psychological perspective, comprising cognitive and emotional aspects (Bowden, 2009). Psychological engagement includes three elements: vigor, absorption, and dedication: (i) vigor means the energy and psychological resilience of the consumer; (ii) absorption indicates the degree to which consumers are attentive; (iii) dedication refers to the extent of consumers' feeling of significance, incentive, and encouragement toward the specific entity (Cheung et al., 2015). The importance of this state lies in the fact that psychologically engaged customers are more attached emotionally and cognitively, resulting in highly loyal customers to products or firms (Jahn and Kunz, 2012). On the other hand, customer engagement can be studied strictly from a behavioral point of view. Van Doorn et al. (2010) define behavioral engagement as the proactive efforts that customer makes toward a firm or brand, affecting the firm or brand in ways other than purchase alone.

Although the psychological perspective is more widely endorsed in previous research, we embrace the behavioral approach in our study. There are two reasons for this decision. First, the psychological conceptualization usually deviates from the main component of engagement (i.e., behavior; Van Doorn, 2010) and the behavioral engagement is the main element that serve to differentiate highly engaged from no or less engaged consumers (Van Doorn et al., 2010). Second, dimensions of consumer engagement from a psychological perspective vary greatly across studies. For example, So et al. (2014) employed a consumer engagement scale that includes enthusiasm, attention, absorption, interaction, and identification. Hollebeek et al. (2014) proposed that cognitive processing, affection, and activation are the dimensions of consumer engagement. This lack of consensus regarding the dimensions of consumer engagement complicates its measurement and conceptualization. In contrast, consumer behavioral intentions are identified unanimously as the behavioral engagement dimensions (Berezina et al., 2016).

The behavioral engagement has been usually conceptualized as showing preferences for a company or brand by posting positive messages and recommendations to others (Cambra-Fierro et al., 2016; Van Doorn et al., 2010). That is, behavioral engagement is demonstrated by consumers whose likelihood of spreading E-WOM behaviors is high as well. For instance, Islam and Rahman (2015) argued that engaged consumers are more likely to share their experiences, provide feedback and recommend the product to other potential consumers. In sum, intention to recommend has been considered as a key dimension of behavioral engagement (Van Doorn et al., 2010) and previous research has traditionally included it when operationalizing behavioral engagement (e.g., Flavián et al., 2020).

Following endorsement literature, behavioral engagement is also related to consumers' intention to follow a recommendation or adopt the E-WOM message. For instance, a recent study shows that consumer engagement with a celebrity endorsed e-cigarette advertising on Instagram increases the likelihood of using the advertised product (Phua et all., 2018). Similarly, a recent study by Whang and Im (2021) shows that humans respond positively to VA recommendations. Furthermore, research suggests that, compared to humans, AI agents, such as a VA, may not be perceived as having selfish intentions when making a recommendation (Garvey et al., 2022). This may further develop trust between the AI and the consumer, which is determinant in encouraging engagement by accepting its AI recommendations (Lin et al., 2021). Overall, these trust enhancing factors should further the relationship building process, which is integral in the development of engagement and thus forming the intent to follow recommendations provided by the VA.

In addition, continuance intention to use is considered to be another form of consumer behavioral engagement (Kim et al., 2013). When consumers feel strong engagement with an object, they feel a strong willingness to retain the relationship with that object; that is, they invest time using that object and looks for continual interactions (Aro et al., 2018). Prior research (e.g., Liébana-Cabanillas et al., 2018) analyzed the types of behavioral engagement with mobile applications usage, and found that the intention to continue using the apps is the main engagement behavior. In addition, in the context of MOOCs, it has been highlighted that when students develop a high engagement with the learning platform, they keep using it for their online learning (Sun et al., 2020).

In sum, in a VA context, consumers may be engaged with the VA by three behavioral intentions: to recommend the usage of VAs for product recommendations, to follow the VAs' recommendations, and to continue using the VA.

4.3 HYPOTHESES DEVELOPMENT

4.3.1 The influence of social presence on perceived benefits and costs

Social presence makes consumers feel that they are in the company of another social entity (Chattaraman et al., 2019). Research on interpersonal communication suggests that connectedness with others is grounded on effortless communication resulting from convenient natural common language, nonverbal cues, and interactivity speed (Hartley, 2002). In addition, studies in cognitive neuroscience find that face-to-face communication increases an individual's ability to process effortlessly the information (Heninger et al., 2006). Arguably, when individuals are able to communicate in an effortless manner with another entity can be considered as convenient. Further work in a technology context suggests that reducing effort in interactions with technology is associated with increased convenience (Mitzner et al., 2010). Therefore, and adapted to our framework, when individuals using a VA perceive that the recommendation is coming from a social entity and not from a machine, the recommendation would be easier to process, resulting in a convenient interaction.

The ASP in service robots evokes the perception of conspecific (Van Dorn et al., 2017). More particularly, social presence leads to perceive the technological service agents as a helpful, skillful and efficacious social entity. Similarly, the social presence lead consumers to perceive robots as entities representing human abilities, intentions and beliefs (Sidner et al. 2004). Thus, the robot shifts away from scenarios in which it is perceived as machine and instead become perceived as a real person "*that can create social and emotional connections with their human partners"* (Cabibihan et al. 2014, p. 311) and thus users would develop a compatibility feeling. According to the advice communication theory (MacGeorge et al., 2016), people tend to seek advice from humans rather than from machines. More particularly, in face-to-face communication, individuals are more likely to seek advice from people who are similar to them (i.e., have lived similar circumstances). Accordingly, social presence may motivate individuals to perceive the compatibility with VAs and receive the recommendation in the same way as they would with real humans (Chattaraman et al., 2019).

Humans are socially oriented beings, and when they perceive social presence, thus apply social roles when interacting with technology such as politeness, pausing for response during interactions in the same way as they would with another human during in-person interactions (Moon, 2000). More specifically, it has been argued that VAs trigger the feeling of social presence (Chattaraman et al., 2019), then when receiving recommendations, consumers tend to apply social roles like they receive a recommendation from a real person. In-person communication is synchronous and object to the turn-taking rules. Each individual always has his or her turn to speak and let the other to speak in turn, thing that lead the individuals fully engage in the interaction with and perceive it as targeted to him (Okol'nishnikova and Iuldasheva, 2013). In addition, in-person communication is often one-to-one communication, and not one-to-many, directing the message to a specific individual. Therefore, the communication might be perceived as personalized (O'Sullivan, 2005). Accordingly, due to the social presence, consumers would perceive the VA as a real person giving personalized recommendations.

In sum, based on all these, the following hypotheses are proposed regarding the effect of social presence on the perceived benefits of VAs' recommendations:

> **H1.** The social presence of the VA has a positive effect on its perceived convenience.
>
> **H2.** The social presence of the VA has a positive effect on its perceived compatibility.
>
> **H3**. The social presence of the VA has a positive effect on its perceived personalization

According to Wang et al. (2007), social presence is composed by intimacy and immediacy (Wang et al., 2007). First, intimacy refers to the feeling of being in a close personal association and belonging together (Laurenceau et al., 1998). Adapted to technology context, the connection and the sense of belonging through intimacy lead consumers to perceive the technology as human being (Van Dorn et al., 2017). According to interpersonal communication theory (Jehn and Shah, 1997), it has been shown that individuals experience less cognitive effort in human-human interactions compared to human-machine interactions, because they perceive the counterpart thinking and interacting like them, thing that engage comfort and communication fluidity. Second, immediacy reflects the psychological distance between a communicator and the recipient of the communication (Wiener and Mehrabian, 1968). In technology context, immediacy refers to how readily the technology can exchange information with users (Walther, 1992). Immediacy leads to high interactivity which can increase communication effectiveness (e.g., accuracy and quick response [Liu and Shrum, 2002]) and, consequently, reduce cognitive effort made to understand the communication. Furthermore, in communication education research, Christophel (1990) reported that instructors with higher immediacy were viewed as more positive and effective, leading to a decrease in mental effort to assimilate the course.

Previous studies provide evidence that social presence of computers make individuals perceive they are "*socially present*", resulting in the application of social norms when interacting with them and establishing a familiar and personal connection with them (Epley et al., 2007). The feeling of familiarity and personal connection created through social presence may lead consumers to perceive the VAs as friends rather than as perpetrators (Qiu and Benbasat, 2009), increasing therefore their likeability and trustworthiness (Benlian et al., 2020) and thus overriding potential sources of intrusiveness. Moreover, Kim and McGill (2011) have shown that people feel more powerful in the presence of social entities rather than machines, and thus believe that they have more control over them, reducing behavioral uncertainty and intrusiveness concerns vis-à-vis machines. Applying this logic to the context of VAs, we argue that social presence of VAs attenuates VAs' intrusive effects.

Based on all above, we propose the following hypotheses regarding the effect of social presence on the perceived costs of VAs:

H4. The social presence of the VA has a negative effect on its perceived cognitive effort.

H5. The social presence of the VA has a negative effect on its perceived intrusiveness.

4.3.2 The influence of perceived benefits and costs on perceived value

Research related to innovative technologies lists convenience as a benefit and, thus, a decisive reason to adopt a given service (Ukpabi and Karjaluoto, 2017). Scholars argue that convenience is at the forefront of consumer evaluation of service and consumer behavior (Farquhar and Rowley, 2009). People derived value from convenient and efficient service delivery (Childers et al., 2001). For example, perceived value of mobile services is primarily driven by the degree of effectiveness and efficiency of achieving a goal or task (Kleijnen et al., 2007). In voice-based technology context, Ostrom et al. (2019) argued that VA brings great value to consumers, as it can offer convenience and speed, and consequently considered it the most innovative and valuable technology (Klaus and Zaichkowsky, 2020). According to Luger and Sellen (2016), consumers feel that it is often easier and more convenient to use voice input than to type, one reason being that voice is felt to be faster. More particularly, once it hears the keyword, the VA consumes the user's voice, interprets the language, and processes a response all in real-time without any additional effort (Grover et al., 2020). Additionally, VA gives recommendations based on consumer historical, preferences and habits, to which this agent has access through algorithm-based system (Ling et al., 2021). Thus, the consumer has a quick and effortless information, which may increase his or her perception of value (Ukpabi and Karjaluoto, 2017).

Voice allows consumers to replicate conversations that are similar to what happens in a face-to-face interaction. With the voice characteristic and AI features, VAs can mimic a humanistic and natural language, fulfill consumer's requests, and offer suggestions for products or services. In this case, VA acts like a human recommendation agent in a real store (Xiao and Benbasat, 2007); consequently, people would perceive a kind of similarity. Also, with the personalized services that VAs are able to offer (e.g., tailored recommendations, customized products) to one's needs, consumers may feel like a human intellectual ability and intelligence. Data from 2017 found that 41% of people who owned a VA said that they feel comfortable while communicating with VA, experiencing a feeling of compatibility between themselves and the technology (Smith, 2020). With this perceived compatibility, consumers' perceived value of VAs' recommendations may increase (Park et al., 2018).

One of the most relevant personalized services in new media communication is product recommendations (Rhee and Choi, 2020). The fundamental idea of personalization is to treat each consumer as a unique entity and design the personalized recommendation message based on his or her preferences (Kalyanaraman and Sundar, 2006). A message that matches the consumer's preferences has been argued to be perceived as a stronger and more useful than a standardized message that mismatches (Ho and Bodoff, 2014). By serving consumers at the individual level rather than "*mass*" level (Riemer and Totz, 2003), personalization builds deeper one-to-one consumer relationship (Riecken, 2000), which is expected to increase consumer perceived service quality and value (e.g., Hagel and Rayport, 1996). Moreover, personalization serves to increase consumer well-being, improves their decision making and helps them perform tasks more quickly (Gironda and Korgaonkar, 2018). Similarly, in VA context, personalization leads to boost cross-selling, consequently decreasing the search efforts of individuals, which may lead consumers to see the VA as valuable (Kristensson, 2019).

Based on all above, we propose the following hypotheses regarding the effect of VAs' perceived benefits on their recommendations:

H6. Perceived convenience of the VA has a positive effect on perceived value of VAs' recommendations.

H7. Perceived compatibility with the VA has a positive effect on perceived value of VAs' recommendations.

H8. Perceived personalization of the VA has a positive effect on perceived value of VAs' recommendations.

Cognitive effort is derived from the complexity innovation characteristic (Kraus et al., 2019). A VA often makes functional errors by failing to understand consumer commands when the utterance has disfluent speech segments, such as stuttering, false syntactic structures, and erroneous articulation (Kim and Choudhury, 2021). For example, a study performed by Cowan et al. (2017) on Siri users, suggested that they perceive a large cognitive effort when Siri did not accurately understand what they said. Furthermore, Velkovska and Zouinar (2019) noted the cognitive effort related to issues connected to the use of indexical terms such as "*here*" or "*it*" by consumers when interacting with their VA. In the same vein, Lee et al. (2019) mentioned that VAs receive not only simple queries from the consumer, but also several emotional inputs (i.e., aggressive tones). VAs' inability to understand the context and the consumer's emotional state may increase cognitive effort in the interaction, being considered one of the biggest cognitive costs that consumers perceive from these systems and diminishing the perceived value of their recommendations.

Technology intrusiveness represents the degree to which a technology enables individuals to be reachable (Benlian et al., 2020). In technology context, it has been found that when technology is perceived as intrusive, this can lead to a decrease in the perceived value of this technology services (Lau et al., 2019). The intrusiveness of VAs can be considered potentially high, as they not only have to constantly listen to users' wake up keyword in order to be activated but also can make errors in the form of unintentional microphone activations (Lau et al., 2019). These unintentional voice activations have been found to increase feelings of invasion and intrusiveness because they imply that VA providers might collect information about consumers and their behaviors in an inconspicuous manner in order to create detailed consumer profiles that they might share with third-party service providers (Jeon et al., 2020).

Taking in consideration all the above, we propose the following hypotheses regarding the effect of VAs' perceived costs on their recommendations.

> **H9.** Perceived cognitive effort with VA has a negative effect on perceived value of VAs' recommendations.

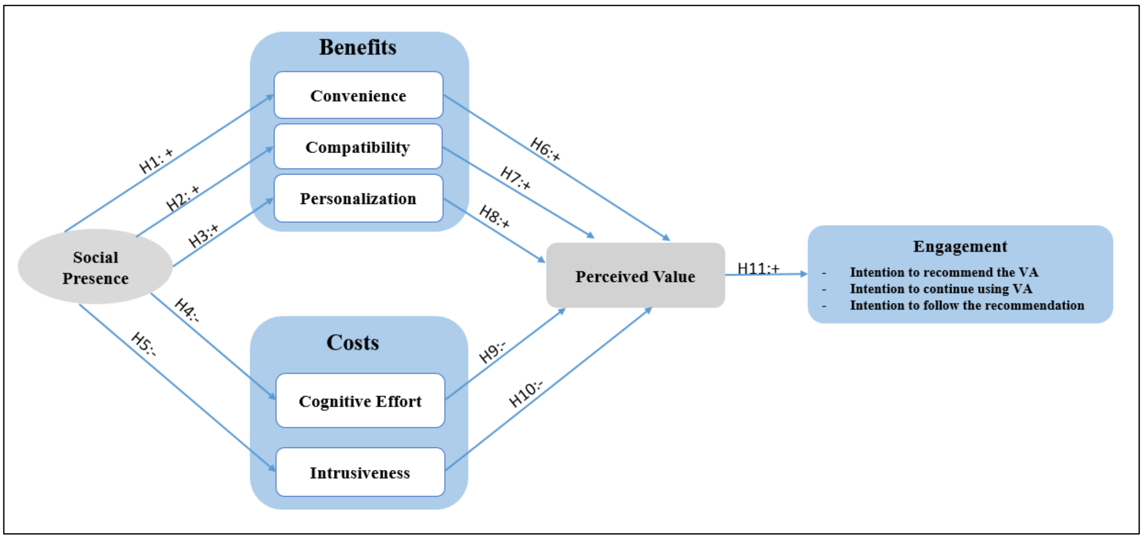
> **H10.** Perceived intrusiveness of the VA has a negative effect on perceived value of VAs' recommendations.

4.3.3 The influence of perceived value on engagement

Hollebeek et al. (2014) claimed that consumer engagement behaviors are consequences of perceived value. For example, when users perceive a high degree of value from consumption experiences, they are more prone to engage in behaviors such exchanging reviews, recommendations as well as referrals about their experiences (Hsu and Lin, 2016). In the settings of mobile services, it has been found that the more consumers value the mobile use experience, the more likely they will engage in spreading positive E-WOM (Cheshin et al., 2018). Therefore, when consumers perceive great value from VAs, they may more likely recommend them. Similarly, prior studies have found that adopting E-WOM is an outcome of customers' perceived value of online platforms (Chen et al., 2017). When users perceive that the social media platform is valuable, they are more likely to adopt these recommendations received through these platforms. Also, in mobile apps context, it has been found that perceived value of mobile apps exerts direct and positive impacts on intention to follow the information brought by these devices (Cheshin et al., 2018). Thus, as perceived value increases, we expect a greater consumer intention to follow the VA recommendation. In the same vein, previous research has found a positive relationship between perceived value and continuance use intention in different contexts, such as digital music or blogs (Turel et al., 2010) and smart healthcare devices (Lee and Lee, 2020). A positive perception of the value means that the benefits outweigh the costs, such that it makes sense to continue using the product. In the VA context, when consumers perceive value derived from using that device, they form a positive perception toward the VA that further leads to continued performance of the action. Based on all above, we expect that perceived value of VAs' recommendations increase all behavioral intentions forming consumer engagement and the following hypothesis is finally proposed:

> **H11**. Perceived value of VA recommendations has a positive effect on consumer engagement with the VA.

Figure 4.1 Conceptual research model



4.4 RESEARCH METHODOLOGY

4.4.1 Data collection

To test our hypotheses, a quantitative study was undertaken with VAs' users. Participants are US residents that were recruited through an online survey; a market research company assisted us in the process. Data were collected in November 2021, and 423 members participated voluntarily in the study. To take part, participants had to be users of VAs to get product or service recommendations at least once. With this aim, a qualifier sentence was included to guarantee that participants were VA users and, in addition, a question served to assure that they belonged to the segment under study ("*How often do you use VA to get recommendations*?"). Only those respondents who were users of VAs to get recommendations at least once, could continue with the questionnaire, thus ensuring the reliability of the responses. A total of 316 valid responses were obtained; therefore, in our sample of VA users, a 74.7% of respondents confirmed they used VAs to get recommendations.

Of the respondents, 48.73% were men, 51.59% were aged between 18 and 30, and 50% had undergraduate degree (Table 4.1 includes more detailed socio-demographic information of participants). 42.42% of the participants use Alexa (Amazon) as a VA, followed by Siri (Apple) 28.62%. Regarding the participants' expertise in using VAs, 55.22% are users for more than 3 years. In addition, it should be highlighted that 56.5% of participants report to use VAs to get product and service recommendations with a great frequency (see Table 4.1).

Table 4.1 Sample socio-demographic characteristics

		Frequency	%
Gender	**Male**	154	48.73
	Female	159	50.32
	Prefer not to say	3	0.95
Age	**18-25**	111	35.13
	26-30	52	16.46
	31-35	51	16.14
	36-40	37	11.71
	41-45	24	7.59
	46-50	13	4.11
	51-55	12	3.80
	56-60	6	1.90
	61-65	4	1.27
	66 years old and over	6	1.90
Education level	**Primary school**	2	0.63
	High school degree	92	29.11
	Undergraduate degree	158	50.00
	Graduate degree	64	20.25
Citizenship	**American**	300	94.94
	Other	16	5.06

The information was obtained through a questionnaire with closed questions. The research constructs were operationalized using items adapted from previous research (see Table 4.3). The variables were measured using 7-point Likert scales, where 1 indicated "*strongly disagree*" and 7 "*strongly agree*". All constructs were considered as first-order and reflective, except for engagement, which is considered as a second-order formative construct. A pre-test of the questionnaire was carried out to correct possible defects and to identify problems that might arise during the information-gathering process. The surveys were administered on 20 regular users. These respondents had similar characteristics to the target sample that was to be surveyed. The pre-test requested the respondents to complete the questionnaire. As a result of these pre-test, some of the scales were adapted to facilitate understanding and to avoid erroneous interpretations. In addition, we applied procedural remedies to minimize the risk of common method variance (Reio, 2010) such as, randomly counterbalancing the stimuli order, separating the items with trivial questions, promising complete anonymity and positioning the demographic questions at the end of the questionnaire (Podsakoff, 2003).

4.4.2 Estimation procedure: Two-step approach PLS-SEM

The data was analyzed using structural equation modeling (SEM) based on partial least squares (PLS) approach with SmartPLS 3.0 software (Ringle et al., 2015). We selected the PLS-SEM approach for the following reasons. First, this approach is widely used in recent research (e.g., Amin et al., 2022; Mishra et al., 2021) and it is based on component-based structural equation modeling (Hair et al., 2011). Second, the ability of PLS-SEM to deal with higher-order constructs (Sarstedt et al., 2019) and mediation (Nitzl et al., 2016) in a single model at the same time. In this study, we have proposed the engagement as a (second) higher-order construct. Moreover, PLS is recommended for prediction-based models that focus on identifying the key predictor or driver constructs (Hair et al., 2011), which aligns with the research objectives of this study.

As aforementioned, engagement is referred to as a second-order formative construct that is measured by three first-order reflective constructs (i.e., the dimensions of engagement; intention to recommend the VA, intention to follow the recommendation of the VA, and intention to continue using the VA). Second order constructs were proposed from a methodological standpoint because they reduce the number of hypothesized relationships in the model, making it more parsimonious (Thien, 2020). It also serves to reduce collinearity issues (Hair et al., 2017; Sarstedt et al., 2019), makes results easier to interpret, and aids to generate reliable and valid empirical results (Thien, 2020). All the three dimensions of the engagement have different conceptual meanings, which are reflected in their measures. In summary, the first order constructs are measured in a reflective way by their own measurement item, whereas the second order construct is measured in a formative way by their first order constructs item using a two-stage approach (Sarstedt et al., 2019).

Specifically, we use a two-step approach, as suggested by Becker et al. (2012) and Hair et al. (2017), to test the higher-order reflective-formative construct. In the first step, we use a repeated indicator approach to obtain the latent variable scores of the first-order constructs used to measure engagement. In the second step, the latent variable scores obtained previously are included as the measures of engagement and we calculated their weights and significance. The collinearity of the indicators (using the variance inflation factor [VIF]) and the significance of the indicator weights were used to determine the formative measure. The results are shown in Table 4.2 VIF values are below the 3.3 threshold (Hair et al., 2019), meaning that collinearity is not a serious concern. We used the 5000 resample bootstrap technique to assess the significance of the weights, and the results show that all the weights are significant at $p < 0.001$ level. This demonstrates the relative contribution of all behavioral intentions to form engagement.

Table 4.2 Assessment of higher-order construct

Higher-order construct	Formative indicators	Outer weights	VIF	t-value
Engagement	Intention to continue using the VA	0,363	3,069	50,597***
	Intention to recommend the VA	0,363	3,143	49,525***
	Intention to follow the recommendation of the VA	0,353	2,903	57,093***

Notes: ***p < 0.001; VIF (Variance Inflation Factor). As explained before, latent variable scores of the first-order constructs (calculated in a previous step) were used to measure engagement. Each behavioral intention was measured using three items: continuance intention to use the VA (adapted from Bhattacherjee, 2001), intention to recommend the VA (adapted from Casaló et al., 2017), intention to follow the recommendation (adapted from Cheung et al., 2009). All these measures also comply with validity requirements in the previous step.

4.4.3 Measurement validation

Once latent variable scores were obtained to measure engagement, a confirmatory factor analysis was carried out to confirm the dimensional structure of the scales. Specifically, for reflective constructs, we examined factor loadings to make an initial assessment of the internal consistency of the constructs. Factor loadings exceeded the 0.7 threshold (Henseler et al., 2009) in their respective constructs (see Table 4.3). The reliability of the measures was then analyzed using composite reliability (CR). The CR values are shown in Table 4.3; they exceed the recommended value of 0.7 (Hair et al., 2011). Similarly, Cronbach's α surpassed the recommended 0.7 threshold for all reflective constructs (Nunnally and Bernstein, 1994), as can also be seen in Table 4.3 Convergent validity was also assessed using average variance extracted (AVE), which should be greater than 0.5 (Fornell and Larcker, 1981). The results shown in Table 4.3 meet this criterion. Finally, the results shown in Table 4.4 confirm the discriminant validity of the measures, as the square roots of the AVE of each construct are greater than their corresponding inter-construct correlations (Fornell and Larcker, 1981).

Table 4.3 Reflective measurement scales

Items	Factor loadings	Cronbach's α	CR	AVE
SOCIAL PRESENCE (Gefen and Straub, 2003)		0.953	0.963	0.811
SP1. **While receiving recommendation from the VA, I feel like a face-to-face recommendation.**	0.843			
SP2. **While receiving recommendation from the VA, I feel a sense of human contact.**	0.928			
SP3. **While receiving recommendation from the VA, I feel a sense of sociability.**	0.908			
SP4. **While receiving recommendation from the VA, I feel a sense of human warmth.**	0.913			
SP5. **While receiving recommendation from the VA, I feel a sense of human sensitivity.**	0.921			
SP6. **While receiving recommendation from the VA, I feel a sense of realism and belonging.**	0.889			
CONVENIENCE (Mathwick et al., 2001)		0.700	0.868	0.767
CV1. **It is convenient to me to get a recommendation from the VA**	0.904			
CV2. **I do not make much time to understand a recommendation from the VA**	0.847			
COMPATIBILITY (Meuter et al. 2005)		0.939	0.961	0.892
CMP1. **Using VA for recommendations fits my needs**	0.925			
CMP2. **Using VA is compatible with the way I normally obtain the recommendations**	0.948			
CMP3. **Using VA for recommendations is in line with my preferences**	0.959			
PERSONALIZATION (Komiak and Benbasat, 2006)		0.935	0.954	0.838
PRS1. **I feel the VA understands my needs when making a recommendation**	0.907			
PRS2. **I feel the VA knows what I want when making a recommendation**	0.936			
PRS3.**CI feel the VA takes my needs as its own preferences when making a recommendation**	0.894			
PRS4. **I feel the VA is matching with my interests when making a recommendation**	0.923			
COGNITIVE EFFORT (Dabholkar and Bagozzi, 2002)		0.935	0.958	0.884
CE1. **Receiving recommendations from the VA is complicated**	0.937			
CE2. **Receiving recommendations from the VA is difficult**	0.954			
CE.3 **Receiving recommendations from the VA requires a lot of effort to understand it**	0.931			
INTRUSIVENESS (Lau et al., 2019)		0.919	0.949	0.861
ITRS1.**While receiving the recommendation from the VA, I feel I am under surveillance**	0.936			
ITRS2. **While receiving the recommendation from the VA, I feel being monitored**	0.959			
ITRS3. **While receiving the recommendation from the VA, I feel the VA is listening everything around me**	0.887			
PERCEIVED VALUE (Liu, Zhao et al., 2015)		0.955	0.967	0.881
PV1. **I believe that using the VA for recommendations is valuable.**	0.929			
PV2. **I believe that using the VA for recommendations is worthwhile.**	0.946			
PV3. **I believe that using the VA for recommendations is beneficial**	0.940			
PV4. **Overall, the use of the VA for recommendations, delivers a high value.**	0.940			

Table 4.4 Discriminant validity

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Social Presence (1)	**0.901**							
Convenience (2)	0.327	**0.876**						
Compatibility (3)	0.473	0.708	**0.944**					
Personalization (4)	0.548	0.616	0.679	**0.915**				
Cognitive Effort (5)	-0.010	-0.373	-0.199	-0.275	**0.940**			
Intrusiveness (6)	-0.152	-0.292	-0.272	-0.303	0.170	**0.928**		
Perceived Value (7)	0.541	0.647	0.686	0.705	-0.252	-0.376	**0.939**	
Engagement (8)	0.546	0.643	0.734	0.702	-0.267	-0.389	0.871	**-**

4.5 RESULTS

4.5.1 Structural model: Direct effects

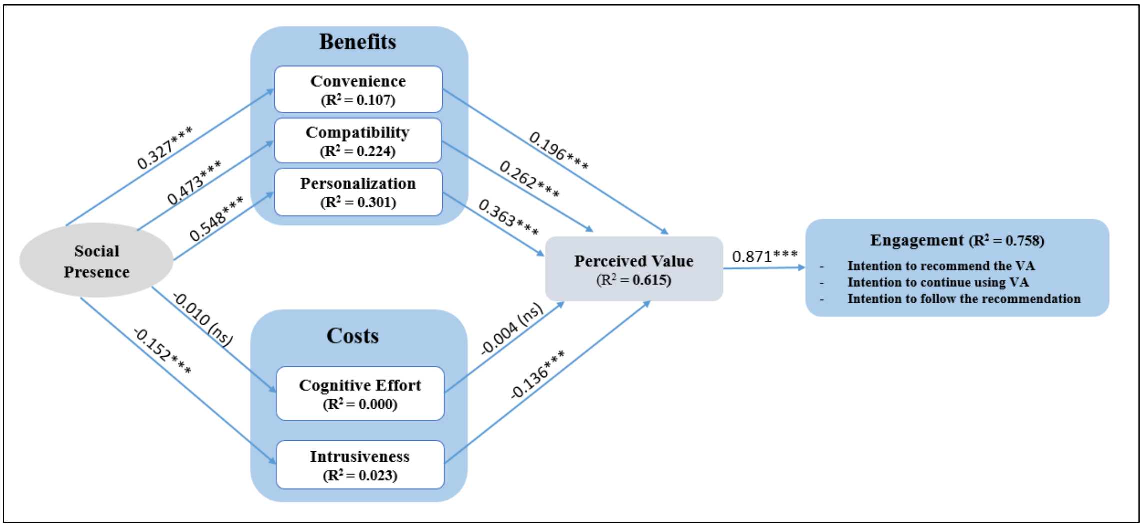
Having confirmed the reliability and validity of the measurement scales and the dimensionality of the constructs, we next evaluate the direct effects proposed in the research model through PLS, again using SmartPLS software version 3.0. The path relationships and the R^2 levels of the endogenous latent variables are initially assessed, and a bootstrapping procedure method with 10.000 subsamples is conducted to calculate the statistical significance of the path relationships (Temme et al., 2006).

We find support for nine of the eleven proposed hypotheses, except for H4 and H9 (see Figure 4.2). Social presence is a strong predictor of the benefits of VAs' recommendations, including convenience (β=0.327, p<0.001), compatibility (β=0.473, p<0.001) and personalization (β= 0.548, p<0.001). Hence, H1, H2, and H3 are supported. Whereas, social presence is negatively related to the cost of intrusiveness (β= -0.152, p<0.001) and does not affect cognitive effort (β= -0.010, p>0.05). Therefore, H5 is supported and H4 is rejected.

Personalization is the strongest determinant of the perceived value of VAs' recommendations (β= 0.363, p<0.001). Convenience (β= 0.196, p<0.001), together with compatibility (β= 0.262, $p<0.001$), positively influence perceived value too. In contrast, intrusiveness (β=-0.136, $p<0.001$) has a negative effect on perceived value. Regarding the cognitive effort, a non-significant effect (β=-0.004, $p>0.05$) on perceived value is found. Therefore, H6, H7, H8 and H10 are supported whereas H9 is rejected. Lastly, perceived value of VAs' recommendations has a great impact on engagement (β= 0.871, $p<0.001$), supporting H11.

As to the explanatory power of the research model, we can partially explain the study's main endogenous variables: perceived value (R^2=0.615) and engagement (R^2=0.758). According to Chin (1998), these findings suggest that the R^2 values are moderate to substantial.

Figure 4.2 Structural analysis of the research model



Notes : **$p<0.01$ ***$p<0.001$ ns: non-significant

4.5.2 Indirect effects

Looking at these results, social presence and both benefits (convenience, compatibility and personalization) and costs (cognitive effort and intrusiveness) may have indirect effects on perceived value and engagement. Therefore, these potentially mediated relationships were analyzed following Chin (2010) and Zhao et al. (2010), by calculating bias-corrected and accelerated confidence intervals of such effects. To do that, we used

10,000 subsamples, with no sign change. Table 4.5 shows the results of these analyses. Regarding the benefits of VAs' recommendations, the table show significant and positive indirect effects of convenience, compatibility and personalization on engagement through perceived value. Turning to the costs, while intrusiveness significantly influences negatively engagement via perceived value, perceived value does not mediate the effect of cognitive effort on engagement. In addition, social presence exerts a positive indirect effect on perceived value via perceived benefits (convenience, compatibility and personalization) and the intrusiveness cost. However, cognitive effort does not mediate this relationship. Finally, social presence also exerts a positive indirect effect on engagement. In this case, the three benefits and the intrusiveness cost, first, and perceived value, second, sequentially mediates this indirect effect Again, the indirect effect of social presence on engagement is not significant via cognitive effort.

Table 4.5 Indirect effects

Indirect paths							**Path coeff.**	**Sig.**
Social Presence	→	Convenience	→	Value			0.064*	0.014
Social Presence	→	Compatibility	→	Value			0.124***	0.000
Social Presence	→	Personalization	→	Value			0.199***	0.000
Social Presence	→	Convenience	→	Value	→	Engagement	0.056*	0.014
Social Presence	→	Compatibility	→	Value	→	Engagement	0.108***	0.000
Social Presence	→	Personalization	→	Value	→	Engagement	0.173***	0.000
Social Presence	→	Intrusiveness	→	Value			0.021*	0.049
Social Presence	→	Cog. Effort	→	Value			0.000n.s.	0.986
Social Presence	→	Intrusiveness	→	Value	→	Engagement	0.018*	0.050
Social Presence	→	Cog. Effort	→	Value	→	Engagement	0.000n.s.	0.987
Convenience	→	Value	→	Engagement			0.171**	0.002
Compatibility	→	Value	→	Engagement			0.229***	0.000
Personalization	→	Value	→	Engagement			0.316***	0.000
Cog. Effort	→	Value	→	Engagement			-0.003n.s.	0.918
Intrusiveness	→	Value	→	Engagement			-0.119***	0.000

Notes: *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$; n.s.: Non-significant effect

4.6 DISCUSSION

Consumers are increasingly using AI-based devices like VAs to obtain product and service recommendations. Focusing on VAs, this study explains how the perceived value derived from these recommendations is formed, the main consequences of this value and serves as a guide for practitioners to highlight the relevant features to take into account in the VA design. To do that, we combine social presence (e.g., Van Doorn et al., 2017), cost-benefit paradigm (Kleijnen et al., 2007), perceived value (Zeithaml et al., 2020) and consumer engagement (Hollebeek, 2011; Hollebeek et al., 2014). Specifically, our results uncover first the relevant benefits and costs determining the perceived value of VAs' recommendations. In this respect, positive relationships between convenience, compatibility, personalization and perceived value of VAs' recommendations are found. Particularly, this value was found to be strongly influenced by personalization, which is in line with Hagel and Rayport, (1996) and Hernandez-Ortega and Ferreira (2021), who suggested that personalization enhances consumers' valuable experiences. In the same vein, Ho and Bodoff (2014) highlighted that personalized IT services offer the right content in the right form to the right user at the right time and location. Conversely, intrusiveness cost influences negatively the perceived value of VAs' recommendations. Interestingly, though prior research suggested that cognitive effort often is considered as the strongest impediment in human-robot interactions (Cowan et al., 2017), the cognitive effort was found to be an insignificant cost in the context of VAs. This may be explained by the fact that participants are VAs' heavy users; however, cognitive effort may be more relevant at their initial stage of usage, when individuals perceive technology to be complicated to use and require mental effort (Davis, 1989).

Second, social presence is found to be a relevant predictor of the aforementioned benefits (i.e., convenience, compatibility and personalization). Whereas, social presence has been found negatively related to the cost of intrusiveness. Furthermore, it has been outlined that social presence influences indirectly, via costs and benefits, perceived value of VAs' recommendations. According to Cabibihan et al. (2014), consumers can be easily persuaded by people they have close relationships with and feel connected to. Since consumers gain a sense of social relationship - through social presence - with their VAs, thus, the VA performs the role of a peer consumer by providing recommendations and product information.

Finally, we find that perceived value of VAs' recommendations may help increase consumer engagement with the VA in general. In addition to this, since the approach to measure consumer engagement in this work is based on brand engagement in a social media context (Hollebeek, 2011; Hollebeek et al., 2014), we also validate a consumer engagement scale in the VAs' context, which comprises three behavioral intentions: 1) to recommend the VA, 2) to continue to use the VA and 3) to follow the recommendation of the VA.

4.6.1 Theoretical implications

In order to better understand the background of the perceived value and the consumer engagement with VAs, this study has followed the costs-benefits paradigm (Kleijnen et al., 2007) and integrated the ASP concept (Van Doorn et al., 2017) to develop a conceptual model whose results allow us to contribute to contemporary research on VAs and shed some light on this emerging topic in three ways.

First, we included social presence in our conceptual model to highlight its main effect in predicting the drivers and barriers of the perceived value of the VAs' recommendations. The results suggest that social presence is a relevant predictor of benefits, including convenience, compatibility and personalization, thing that is consistent with findings of previous studies in psychology and communication theories (MacGeorge et al., 2016; O'Sullivan, 2005). More precisely, the study found a strong empirical evidence supporting that social presence is an important driver of personalization. This finding is supported by implicit personality theory (Verhagen et al., 2014), which suggests that agents that create a feeling of social presence and mutual connection are likely to increase the feeling that the content they offer is appropriate. Regarding convenience, our result extends, within the context of VAs, the findings of cognitive neuroscience studies suggesting that social presence increases individual's ability to process effortlessly and easily the information (Heninger et al., 2006). As to compatibility, our findings support Van Doorn et al. (2017), who suggests that the more ASP resembles a human, the more consumers may infer human capabilities (e.g., warmth and competence), thing that lead consumers to perceive VAs as a social entity similar to them. Whereas, social presence has been found negatively related to the cost of intrusiveness. This suggest that when consumers perceive a higher degree of social presence, they worry less about intrusiveness concerns of the VA, because they perceive it as a person who can be trusted rather than as a machine. In turn, we did not find a meaningful relation between social presence and cognitive effort. A plausible explanation is that consumers may perceive that VAs trigger social presence, but that perception is limited to the intrusiveness and privacy aspects and may not lead to mitigate the issues related to functional aspects such as cognitive effort.

Second, although VAs have been one of the most interesting research topics in the information systems (IS) field in the past decade, most prior research focus on the examination of their initial stage of adoption and usage (e.g., Park and Ohm, 2014), and relatively little is known about the perceived value of VAs' when used to get product or service recommendations. Therefore, our research comes as the first study that develops a model which explains the benefits and the costs involving in the process of VAs' recommendations value. The analyses show strong support for our conceptual model. More particularly, our results illustrate that personalization is the strongest determinant of the perceived value. This finding is in accordance with the view that personalization is the overarching characteristic of VAs (e.g., Kraus et al., 2019; Rhee and Choi, 2020; Pal et al., 2020). This can suggest that consumers perceive a great value of the VA when they receive personalized recommendations. This finding extends the results of previous research in different contexts such as websites (Ho and Bodoff, 2014), mobile services (Wang et al., 2020), IS (Hagel and Rayport, 1996) and augmented reality (Lau et al., 2019), to the VAs field. Additionally, convenience positively influences perceived value. If consumers perceive the performance of the VAs in getting recommendation as effortless and quick, they perceive a greater value. This result is in line with previous research which have suggested that convenience is a benefit that drives people to perceive the value of an innovative technology (Ukpabi and Karjaluoto, 2017). In addition, higher compatibility is found to lead to higher VAs value perception. This relationship has been examined previously by Yang et al. (2016) in the context of mobile services and by Rauschnabel et al. (2015) in the context of smart glasses. Value perceptions about new technologies have been traditionally linked to the compatibility the systems offer (Pagani, 2004). Therefore, this finding comes to extend this relationship within the context of VAs technology.

Moreover, our results stress the relevance of intrusiveness as potential inhibitor for maximizing the perceived value of VAs' recommendations. The core rationale behind this relationship is that intrusive technology features lead consumers to feel fear that their private information could be stolen from the VA, or that the companies that hold data will use it for a purpose other than that originally intended. This fear would deprive consumers from using the technology. In the same vein, there is support for this result from previous studies in smart technologies (Lau et al., 2019), which highlight that intrusiveness lead consumers to not perceive the technology as valuable. In contrast, cognitive effort does not constitute a significant cost influencing perceived value. In relation to previous research in the domain of innovation theory, this result is surprising, because cognitive effort often is considered as the strongest impediment in human-robot interactions (Cowan et al., 2017; Velkovska and Zouinar, 2019). However, in the current study, this finding may be explained by the fact that the current generation of VAs are technologically far superior and possess a variety of novel skills that have improved their functions and technical features (e.g., Neural Text-to Speech technology [NTTS]), which could mitigate the relevance of cognitive effort.

Third, the current study examines how perceived value of VAs' recommendations accounts for consumer engagement. The greater the value consumers perceive from VA, the more likely they would feel comfortable in using the device and would involve in engagement behaviors. The current outcome is consistent with previous studies, which also confirmed a positive association between perceived value and consumer engagement; for example, with virtual communities (Chen, 2017; Hsu and Lin, 2016). Moreover, even though previous literature suggests that intentions to spread E-WOM and intention to continue to use are two of the indicators most used for measuring behavioral engagement with technology (Pal et al., 2021; Moriuchi, 2019), we adapt this academic understanding of consumer behavioral engagement to the specific context of VAs' recommendations by adding a third dimension, E-WOM adoption; that is, the intention to follow the VA recommendation.

4.6.2 Practical implications

The study's findings also have implications for practitioners and other stakeholders working toward increasing the value of VAs. In practice, these results would assist service providers and VAs' designers in understanding how VAs should be designed in order to enhance the value creation and consumer engagement with the VA. Indeed, maximizing perceived value is crucial to increase engagement (in our case, perceived value predicts 75.8% of engagement). If practitioners manage to increase perceived value among VAs, they may potentially fulfill consumers' needs, who may consequently express higher levels of engagement with the VAs in terms of greater intention to recommend the device, to continue using it and to follow their recommendations. First, the study highlights the relevant role of social presence aspect in VAs. Designers should thus focus on developing reliable VAs able to develop natural and intuitive conversations and establish a bond with consumers, as to evoke a sense of social presence, which in turn may maximize convenience, sense of compatibility and personalization, and minimize intrusiveness feeling. This would enhance perceived value and consumer engagement. VA's designers should, for instance, include in VAs informal and natural speech using greetings, closings or even a name, as well as develop devices which could be able to listen, expressing warmth, showing concern for the consumer and understanding the queries he/she is interested in.

Second, as both benefits and costs show a direct influence on perceived value of VAs' recommendations, practitioners need to maximize VAs' convenience, compatibility and personalization and minimize their intrusiveness. According to the results of the study, personalization is the main driver of perceived value. Therefore, VAs' designers should enhance the use of machine learning and AI technologies in order to better collect and analyze data about user preferences and the products or services that the consumer is interested in. Additionally, VAs' developers can introduce various social analytic techniques, like sentiment analysis, visual analytics, and opinion mining, which allow them to treat the consumers' as co-creators of their own personalized recommendations. Moreover, our study highlights the relevant role of compatibility in generating perceived value. Here, developers should make VAs more humanlike in terms of voice feature and

AI capabilities to understand and interpret consumer instructions in a natural way. We expect, for instance, to improve the quality of voice accent and support different languages, so that consumers can feel a greater sense of compatibility between themselves and the VA. With no doubt, such expansion will increase perceived value of their recommendations.

4.6.3 Limitations and future research lines

The present study has limitations that open avenues for future research on AI-based services. First, the research was conducted based on a general recommendation search through VAs, in hospitality context. This empirical model should also be tested by distinguishing the type of the hospitality-related products. For example, the relative importance of the antecedents of perceived value and its influence on consumer engagement may depend on the type of the recommendation received (e.g., recommendation about hedonic vs. utilitarian product/service). Additionally, although we shed some light on the main benefits and costs that build the perceived value of the VAs' recommendations, further key variables may be examined. In this way, as an AI-based device, future research could explore the perceived intelligence of the assistant (e.g. mechanical, thinking and feeling [Huang and Rust, 2021]) and examine its effect on generating perceived value and engagement.

Second, data were collected from regular VAs' users in the United States market. As the development of new technology services and the maturity of the markets differ by country and culture, future research should focus on different nations and cultures with different levels of technological development to enhance the generalization of our model and findings.

Third, this study examines perceived value of VAs' recommendations, but does not differentiate between types of assistants. Future research might compare consumers' experiences with smartphone-based VAs, such as Siri and Google Assistant, and their experiences with in-home VAs, such as Alexa and Google Home. Receiving recommendations from different types of VAs may vary their recommendations perceived value and the consumer engagement with the assistant. Moreover, the study examines engagement from the perspective of consumer intentions. While intentions do appear to be a reliable indicator of actual behavior (e.g., Venkatesh and Davis, 2000), it would be fruitful to examine actual behavioral data and to conduct such analysis in a longitudinal form to gain a deeper understanding of consumer engagement with VAs.

CHAPTER V. CONCLUSIONS, IMPLICATIONS, LIMITATIONS AND FUTURE RESEARCH LINES

5.1 SUMMARY OF THE RESULTS

The main purposes of this doctoral dissertation are to comprehend how E-WOM influences consumer behavior, to identify the principal new trends in E-WOM literature, as well as to investigate the new recommendation systems based on AI, by presenting two research models centered on "*AI-WOM*" (a new concept proposed in this thesis).

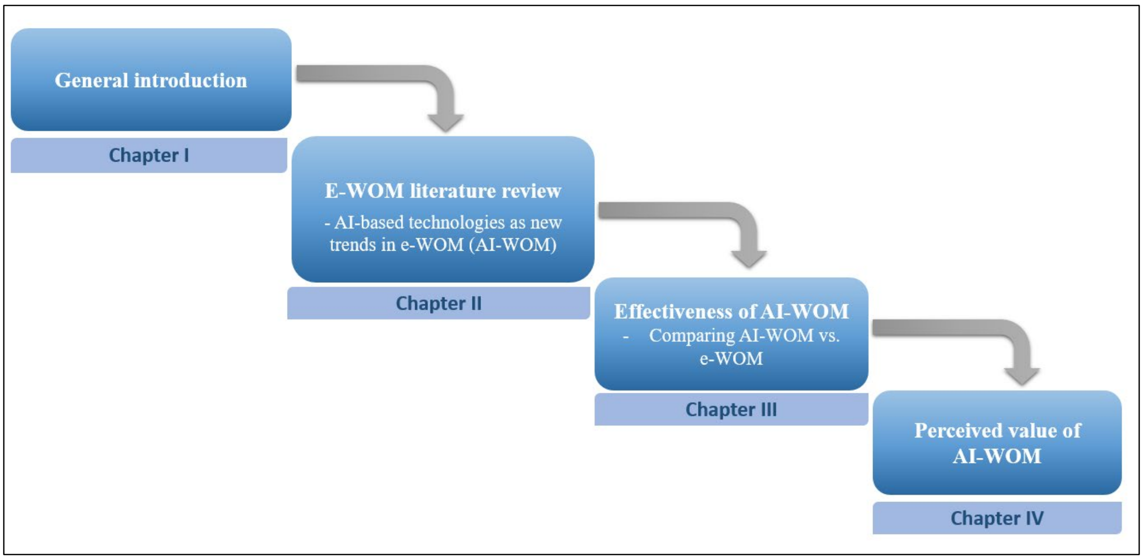
This thesis is based on one theoretical study (chapter II) and two empirical studies (chapters III and IV) (see Figure 5.1). The theoretical study aims to summarize the existing literature on E-WOM as well as to highlight the potential future research lines in the E-WOM field. Next, the first empirical study, compares the effect of E-WOM (written online reviews) vs. AI-WOM (AI-based voice assistant recommendations) on consumer perceptions and behavioral intentions. Then, the second empirical study comes to determine the perceived value of the voice assistants (VAs) recommendations, and evaluate their effects on consumer engagement.

After conducting an extensive literature review on E-WOM throughout the second chapter of this doctoral thesis, it has been found that the characteristics of the E-WOM communication elements (message, sender and receiver) in online reviews influence, among others, the attitudes of consumers (Vermeulen and Seegers, 2009), their perceptions (Di Pietro et al., 2012), evaluations (Lee at al., 2008; Vermeulen and Seegers, 2009) and intentions (Casaló et al., 2011b; Casaló et al., 2015). More particularly, the chapter highlighted that 1) valence, relevance and understandability are the most important antecedents of message usefulness and the receiver's behavioral intentions, 2) source credibility is the sender characteristic that most affects the receiver's behavioral intentions, and 3) consumer susceptibility to interpersonal influence is the receiver characteristic that most influences their attitudes and behavioral intentions. In addition, this literature review highlighted some new trends and research opportunities in E-WOM field. First, the need for more research into online fake reviews to better understand E-WOM sender motivations, second, the importance of managing the negative reviews by hospitality companies (e.g., responding appropriately, developing a partnership with consumers), third, the relevant moderating role of the E-WOM platform for the relationships previously suggested, and lastly the growing importance of various technological developments/applications based on AI (e.g. VAs) as a novel trend in E-WOM communication that can increase the effectiveness of this communication.

After concluding that the use of AI-based recommendation systems is one of the major trends in E-WOM. The third chapter sought to examine the effectiveness of these technologies in providing E-WOM. To do this, an empirical study has been carried out in order to compare the influence of traditional E-WOM received through online written reviews with AI-WOM received through VAs, on consumer behavior. As a result, it has been found that recommendations received from a VA are more credible and useful -through credibility- and, consequently, generate higher behavioral consumer intentions (e.g., intention to follow the recommendation received, intention to recommend the recommended product/service, and intention to buy the recommended product/service) than written recommendations. In parallel way, it has been studied the effectiveness of the content type of recommendations (commercial vs. non-commercial). In this respect, it has been found that the non-commercial recommendations generate greater credibility and usefulness, as well as greater behavioral intentions. Moreover, the findings highlighted that these effects are stronger when the non-commercial recommendation focuses on search products than when it focuses on experience products.

Confirming that recommendations received by AI-based VAs generate better behavioral intentions than those received through online consumer reviews, the fourth chapter came to explain how these recommendations generate value. Based on cost-benefit paradigm (Kleijnen et al., 2007), convenience, compatibility and personalization are selected as benefits of the VAs and, cognitive effort and intrusiveness as costs. Specifically, it has been found that all the benefits generate a great perceived value of VAs' recommendations- more particularly, the personalization has been found to be the strongest determinant of this value - whereas the intrusiveness has been found to be the only inhibitor of perceived value. Moreover, this study has also introduced into the investigated model the effect of Automated Social Presence (ASP) (Van Doorn et al., 2017) on the suggested benefits and costs, as this is one of the key features of VA Chattaraman et al., 2019). The study's results found that ASP is a relevant predictor of benefits, especially personalization. In addition, regarding costs, ASP significantly reduces intrusiveness but there is not significant relationship between ASP and cognitive effort. Furthermore, the study has considered three consumer intentions (intention to recommend the VA, intention to continue using the VA, and intention to follow the VA recommendation) as forms of consumer engagement with the VA, finding a positive association between perceived value and consumer engagement.

Figure 5.1 General research flowchart



Source: own elaboration

5.2 SUMMARY OF THEORETICAL IMPLICATIONS

This doctoral thesis offers series of implications for theory to E-WOM literature and the emerging application of artificial intelligence (AI)-based technologies in this field. First, throughout an extensive literature review (chapter II), the research has contributed to existing research works, by being the first study built on the social communication framework to classify E-WOM research papers in hospitality context, analyze the E-WOM communication elements and its influence on consumer behavior, and propose some E-WOM aspects for future research lines. Indeed, existing studies focuses only on one or two consumer response variables, and did not examine the interrelationships among E-WOM's key elements. Therefore, the present study explores theoretically how the characteristics of each key element (message, sender, receiver) affects the receiver's response variables (perceptions, evaluations, behavioral intentions and actual behaviors) in hospitality context. In addition, the research has bridged AI–based technologies field and E-WOM literature, to develop the concept of AI-WOM and highlight the potential importance of AI-based recommendation systems.

Second, given this highlight, the third chapter of this doctoral dissertation came to explain the effectiveness of AI-WOM, by comparing empirically the influence of voice recommendation made by VAs (AI-WOM) and text recommendation (traditional E-WOM) received through written online reviews on consumer behavior. To do this, the study extends the Media Richness Theory, which has been applied to previous contexts such as organizational information (Daft and Lengel, 1986), emails (Schmitz and Fulk, 1991), websites (Hopkins et al., 2004), online stores (Brunelles, 2009), mobile Apps (Anandarajan et al., 2010), or social media (Xiao et al., 2021). to the field of AI-based technologies. Specifically, due to its greater richness, the effectiveness of VAs' recommendations in predicting consumer behavioral intentions seems to be higher.

Besides, the integration of both credibility and usefulness in the research model served to confirm their same relevant roles - as in the context of online consumer reviews- in predicting behavioral intentions in the new context of voice recommendations. Furthermore, based on perceived stability theory (Shiman, 1978) and risk theory (Dowling and Staelin, 1994), this research advances the role of product type (search vs. experience) within the field of VA recommendations.

Third, this thesis - through the chapter IV- seeks to better understand the background of the VAs' recommendations perceived value and the consumer engagement with that VAs', by combining the costs-benefits paradigm (Kleijnen et al., 2007) with the ASP concept (Van Doorn et al., 2017). This theoretical framework has highlighted a strong empirical evidence that social presence, benefits perceived from the VAs (convenience, compatibility and personalization) and intrusiveness cost, predict strongly the perceived value of VAs recommendations. These findings are consistent with previous studies in psychology and communication theories (MacGeorge et al., 2016; O'Sullivan, 2005), implicit personality theory (Verhagen et al., 2014) and ASP concept (Van Doorn et al., 2017), which suggests that agents that create a feeling of social presence and mutual connection, are likely to increase the feeling that the content they offer is appropriate, thus increasing its value. In addition, regarding the three aforementioned benefits, it has been highlighted that personalization is the strongest benefit that determines the perceived value of VAs' recommendations, thing that is in accordance with the view that personalization is the overarching characteristic of VAs (e.g., Kraus et al., 2019; Rhee and Choi, 2020; Pal et al., 2020). Furthermore, conversely to intrusiveness, it has been suggested that cognitive effort does not constitute a significant cost influencing perceived value of VAs' recommendations, probably because AI-digital assistants are no longer novel technologies and individuals are already accustomed to using these kinds of devices. This is consistent with the Technology Acceptance Model (TAM), that suggests that individuals perceive technology to be complicate to use and require mental effort at their initial stage of usage (Davis, 1989). This finding is surprising and would contribute significantly to previous research that considering cognitive effort as the strongest impediment in human-robot interactions (Cowan et al., 2017; Velkovska and Zouinar, 2019).

Finally, the current thesis examined how perceived value of VAs' recommendations, accounts for consumer engagement with theses assistants. The greater the value consumers perceive from VA, the more likely they would feel comfortable in using the device and would involve in engagement behaviors. This current outcome is consistent with previous studies, which also have confirmed a positive association between perceived value and consumer engagement in different contexts (Chen, 2017; Hsu and Lin, 2016). Moreover, the research adapted the academic understanding of consumer behavioral engagement (Pal et al., 2021; Moriuchi, 2019) to the new context of VAs, by adding three dimensions to consumer engagement: 1) intention to recommend the VA; 2) intention to continue to use the VA and 3) intention to follow the recommendation of VA.

5.3 SUMMARY OF PRACTICAL IMPLICATIONS

This doctoral dissertation also highlights relevant points that need to be considered as a guidance for business managers, as well as for VAs' designers.

Through the literature review, the research makes hospitality managers aware that E-WOM phenomena is a rich source of data that may influence consumer' behavioral intentions. Therefore, managing E-WOM elements (sender, message and receiver) by updating the information, taking actions to foster credible reviews (e.g., offering awards and/or privileged status to those users who provide pictures and/or videos to support their reviews, and those with higher expertise, etc.) may serve to obtain more favorable consumer responses. Also, this theoretical overview suggests managers to respond effectively to negative E-WOM by collaborating with consumers to understand their needs and turn unsatisfied consumers to loyal ones. Moreover, it has been highlighted the crucial role of social cues in the effectiveness of E-WOM platforms, thus brand managers should focus more on involving in their online platforms members of social networks with strong ties (for example, micro influencers are proposed to have greater influence on their followers than macro influencers due to a closer relationship with them [REF.]). On the other side, the literature review stressed that E-WOM field will increasingly be influenced by AI. Specifically, it has been suggested that managers should apply AI technologies, such as AI-based recommendation systems, in their traditional marketing methods. These systems can create extra context-based information from the consumers' earlier communications (i.e., patterns, sensor data from private devices), which personalizes content to a more superior scale than the traditional E-WOM. Thus, firms could offer suitable brand/product-related content to engage their consumers and strengthen their brands among E-WOM communication.

Second, the effectiveness of these AI-based recommendations (specifically VAs) has been highlighted in this thesis. VA are considered a richer medium than written communication. Thus, designers should continuously improve the richness of the medium. For example, it could be useful to introduce an innovative technology able to convey human quirks, to solve accent and language problems, as well as to carry fluctuations in tone when pronouncing words. Implementing a new technology that allows consumers to hold long-term conversations is also recommended. Also, consumers tend to personalize the VAs when they receive from them a useful recommendation

(Capgemini, 2019). Therefore, it will become increasingly important for VAs to have a persona and become more life-like.

Third, the crucial highlighted role of credibility of the VA recommendations in developing behavioral intentions may lead product and retail managers to take advantage from this point by boosting the implementation of voice technology in their customer services as well as in their marketing communication services such as new product launch campaigns. In the same vein, business managers should focus on increasing the usefulness of their VAs, by developing devices that offer value-added services, such as reciting recipes containing the business brand products or even reading out lists of ingredients when people cook their dishes.

Fourth, it has been stressed the relevant role of social presence in generating value of VAs' recommendations. Designers should thus focus on developing reliable VAs able not only to interact, but also to develop natural and intuitive conversations and establish a bond with consumers. for example, including informal and natural speech using greetings, closings or even a name, as well as developing abilities to listen, expressing warmth and showing concern for the consumer. Moreover, in order to improve this perceived value, practitioners need to maximize VAs' convenience, compatibility and personalization and minimize their perceived intrusiveness. Therefore, VAs' designers should introduce various social analytic techniques, like sentiment analysis, and opinion mining. Additionally, developers should make VAs more humanlike in terms of voice feature and AI capabilities to understand and interpret consumer instructions in a natural way.

Finally, this research assisted service providers and VAs' designers in understanding how VAs should be designed in order to enhance the perceived value of their recommendations and consumer engagement. Indeed, maximizing perceived value is crucial to increase engagement. If practitioners manage to increase perceived value of VAs' recommendations, they may potentially fulfill consumers' needs, who may consequently express higher levels of engagement with the device.

The Table 5.1 summarizes the research objectives, the results obtained across this thesis as well as the theoretical and practical implications.

Table 5.1 Summary of results and implications

Chapters	Research objectives	Main results	Theoretical implications	Practical implications
Chapter II	**Objective 1.** Offer a holistic framework explaining how key E-WOM elements' characteristics (i.e., sender, message and receiver) affects consumers' perceptions, evaluation and behaviors.	- Relevance, valence, understandability and visual cues are the most important message characteristics and antecedents of its usefulness and the receiver's behavioral intentions. - Source credibility is the most relevant sender characteristic influencing the receiver's behavioral intentions. - Consumer susceptibility to interpersonal influence is the receiver characteristic that most influences receiver's attitudes and behavioral intentions.	- E-WOM research papers in the hospitality field are classified based on the social communication framework - E-WOM message is a rich source of data that potentially influences consumers' behavioral intentions in hospitality sector. - Lack of source credibility leads to psychological discomfort and, consequently, weak consumer behavioral intentions. - Individuals susceptible to interpersonal influence are more likely to purchase, products that they perceive will improve their reputations in the eyes of others.	- Managing E-WOM elements (sender, message and receiver) may help obtain more favorable consumer responses. - Updating information and making it more visual and attractive can increase the persuasiveness of the message. - Business managers should encourage credible reviews by offering awards and/or privileged status to those users who provide pictures and/or videos to support their reviews, and/or to those with higher expertise, etc. - Brand managers should adopt strategies to employ celebrities and/or opinion leaders to promote their products/services, and reward loyal consumers by casting them as role models
	Objective 2. Identify new trends and research opportunities in E-WOM, specifically those due to the technological applications based on AI (e.g., voice recommendation systems).	- More research into online fake reviews is needed to better understand sender motivations. - The need to actively manage negative reviews. - Online platforms type is relevant in moderating the effect of E-WOM on consumer behavior. - Development of AI-WOM.	- New trends in E-WOM are identified. - Bridging AI and smart technologies field and E-WOM literature, to develop the concept of AI-WOM and highlight the potential importance of AI-based recommendation systems	- Understanding senders' motivations for posting fake reviews can help managers implement appropriate defense strategies and improve customer-company relationships. - Implementing appropriate management of negative reviews by responding appropriately and developing a partnership with consumers can help practitioners to understand consumers' needs, and turn unsatisfied customers into loyal customers. - Managers should carefully choose the platforms on which their products/services are promoted, by focusing more on personal blogs (i.e., micro-influencers) due to their higher social cues. - Companies need to change to AI-based recommendation systems, which can deliver meaningfully superior flexibility to target consumers in terms of valuable, personalized, and relevant content. - Firms could use AI technologies to offer suitable brand/product-related content to engage their consumers.

Chapter III (1st empirical study)	**Objective 3.** Compare the influence of the traditional E-WOM received through written online reviews to the AI-WOM received through VA, on consumer behavior, controlling for the non-commercial content of the recommendations.	- Voice recommendation (AI-WOM) is perceived more credible and useful- through credibility- than text recommendation (E-WOM) (**H1** is supported). - Non- commercial recommendation is perceived more credible and useful- through credibility- than commercial recommendation. (**H2** is supported). - Perceived credibility of the recommendation is a strong predictor of its perceived usefulness (**H3** is supported). - Perceived credibility and perceived usefulness of the recommendation influence positively consumer behavioral intentions: (a) to follow the recommendation, (b) to purchase the product/service, and (c) to recommend the product/service (**H4 and H5** are supported).	- Extending the theory of Media Richness by applying it within the field of AI-based technologies in general and VAs in particular. - VAs are a richer medium than written communication, closer to as an "*in person*" interaction. - The suitability of the Attribution theory framework in understanding the impact of content recommendation type on consumer behavioral intentions. - Credibility and usefulness are key factors to explain the influence of AI-WOM on consumer behavior.	- Designers should increase the richness of the VAs by: - Enhancing the voice feature, via introducing a technology that conveys human quirks and carry fluctuations in tone when pronouncing words. - Implementing new technology allowing consumers to hold - long-term conversations with VAs - Humanizing more VAs by attributing to them a persona. - Solving accent and language problems by building a voice-enabled technology that recognizes commands easily. - Product and retail managers should take advantage from the great perceived credibility and usefulness of VAs recommendations by implementing VAs in their marketing communication services (e.g., using VAs for launching and recommending new products), as well as offering value-added services, such as reciting recipes containing the supermarket brand products.
	Objective 4. Examine whether the effectiveness of AI-WOM differs when focusing on search vs. experience products.	- There is no interaction effect of recommendation modality (voice vs. text) and product type (product vs. service) on perceived credibility nor usefulness (**H6** is not supported). - The effect of non-commercial recommendation on perceived credibility and usefulness is higher for search products than for experience products (**H7** is supported).	- Advancing the role of product type within the field of VA recommendations by distinguishing between search and experience products.	- Product managers should be aware when implementing their marketing strategies that: - Whether a product or service is recommended, the effect of voice recommendations on consumer perceptions and behaviors does not change. - The non-commercial recommendation is perceived more credible and useful, when it is about search products, than about experience products (i.e., services).
Chapter IV (2nd empirical study)	**Objective 5.** Define the relevant costs and benefits associated to VAs and their role in	- The benefits of convenience, compatibility and personalization of the VA influence positively the perceived value of VAs' recommendations (**H6, H7 and H8** are supported).	- Extending the cost-benefits paradigm (Kleijnen et al., 2007), applied in previous contexts (e.g., websites [Ho and Bodoff, 2014], mobile services	- VAs' designers should maximize convenience, compatibility and personalization and minimize their intrusiveness. For example, by: - Collecting and analyzing data about user preferences

	developing the perceived value of VAs' recommendations.	- The cognitive effort cost of VA does not influence the perceived value of VAs' recommendations (**H9** is rejected). - The intrusiveness cost of VAs influences negatively the perceived value of VAs' recommendations (**H10** is supported).	[Wang et al., 2020], and augmented reality [Lau et al., 2019]), to the context of VAs.	and the products that the consumer is interested in. - Introducing sentiment analysis and opinion mining. - Enhancing human-like aspects in term of voice feature and cognitive capabilities - Reducing the intrusiveness by clearly communicate audio logs as a privacy feature to consumers (e.g., delete entries from the interaction history); and introduce incognito mode for VAs
	Objective 6. Analyze how social presence may influence the formation of perceived value of VAs' recommendations.	- Social presence of the VA influences positively affects its convenience, compatibility and personalization (**H1, H2** and **H3** are supported). - Social presence of the VA does not affect its perceived cognitive effort (**H4** is rejected). - Social presence the VA influences negatively its intrusiveness (**H5** is supported).	- Extending, within the context of VAs, cognitive neuroscience studies (Heninger et al., 2006), suggesting that social presence increases convenience. - Contributing to Van Doorn et al., 2017, suggesting that ASP of automated technologies generates value toward technology - Supporting implicit personality theory (Verhagen et al., 2014), suggesting that social presence increases the personalization feeling - New finding in technology perceived risks and privacy concerns literature (Lau et al., 2018; Manikonda et al.; 2018), by highlighting the VA social presence mitigates their intrusiveness.	- VAs' designers should focus on: - Enhancing natural and intuitive conversations and establish a bond with consumers - Including informal and natural speech using greetings, closings or even a names - Developing devices which could be able to listen, expressing warmth, showing concern for the consumer understanding their queries.
	Objective 7. Evaluate the effect of perceived value of VAs' recommendations on consumer engagement.	- Perceived value of VAs' recommendations strongly predicts the engagement with these VAs (**H11** is supported).	- Contributing to previous studies (Chen, 2017; Hsu and Lin, 2016), by confirming the positive association between perceived value and consumer engagement with VAs. - Contributing to the academic understanding of consumer behavioral engagement by highlighting three dimensions of engagement with VAs (intention to recommend the VA, intention to continue to use the VA and intention to follow the recommendation of the VA).	- Practitioners should take into account all the previous actions to maximize perceived value of VAs' recommendations as this is crucial to increase engagement. In the current study, perceived value predicts 75.8% of consumer engagement with the VA.

5.4 LIMITATIONS AND FUTURE RESEARCH LINES

Despite this doctoral thesis makes interesting theoretical and managerial implications, it has some limitations that constitute opportunities for further research. First, the literature on E-WOM is vast, and the literature review chapter does not take it all into consideration. The current research, for instance, focused on E-WOM from the standpoints of communication theory and the consumer, but did not investigate market-oriented studies. Future research should broaden this literature and expand the number of articles studied from other analytic vantage points. Also, as the E-WOM communication research is always evolving, it is highly suggested that a systematic literature review could be conducted to enhance the knowledge of the effects of the three E-WOM elements (message, sender, and receiver) on the decision-making processes of consumers.

Second, the data collection for both empirical studies (chapters III and IV), were collected from United States. However, several research works have noted the importance of incorporating cultural differences when dealing with AI-based technologies and consumer behavior (Huang and Zhang, 2020). In this line, further studies may compare the consumers' behaviors towards AI-based VAs across cultures exploring, for example, potential differences between individualistic and collectivistic countries.

Third, in the first empirical study (Chapter III) that compares the influence of the written online reviews with recommendations provided by VAs, on consumer behavior, it has been considered, in the experiment design, recommendations provided by female voice. Previous studies demonstrated that traits inferred from voice characteristics (e.g., gender) may affect the effectiveness of the information persuasion (Nass and Moon, 2000). Future studies should examine how different voice characteristics (female vs. male) affect the way consumers perceive and behave toward the VAs' recommendations. In addition, the same experiment design, does not take into account any control variable. According to traditional literature on psychology, personality traits may affect significantly people persuasion information process (e.g., McCrae and Costa, 1987). Therefore, further research should control for consumers' personality traits (e.g., Big Five Model), which may affect the behavioral intentions toward the VA's recommendation.

Fourth, the empirical model testing the perceived value of VAs' recommendation (Chapter IV), was conducted based on a general recommendation search through VAs, in hospitality context. This empirical model should also be tested by distinguishing the type of the hospitality-related products. For example, the relative importance of the antecedents of perceived value and its influence on consumer engagement may depend on the type of the recommendation received (e.g., recommendation about hedonic vs. utilitarian product/service). Additionally, the same model shed some light on the main benefits and costs that build the perceived value of the VAs' recommendations, however, further key variables may be examined. In this way, as an AI-based device, future research could explore the perceived intelligence of the assistant (e.g. mechanical, thinking and feeling [Schepers et al., 2022; Huang and Rust, 2021]) and examine its effect on generating perceived value and engagement.

Fifth, both empirical studies do not differentiate between types of VAs. Future research might compare consumers' experiences with smartphone-based VAs, such as Siri and Google Assistant, and their experiences with in-home VAs, such as Alexa and Google Home. Receiving recommendations from different types of VAs may vary their perceived value and the consumer engagement with the assistant.

Finally, the whole context research focuses on consumer intentions perspective. While intentions do appear to be a reliable indicator of actual behavior (e.g., Venkatesh and Davis, 2000), it would be fruitful to examine actual behavioral data and to conduct such analysis in a longitudinal form or field study to gain a deeper understanding of consumer behavior with VAs.

CAPITULO VI. CONCLUSIONES, IMPLICACIONES, LIMITACIONS Y FUTURAS LÍNEAS DE INVESTIGACIÓN

6.1 RESUMEN DE RESULTADOS

El objetivo principal de esta tesis doctoral es comprender cómo influye el boca-oído electrónico (E-WOM) en el comportamiento del consumidor, identificar las principales nuevas tendencias en la literatura del E-WOM, así como investigar los nuevos sistemas de recomendación basados en la inteligencia Artificial (IA), presentando un marco conceptual y proposiciones comprobables centradas en el concepto que denominamos "*IA-WOM*".

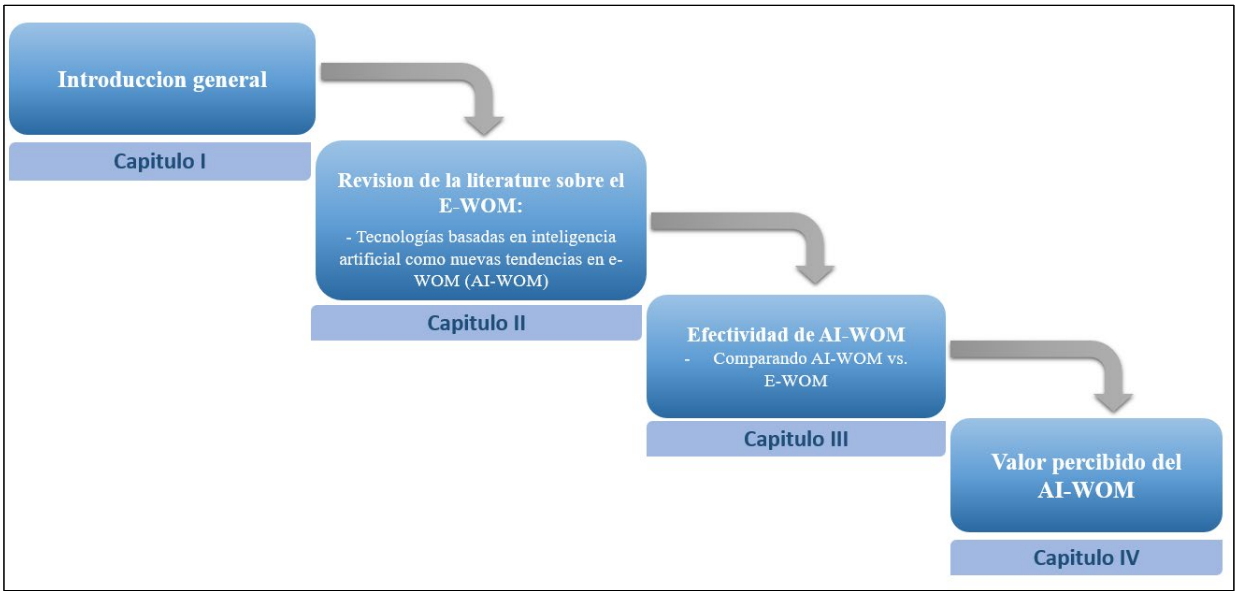
Esta tesis se basa en un estudio teórico (capítulo 2) y dos estudios empíricos (capítulos 3 y 4). El estudio teórico pretende resumir la literatura existente sobre el E-WOM basada en la teoría de la comunicación social, así como destacar las posibles líneas de futuras de investigación en el campo del E-WOM. A continuación, el primer estudio empírico compara el efecto de E-WOM (reseñas escritas en línea) frente al IA-WOM (recomendaciones del asistente de voz [AV] basado en la IA) sobre las percepciones de las intenciones del comportamiento de los consumidores. Luego, el segundo estudio empírico viene a determinar el valor percibido de este IA-WOM y a evaluar sus efectos sobre el engagement del consumidor (Figura 6.1).

Tras realizar una amplia revisión bibliográfica sobre el E-WOM a lo largo del segundo capítulo de esta tesis doctoral, se ha constatado que las características de los elementos de la comunicación del E-WOM (mensaje, emisor y receptor) en las reseñas online influyen, entre otros, en las actitudes de los consumidores (Vermeulen y Seegers, 2009), en sus percepciones (Di Pietro et al., 2012), en sus evaluaciones (Lee at al., 2008; Vermeulen and Seegers, 2009) y en sus intenciones (Casaló et al., 2011b; Casaló et al., 2015). Más concretamente, el capítulo destacó que 1) la valencia, la relevancia y la comprensibilidad son los antecedentes más importantes de la utilidad del mensaje y de las intenciones de comportamiento del receptor, 2) la credibilidad de la fuente es la característica del emisor que más afecta a las intenciones de comportamiento del receptor, y 3) la susceptibilidad del consumidor a la influencia interpersonal es la característica del receptor que más influye en sus actitudes e intenciones de comportamiento. Además, esta revisión bibliográfica puso de manifiesto algunas nuevas tendencias y oportunidades de investigación en el campo del E-WOM. En primer lugar, la necesidad de investigar más sobre las reseñas falsas online para comprender mejor las motivaciones del emisor, en segundo lugar, la importancia de gestionar las reseñas negativas por parte de las empresas (por ejemplo, responder adecuadamente, desarrollar una colaboración con los consumidores), en tercer lugar, el relevante papel moderador de la plataforma del E-WOM para las relaciones anteriormente sugeridas y, y, por último, la creciente importancia de diversos desarrollos tecnológicos/aplicaciones basadas en la IA (por ejemplo, los AVs) como nueva tendencia en la comunicación E-WOM, que puede aumentar la eficacia de esta comunicación.

Tras concluir que el uso de los sistemas de recomendación basados en la IA es una de las principales tendencias de la E-WOM. El tercer capítulo pretendía examinar la eficacia de estas tecnologías a la hora de proporcionar E-WOM. Para ello, se ha llevado a cabo un estudio empírico con el fin de comparar la influencia del E-WOM tradicional recibido a través de reseñas escritas online con el IA-WOM recibido a través del AV basadas en la IA, en el comportamiento del consumidor. Como resultado, se ha encontrado que las recomendaciones recibidas de un AV son más creíbles y útiles - por su credibilidad- y, en consecuencia, generan mayores intenciones de comportamiento del consumidor (por ejemplo, intención de seguir la recomendación recibida, intención de recomendar el producto/servicio e intención de comprar el producto/servicio recomendado) que las recomendaciones escritas. Paralelamente, se ha estudiado la eficacia del tipo de contenido de las recomendaciones (comercial vs. no comercial). En este sentido, se ha encontrado que las recomendaciones no comerciales generan mayor credibilidad y utilidad, así como mayores intenciones de comportamiento. Además, los resultados destacaron que estos efectos son más fuertes cuando la recomendación no comercial se centra en productos de búsqueda que cuando se centra en productos de experiencia.

Al confirmar que las recomendaciones recibidas por los AV basados en IA generan mejores intenciones de comportamiento, que las recibidas a través de las reseñas escritas online, el cuarto capítulo vino a explicar cómo estos AV generan valor cuando se recibe a través ellos las recomendaciones. Basándose en el paradigma coste-beneficio (Kleijnen et al., 2007), se seleccionan la comodidad, la compatibilidad y la personalización como beneficios de los AV, y el esfuerzo cognitivo y la intrusividad como costes. En concreto, se ha encontrado que todos los beneficios generan un gran valor percibido de las recomendaciones realizadas por AV - en particular, la personalización ha resultado ser el determinante más fuerte de este valor -, mientras que la intrusividad ha resultado ser el único inhibidor de ese valor percibido. Además, este estudio también ha introducido en el modelo investigado, el efecto de la presencia social automatizada (ASP) (Van Doorn et al., 2017) en los beneficios y costes sugeridos, ya que esta es una de las características clave del AV (Chattaraman et al., 2019). Los resultados del estudio encontraron que la presencia social es un predictor relevante de los beneficios, especialmente de la personalización. Además, en cuanto a los costes, la presencia social reduce significativamente la intrusividad, sin embargo, no existe una relación significativa entre la presencia social y el esfuerzo cognitivo. Asimismo, el estudio ha considerado tres intenciones del consumidor (la intención de recomendar el AV, la intención de seguir utilizando el AV y la intención de seguir la recomendación del VA) como formas del engagement del consumidor con el AV, encontrando una asociación positiva entre el valor percibido de las recomendaciones realizadas por AV y el engagement del consumidor.

Figura 6.1 Diagrama de flujo general de la investigación



Fuente: elaboración propia

6.2 RESUMEN DE IMPLICACIONES TEÓRICAS

Esta tesis doctoral ofrece una serie de implicaciones teóricas para la literatura del E-WOM y la aplicación emergente de las tecnologías basadas en la IA en este campo. En primer lugar, a través de una extensa revisión bibliográfica (segundo capítulo) la tesis ha contribuido a los trabajos de investigación existentes, al ser el primer estudio construido sobre el marco de la comunicación social para clasificar los trabajos de investigación sobre el E-WOM en el contexto de la hostelería, analizar los elementos de comunicación del E-WOM y su influencia en el comportamiento del consumidor, y proponer algunos aspectos del E-WOM para futuras líneas de investigación. De hecho, los estudios existentes se centran sólo en una o dos variables de respuesta del consumidor, y no examinan las interrelaciones entre los elementos clave del E-WOM. Por lo tanto, la presente tesis explora teóricamente cómo las características de cada elemento clave (mensaje, emisor, receptor) afectan a las variables de respuesta del receptor (percepciones, evaluaciones, intenciones de comportamiento y comportamientos reales) en el contexto de la hostelería. Además, la investigación relaciona el campo de las tecnologías basadas en la IA y la literatura sobre E-WOM, para desarrollar el concepto de IA-WOM y destacar la importancia potencial de los sistemas de recomendación basados en la IA.

En segundo lugar, teniendo en cuenta este punto destacado, el tercer capítulo de esta tesis doctoral vino a explicar la eficacia del IA-WOM, comparando empíricamente la influencia de la recomendación de voz realizada por los AV (IA-WOM) y la recomendación de texto (E-WOM tradicional) recibida a través de reseñas escritas online, sobre el comportamiento del consumidor. Para ello, el estudio extiende la Teoría de la Riqueza de Medios, que ha sido aplicada a contextos anteriores como la información organizacional (Daft y Lengel, 1986), los correos electrónicos (Schmitz y Fulk, 1991), los sitios web (Hopkins et al., 2004), las tiendas online (Brunelles, 2009), las Apps de móviles (Anandarajan et al., 2010), o las redes sociales (Xiao et al., 2021), al ámbito de las tecnologías basadas en IA. En concreto, debido a su mayor riqueza, la eficacia de las recomendaciones por AV para predecir las intenciones de comportamiento de los consumidores, parece ser mayor. Además, la integración tanto de la credibilidad como de la utilidad en el modelo de investigación sirvió para confirmar sus mismos papeles relevantes - como en el contexto de las reseñas escritas online- en la predicción de las intenciones de comportamiento en el nuevo contexto de las recomendaciones por AV. Además, basándose en la teoría de la estabilidad percibida (Shiman, 1978) y la teoría del riesgo (Dowling y Staelin, 1994), esta investigación avanza en el papel del tipo de producto (búsqueda vs. experiencia) dentro del campo de las recomendaciones por voz.

En tercer lugar, esta tesis - a través del capítulo IV - busca comprender mejor el trasfondo del valor percibido de las recomendaciones realizadas por AV y el engagement del consumidor con los AVs, combinando el paradigma de costes - beneficios (Kleijnen et al., 2007) con el concepto de la presencia social automatizada (Van Doorn et al., 2017). Este marco teórico ha puesto de manifiesto una fuerte evidencia empírica de que presencia social, los beneficios percibidos de los AV (comodidad, compatibilidad y personalización) y el coste de intrusividad, predicen fuertemente el valor percibido de las recomendaciones realizadas por los AV. Estos resultados son coherentes con estudios anteriores de psicología, teorías de la comunicación (MacGeorge et al., 2016; O'Sullivan, 2005), la teoría de la personalidad implícita (Verhagen et al., 2014) y el concepto de presencia social automatizada (Van Doorn et al., 2017), que sugiere que los agentes que crean una sensación de presencia social y conexión mutua, probablemente aumenten la sensación de que el contenido que ofrecen es adecuado, lo que aumenta su valor. Además, con respecto a los tres beneficios mencionados, se ha destacado que la personalización es el beneficio más fuerte que determina el valor percibido, cosa que concuerda con la opinión de que la personalización es la característica primordial de los AV (por ejemplo, Kraus et al., 2019; Rhee y Choi, 2020; Pal et al., 2020). Además, a diferencia de la intrusividad, se ha sugerido que el esfuerzo cognitivo no constituye un coste significativo que influya el valor percibido de las recomendaciones realizadas por los AV, probablemente porque los asistentes digitales de IA ya no son tecnologías novedosas y los individuos ya están acostumbrados a utilizar este tipo de dispositivos. Esto es coherente con el modelo de aceptación de la tecnología (TAM), que sugiere que los individuos perciben que la tecnología es complicada de utilizar y requiere un esfuerzo mental en su fase inicial de uso (Davis, 1989). Este hallazgo es sorprendente y contribuiría significativamente a las investigaciones anteriores que consideran el esfuerzo cognitivo como el impedimento más fuerte en las interacciones humano-robot (Cowan et al., 2017; Velkovska y Zouinar, 2019).

Por último, la tesis actual examinó cómo el valor percibido de las recomendaciones realizadas por los AV influye en el engagement de los consumidores. Cuanto mayor sea el valor percibido por los consumidores, más probable será que se sientan cómodos usando el asistente y participen en comportamientos del engagement. Este resultado es coherente con estudios anteriores, que también han confirmado una asociación positiva entre el valor percibido y el engagement del consumidor en diferentes contextos (Chen, 2017; Hsu y Lin, 2016). Además, la tesis adaptó la comprensión académica del engagement conductual del consumidor (Pal et al., 2021; Moriuchi, 2019), al nuevo contexto los AV, añadiendo tres dimensiones al engagement del consumidor: 1) intención de recomendar el AV; 2) intención de seguir utilizando el AV y 3) intención de seguir la recomendación del AV.

6.3 RESUMEN DE IMPLICACIONES PRACTICAS

Esta tesis doctoral también destaca puntos relevantes que deben ser considerados como una guía para los gerentes de empresas, así como para los diseñadores de AV.

A través de la revisión de la literatura, la investigación hace que los gerentes de la hostelería sean conscientes de que el fenómeno E-WOM es una fuente rica de datos que puede influir en las intenciones de comportamiento de los consumidores. Por lo tanto, la gestión de los elementos del E-WOM (emisor, mensaje y receptor) mediante, por ejemplo, la actualización de la información, la adopción de medidas para fomentar las reseñas creíbles (por ejemplo, ofreciendo premios y/o un estatus privilegiado a aquellos usuarios que proporcionen fotos y/o vídeos para respaldar sus reseñas, y a los que tengan mayor experiencia, etc.), puede servir para obtener respuestas más favorables de los consumidores. Asimismo, esta visión teórica sugiere a los gerentes que respondan eficazmente a los E-WOM negativos colaborando con los consumidores para entender sus necesidades y convertir a los consumidores insatisfechos en leales. Además, se ha destacado el papel crucial de las señales sociales en la eficacia de las plataformas de E-WOM, por lo que los gerentes de marcas deberían centrarse más en involucrar en sus online plataformas, a los miembros de las redes sociales con fuertes vínculos (por ejemplo, se propone que los "*micro-influencers*" tengan mayor influencia en sus seguidores que los "*macro-influencers*" debido a una relación más estrecha con ellos. Por otro lado, el estudio subraya que el campo del E-WOM se verá cada vez más influenciado por la AI. En concreto, se ha sugerido a los gerentes que apliquen las tecnologías de IA en sus estrategias de marketing tradicional como sistemas de recomendación basados en la AI. Estos sistemas pueden crear información adicional basada en las comunicaciones anteriores de los consumidores (por ejemplo, patrones, datos de los sensores de los dispositivos privados), lo que personaliza el contenido a una escala superior al E-WOM tradicional. Así, las empresas podrían ofrecer contenidos adecuados relacionados con la marca o el producto para atraer a sus consumidores y reforzar sus marcas.

En segundo lugar, en esta tesis se ha destacado la eficacia de estas recomendaciones basadas en la IA (concretamente, los AV). Los AVs se consideran un medio más rico que la comunicación escrita. Por ello, los diseñadores deberían mejorar continuamente la riqueza del medio. Por ejemplo, podría ser útil introducir una tecnología innovadora capaz de transmitir las peculiaridades humanas, resolver los problemas de acento y lenguaje, así como llevar las fluctuaciones de tono al pronunciar las palabras. También se recomienda implantar una nueva tecnología que permita a los consumidores mantener conversaciones de larga duración. Además, los consumidores tienden a personalizar los AV cuando reciben de ellos una recomendación útil (Capgemini, 2019). Por lo tanto, será cada vez más importante que los AV tengan una personalidad y se vuelvan más realistas.

En tercer lugar, el papel crucial destacado de la credibilidad de las recomendaciones por AV en el desarrollo de las intenciones de comportamiento, puede llevar a los gerentes a aprovechar este punto impulsando la implementación de la tecnología de voz en sus servicios de atención al cliente, así como en sus servicios de comunicación de marketing, como las campañas de lanzamiento de nuevos productos. En la misma línea, los gerentes de empresas deberían centrarse en aumentar la utilidad de sus AV, desarrollando dispositivos que ofrezcan servicios de valor añadido, como recitar recetas que contengan los productos de la marca de la empresa o incluso leer en alta voz las listas de ingredientes cuando la gente cocine sus platos.

En cuarto lugar, se ha destacado el papel relevante de la presencia social en la generación de valor de los AV. Por ello, los diseñadores deben centrarse en desarrollar AV fiables, capaces no sólo de interactuar, sino también de desarrollar conversaciones naturales e intuitivas y establecer un vínculo con los consumidores. Por ejemplo, incluyendo un discurso informal y natural mediante saludos, cierres o incluso un nombre, así como desarrollando capacidades de escucha, expresando calidez y mostrando preocupación por el consumidor. Además, para mejorar este valor percibido, los profesionales deben maximizar la comodidad, la compatibilidad y la personalización de los AV y minimizar su percepción de la intrusividad. Por lo tanto, los diseñadores de AV deberían introducir diversas técnicas de análisis social, como "*sentiment analysis*" y "*opinion mining*". Además, los desarrolladores deberían hacer que los AV se asemejen más a los humanos en términos de capacidades de IA para entender e interpretar las instrucciones de los consumidores de forma natural.

Por último, esta tesis ayudó a los proveedores de servicios y a los diseñadores de AV a comprender cómo deben diseñarse los AV para mejorar el valor percibido de sus recomendaciones y el engagement de los consumidores. De hecho, maximizar el valor percibido es crucial para aumentar el engagement. Si los profesionales consiguen aumentar el valor percibido de las recomendaciones realizadas por los AV, podrán satisfacer las necesidades de los consumidores, que, en consecuencia, podrán expresar mayores niveles de engagement con el asistente.

La tabla 6.1 resume los objetivos de la investigación, los resultados obtenidos a lo largo de esta tesis y las implicaciones teóricas y prácticas.

Tabla 6.1 Resumen de resultados e implicaciones

Capítulos	Objetivos de la investigación	Resultados principales	Implicaciones teóricas	Implicaciones prácticas
Capítulo II	**Objetivo 1.** Ofrecer un marco holístico que explique cómo las características de los elementos clave del E- WOM (el emisor, el mensaje y el receptor) afectan a las percepciones, la evaluación y los comportamientos de los consumidores.	- La relevancia, la valencia, la comprensibilidady las señales visuales son las características másimportantes del mensaje y los antecedentes de su utilidad y de las intenciones de comportamientodel receptor. - La credibilidad de la fuente es la característica más relevante del elemento emisor, que influye en las intenciones de comportamiento del receptor. - La susceptibilidad del consumidor a la influencia interpersonal es la característica del receptor que más influye en sus actitudes e intenciones de comportamiento.	- Los trabajos de investigación de E-WOM en el ámbito de los viajes, se clasifican en función del marco de la comunicación social - El mensaje E-WOM es una rica fuente de datos que potencialmente influye en las intenciones de comportamiento de los consumidores en el sector dela hostelería. - La falta de credibilidad de la fuente conduce a un malestar psicológico y, en consecuencia, a una débilintención de comportamiento por parte delconsumidor. - Los individuos susceptibles a la influencia interpersonal son más propensos a comprar, productos que perciben que mejorarán su reputación a los ojos de los demás.	- La gestión de los elementos del E-WOM (emisor, mensaje y receptor) puede ayudar a obtener respuestas más favorables de los consumidores. - Actualizar la información y hacerla más visual y atractiva puede aumentar la capacidad de persuasión del mensaje. - Los gerentes deben fomentar la credibilidad de lasreseñas ofreciendo premios y/o un estatus privilegiado a los usuarios que aporten imágenes y/o vídeos que respalden sus reseñas, y/o a losmás expertos, etc. - Los responsables de las marcas deberían centrarse más en involucrar en sus estrategias a los miembros de las redes sociales con fuertes vínculos con los consumidores, para promocionar sus productos/servicios, y recompensar a los consumidores fieles convirtiéndolos en modelos de conducta.
	Objetivo 2. Identificar las nuevas tendencias y oportunidades de investigación en E- WOM, específicamente lasdebidas a las aplicaciones tecnológicas basadas en la I (por ejemplo, los sistemas de recomendación por voz).	- Es necesario investigar más sobre las reseñas falsas online para comprender mejor las motivaciones del emisor. - La necesidad de gestionar activamente las críticas negativas. - El tipo de plataformas online es relevante paramoderar el efecto de la E-WOM en el comportamiento del consumidor. - Desarrollo de IA-WOM.	- Se identifican las nuevas tendencias en E-WOM. - Unir el ámbito de la IA y las tecnologías inteligentes con la literatura del E-WOM, para desarrollar el concepto de IA-WOM, y destacar la importancia potencial de los sistemas de recomendación basados en la IA.	- Entender las motivaciones de los emisores para publicar reseñas falsas puede ayudar a los gerentes a aplicar estrategias de defensa adecuadas y a mejorar las relaciones entre los consumidores y las empresas. - Una gestión adecuada de las críticas negativas, respondiendo adecuadamente y desarrollando una colaboración con los consumidores, puede ayudar a los profesionales a entender las necesidades de los consumidores y convertir a los clientes insatisfechos en clientes fieles. - Los directivos deben elegir cuidadosamente las plataformas en lasque se promocionan sus marcas/productos, centrándose más en los blogs personales (por ejemplo, los "*micro-influencers"*) debido a sus fuertes vínculos sociales con el consumidor.

				- Las empresas deben cambiar a sistemas de recomendación basados en la IA, que pueden ofrecer una flexibilidad significativamente superior para dirigirse a los consumidores en términos de contenido valioso, personalizado y relevante. - Las empresas podrían utilizar las tecnologías de IA para ofrecer contenidos adecuados relacionados con la marca o el producto para atraer a sus consumidores y reforzar sus marcas o productos entre las comunicaciones del E-WOM.
Capitulo III (1.º estudio empírico)	**Objetivo 3.** Comparar la influencia del E- WOM tradicional recibido a través las reseñas escritas online con el IA-WOM recibido a través de AV, en el comportamiento del consumidor, controlando el contenido no comercial de las recomendaciones.	- La recomendación por voz (IA-WOM) se percibe como más creíble y útil - por la credibilidad - que la recomendación por texto (E--WOM) (se apoya **H1**). - La recomendación no comercial se percibe como más creíble y útil -a través de la credibilidad- que la recomendación comercial (se apoya la **H2**). - La credibilidad percibida de la recomendación es un fuerte predictor de su utilidad percibida (se apoya **H3**). - La credibilidad y la utilidad percibidas de la recomendación influyen positivamente en las intenciones de comportamiento del consumidor: (a) seguir la recomendación, (b) comprar el producto/servicio, y (c) recomendar el producto/servicio (se apoyan **H4 y H5**).	- Ampliar la Teoría de la Riqueza de Medios aplicándola en el ámbito de las tecnologías basadas en la IA en general y en los AV en particular. - Los AV son un medio más rico que la comunicación escrita, más cercano a una interacción "*en persona*". - La idoneidad del marco de la Teoría de la Atribución para comprender el impacto del tipo del contenido de la recomendación (comercial frente no-comercial) en las intenciones del comportamiento del consumidor. - La credibilidad y la utilidad son factores clave para explicar la influencia de la IA-WOM en el comportamiento del consumidor.	- Los diseñadores deben aumentar la riqueza de los AV: - Mejorar la función de voz, mediante la introducción de una tecnología que transmite las peculiaridades humanas y lleva las fluctuaciones de tono al pronunciar las palabras. - Implementar una nueva tecnología que permita a los consumidores mantener conversaciones de larga duración con AV. - Humanizar más los AV atribuyéndoles una “persona”. - Resolver los problemas de acento y lenguaje mediante la creación de una tecnología de voz que reconoce los comandos con facilidad. - Los gerentes de productos y del comercio minorista deberían aprovechar la gran credibilidad y utilidad percibidas de las recomendaciones de los AV implementando éstos en sus servicios de comunicación de marketing (por ejemplo, utilizando AV para el lanzamiento y la recomendación de nuevos productos), así como ofreciendo servicios de valor añadido, como la recitación de recetas con los productos de la marca del supermercado.

	Objetivo 4. Examinar si la eficacia de la IA- WOM difiere cuando se centra en los productos de búsqueda frente a los de experiencia.	- No existe un efecto de interacción entre la modalidad de recomendación (voz frente a texto) y el tipo de producto (producto de búsqueda frente de experiencia) sobre la credibilidad percibida ni la utilidad (no se apoya **H6**). - El efecto de la recomendación no comercial sobre la credibilidad y la utilidad percibidas es mayor para los productos de búsqueda que para los de experiencia (se apoya **H7**).	- Avanzar en el papel del tipo de producto dentro del ámbito de las recomendaciones del AV distinguiendo entre productos de búsqueda y de experiencia.	- Los gerentes de productos deben ser conscientes, a la hora de aplicar sus estrategias de marketing, de que: - Independientemente de que se recomiende un producto o un servicio, el efecto de las recomendaciones de voz sobre las percepciones y los comportamientos de los consumidores no cambia. - La recomendación no comercial se percibe más creíble y útil, cuando se trata de productos de búsqueda, que de productos de experiencia (es decir, servicios).
Capitulo IV (2.º estudio empírico)	**Objetivo 5.** Definir los costes y beneficios relevantes asociados a los AV y su papel en el desarrollo del el valor percibido de las recomendaciones realizadas por los AV.	- Las ventajas de comodidad, compatibilidad y personalización del AV influyen positivamente en el valor percibido de sus recomendaciones (se apoyan **H6, H7 y H8**). - El coste del esfuerzo cognitivo del AV no influye en el valor percibido de sus recomendaciones (se rechaza **H9**). - El coste de la intrusividad de los AV influye negativamente en el valor percibido de sus recomendaciones (se apoya **H10**).	- Ampliar el paradigma de coste-beneficio (Kleijnen et al., 2007), aplicado en contextos anteriores (por ejemplo, sitios web [Ho y Bodoff, 2014], servicios móviles [Wang et al., 2020] y realidad aumentada [Lau et al., 2019]), al contexto de los AV.	- Los diseñadores de AV deben maximizar la comodidad, la compatibilidad y la personalización y minimizar su intrusividad. Por ejemplo: - Recogida y análisis de datos sobre las preferencias del consumidor y los productos que le interesan. - Introducción al “sentiment analysis” y “opinion mining”. - Mejora de los aspectos humanos en términos de características vocales y capacidades cognitivas. - Reducir la intrusividad comunicando claramente a los consumidores los registros de audio como una función de privacidad (por ejemplo, eliminar las entradas del historial de interacción); e introducir el modo incógnito para los AV.

	Objetivo 6. Analizar cómo la presencia social puede influir en la formación del valor percibido de las recomendaciones realizadas por los AV.	- La presencia social del AV influye positivamente en su comodidad, compatibilidady personalización (se apoyan **H1, H2** y **H3**). - La presencia social del AV no afecta a su esfuerzo cognitivo percibido (se rechaza **H4**). - La presencia social del AV influye negativamente en su intrusividad (se apoya **H5**).	- Ampliando, en el contexto de los AV, los estudios de neurociencia cognitiva (Heninger et al., 2006), que sugieren que la presencia social aumenta la comodidad. - Contribuyendo a Van Doorn et al. (2017), sugiriendo que la presencia social de las tecnologías automatizadas genera valor hacia la tecnología. - Apoyando la Teoría de la Personalidad Implícita (Verhagen et al., 2014), que sugiere que la presenciasocial aumenta el sentimiento de personalización. - Nuevo hallazgo en la literatura de riesgos percibidos por la tecnología y laprivacidad (Lau et al., 2018; Manikonda et al.; 2018), al destacar la presencia social del AV mitiga su intrussividad.	- Los diseñadores de AV deben centrarse en: - Potenciar las conversaciones naturales e intuitivas y establecer un vínculo con los consumidores. - Incluyendo un discurso informal y natural utilizando saludos, cierres o incluso un nombre. - Desarrollar dispositivos que sean capaces de escuchar, expresando calidez, mostrando preocupación por el consumidor entendiendo sus consultas.
	Objetivo 7. Evaluar el efecto del valor percibido de las recomendaciones realizadas por los AV en el compromiso del consumidor hacia estos asistentes.	- El valor percibido de las recomendaciones realizadas por los AV, predice fuertemente el compromiso hacia estos asistentes (se apoya **H11**).	- Contribuyendo a estudios anteriores (Chen, 2017; Hsu y Lin, 2016), al confirmar la asociación positivaentre el valor percibido y el engagement del consumidor con AV. - Contribuir a la comprensión académica del engagement conductual del consumidor destacandotres dimensiones del engagement con los AV (intención de recomendar el AV, intención de seguir utilizando el AV e intención de seguir la recomendación del AV).	- Los profesionales deben tener en cuenta todas las acciones anteriores para maximizar el valor percibido de las recomendaciones del AV, ya que esto es crucial para aumentar el engagement. En el presente estudio, el valor percibido predice el 75,8% del engagement del consumidor con el AV.

6.4 LIMITACIONES Y FUTURAS LÍNEAS DE INVESTIGACIÓN

A pesar de que esta tesis doctoral plantea interesantes implicaciones teóricas y prácticas, tiene algunas limitaciones que constituyen oportunidades para seguir investigando. En primer lugar, la literatura sobre el E-WOM es muy amplia y el capítulo de revisión de la literatura no la tiene en cuenta en su totalidad. La presente tesis, por ejemplo, se centró en el E-WOM desde el punto de vista de la teoría de la comunicación y del consumidor, pero no investigó los estudios orientados a otros aspectos como el efecto del E-WOM sobre la equidad y/o la reputación de la marca. Las investigaciones futuras deberían ampliar esta bibliografía y aumentar el número de artículos estudiados desde otros puntos de vista analíticos. Además, como la investigación sobre la comunicación E-WOM está siempre en evolución, se sugiere encarecidamente que se realice una revisión sistemática de la literatura para mejorar el conocimiento de los efectos de los tres elementos de la E-WOM (mensaje, emisor y receptor) en los procesos de la toma de decisiones de los consumidores.

En segundo lugar, la recopilación de datos para ambos estudios empíricos (capítulos III y IV), se realizó en Estados Unidos. Sin embargo, varios trabajos de investigación han señalado la importancia de incorporar las diferencias culturales cuando se trata de estudiar el comportamiento de los consumidores hacia las nuevas tecnologías (Huang y Zhang, 2020). Por lo tanto, futuros estudios podrían comparar este comportamiento entre culturas explorando, por ejemplo, las posibles diferencias entre los países individualistas y los colectivistas.

En tercer lugar, en el primer estudio empírico (capítulo III) que compara la influencia de las reseñas escritas en línea con las recomendaciones proporcionadas por AV, en el comportamiento del consumidor, se ha considerado, en el diseño del experimento, las recomendaciones proporcionadas por la voz femenina. Estudios anteriores demostraron que los rasgos inferidos de las características de la voz (por ejemplo, el género) pueden afectar a la eficacia de la persuasión de la información (Nass y Moon, 2000). En futuros estudios se debería examinar cómo las diferentes características de la voz (femenina frente a masculina) afectan a la forma en que los consumidores perciben y se comportan ante las recomendaciones de las AV. Además, el mismo diseño del experimento no tiene en cuenta ninguna variable de control. De acuerdo con la literatura en psicología, los rasgos de personalidad pueden afectar significativamente al proceso de información de la persuasión de las personas (McCrae y Costa, 1987). Por lo tanto, las investigaciones posteriores deberían controlar los rasgos de personalidad de los consumidores (por ejemplo, "*Big Five Model*"), que pueden afectar a las intenciones de comportamiento hacia la recomendación del AV.

En cuarto lugar, el segundo estudio empírico que pone a prueba el valor percibido de las recomendaciones realizadas por los AV (capítulo IV), se realizó sobre la base de una búsqueda de productos/servicios en el contexto de hostelería, sin distinguir entre el tipo de productos. Por ejemplo, la importancia relativa de los antecedentes del valor percibido y su influencia en el engagement del consumidor puede depender del tipo de recomendación recibida (por ejemplo, recomendación sobre un product/servicio hedónico frente a utilitario). Además, el mismo modelo arroja algo de luz sobre los principales beneficios y costes que construyen el valor percibido de las recomendaciones realizadas por los AV, sin embargo, se pueden examinar otras variables clave. De este modo, al tratarse de un dispositivo basado en la IA, futuras investigaciones podrían explorar la inteligencia percibida del asistente (por ejemplo, mecánica, de pensamiento y de sentimiento [Schepers et al., 2022; Huang y Rust, 2021]) y examinar su efecto en la generación del valor percibido y el engagement.

En quinto lugar, ambos estudios empíricos no diferencian entre tipos de AV. Las investigaciones futuras podrían comparar las experiencias de los consumidores con los AV integrados en los teléfonos inteligentes, como Siri y Google Assistant, y sus experiencias con los AV en el hogar, como Alexa y Google Home. Recibir recomendaciones de diferentes tipos de AV puede variar su valor percibido y el engagement del consumidor con el asistente.

Por último, la presente tesis se centra en la perspectiva de las intenciones de los consumidores. Aunque las intenciones parecen ser un indicador fiable del comportamiento real (por ejemplo, Venkatesh y Davis, 2000), sería fructífero examinar los datos reales del comportamiento y realizar dicho análisis de forma longitudinal o en un estudio de campo para comprender mejor el comportamiento del consumidor hacia las recomendaciones basadas en IA.

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APPENDIX

Appendix A: The reference list of the 97 articles revised in the literature review (Chapter II)

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Appendix

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Appendix

Appendix B. Example of the text-based recommendation for search product (Chapter III)

Imagine you are traveling to meet your partner's parents for the first time. For you, it is a very important engagement and you want to impress your future in-laws as possible as you can. For this trip, you need to buy a new suitcase. As you need more information about suitcases, you decide to search some reviews written by other customers. In a social network, you come across this recommendation:

Adam Clark
1 week ago

Last week, I bought C.K.L suitcase. I can honestly say the design of C.K.L suitcase and its easy handling are great. The suitcase is very spacious and elegant. The size is perfect! With pockets and multi-compartments for socks, chargers...etc. Regarding the wheel maneuverability, this suitcase offers the innovative 360-degree spinner wheels with an affordable price.
I highly recommend it!
I rate it with 4.8 of 5 stars!

See More Reviews

Appendix C. Example of the voice recommendation of experience product (Chapter III)

Imagine that you are looking for a restaurant to surprise your partner and invite her/him to a romantic dinner to celebrate your anniversary together. As you need more information about restaurants, you ask your voice assistant to read to you some recommendations based on other customers' choices, and you get the following recommendation:

Please click the following link to get the recommendation. Press play and listen the recommendation to the end:
https://bit.ly/3Re181Z

Appendix D1. Manipulation checks of the pre-test of the study 1 (Chapter III)

Modality %		**Product type%**	
Voice	Text	Search product	Experience product
98	99	100	96

Appendix D2. Manipulation checks of the pre-test of the study 1 (Chapter III)

	Realism	**Involvement**	**Valence**	**Length**	**Quality**	**Brand familiarity**
F	1.4	2.53	0.93	1.30	1.17	1.33
P-Value	0.21	0.15	0.48	0.25	0.32	0.41

Appendix E. Realism and involvement items (Chapter III)

CONSTRUCT
Realism (adapted from Bagozzi el al., 2016)
REAL 1. How likely the scenario would be realistic
REAL2. I How likely the scenario would be believable
REAL3. How likely would you be to encounter a situation similar to the one described in the scenario.
Involvement (adapted from Zaichkowsky, 1985; Mather et al., 2016)
INVL1. Imagining the situation, I would be very interested in the purchase decision
INVL2. Imagining the situation, it would be important to me to make the right purchase decision
INVL 3. Imagining the situation, the purchase decision would mean a lot to me
INVL 4. Imagining the situation, the purchase decision would be relevant to me