Received: 27 February 2022 | Accepted: 21 November 2022

DOI: 10.1002/mar.21765

RESEARCH ARTICLE

Psychology & Marketing WILEY

# Effects of voice assistant recommendations on consumer behavior

Carlos Flavián[1,2] | Khaoula Akdim[1,2] | Luis V. Casaló[1,3]

[1]Department of Marketing Management and Market Research, University of Zaragoza, Zaragoza, Spain

[2]Faculty of Economy and Business, University of Zaragoza, Zaragoza, Spain

[3]Faculty of Business and Public Management, University of Zaragoza, Huesca, Spain

**Correspondence**

Carlos Flavián, Department of Marketing Management and Market Research, University of Zaragoza, Zaragoza, Spain.
Email: cflavian@unizar.es

**Funding information**

Ministerio de de Ciencia e Innovación de España (PID2019-105468RB-I00); Fondo Social Europeo and Gobierno de Aragon (Grupo "METODO" S20_20R; LMP51_21 and pre-doctoral grant 2017-2021 C135/2017).

## Abstract

The present study compares the influence of text-based recommendations; traditionally known as online consumer reviews, and the influence of voice-based recommendations provided by voice-driven virtual assistants on consumer behaviors. Based on media richness theory, the research model investigates how voice versus text modality influences consumers' perceptions of credibility and usefulness, as well as their behavioral intentions and actual behaviors. In addition, the study analyses if these relationships vary based on the type of product and compares the influence of masculine and feminine voices. Two studies were conducted using between-subjects experimental designs, partial least squares-structural equation modeling, and logistic regression. The core finding is that voice-based recommendations are more effective than online consumer reviews in altering consumer behaviors. In addition, the first study showed that the influence of recommendations on behavioral intentions is mediated by consumers' perceptions of their credibility and usefulness. The second study confirmed, in a realistic setting, that voice-based recommendations affect consumer choices to a greater extent. Recommendations for search products and provided by males are also found to be more effective. These results contribute to the voice assistant and e-WOM literature by highlighting the effectiveness of voice-based recommendations in predicting consumer behaviors, confirming that credibility and usefulness are key factors that determine the influence of recommendations, and showing that recommendations are more effective when they focus on search products.

KEYWORDS

artificial intelligence, consumer behavior, e-WOM, online consumer review, recommendations, virtual assistant, voice assistant

## 1 | INTRODUCTION

In recent years, artificial intelligence (AI) technologies have become deeply embedded in, and substantially changed, every aspect of modern life. Among the fastest growing categories of AI technologies are virtual assistants (Ahn et al., 2022). Virtual assistants have been described as dialogue systems, often displaying human-like behaviors, that interact with their users to perform tasks, support interfaces that adapt to users' queries, and as personal agents that proactively support their users, modeling their needs (Bräuer & Mazarakis, 2022).

Based on their input modality, virtual assistants have been segmented into chatbots and voice assistants (Foster & Oberlander, 2007). A chatbot is a computer program that carries out textual conversations (Pizzi et al., 2021), whereas voice assistant is a device, powered by AI, usually integrated as software into various platforms (e.g., smartphones, TVs) and Bluetooth speakers (e.g., Amazon Echo, Alexa), that listen out for wake-up words (i.e., "Alexa…" or "Hey Google…") which activate their functionality. When the device detects its user wake-up word, its software understands what is being said and provides a response in real time (Grover et al., 2020). Voice assistants give advice based on consumers' preferences and habits, to which they have access (Ling et al., 2021). This feature, advice-based consumer preferences, guides consumers during their purchase decision-making processes by providing product/service recommendations.

While the market of voice assistants is still young, the penetration levels of voice-enabled technologies are growing exponentially. The growth of the voice assistant industry is expected to average 28% per year between 2021 and 2023 (Statista, 2021). In addition, forecasts suggest that, by 2023, the number of voice assistants (including integrated software and Bluetooth speakers) will surpass 8.4 billion units —a number greater than the world's 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). In addition, 70% of Google Assistant requests are voice-based, and 43% of these requests seek product 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 (Global Digital Traveler Research Report, 2021).

Thus, voice assistants have emerged as a new recommendation system for consumers, complementing e-WOM, which itself changed the buying environment following the advent of Web 2.0 (Verma & Yadav, 2021). E-WOM has been found to be the most influential online information source in shaping consumer behaviors (Filieri & McLeay, 2014; Serra Cantallops & Salvi, 2014), as its readers tend to perceive it as more reliable due to the poster's independence (Casaló et al., 2010; Park & Lee, 2009). E-WOM has been 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 Internet" (Hennig-Thurau et al., 2004; p. 39). Online consumer reviews are the most common form of e-WOM (Chatterjee, 2001), and are a crucial source of information for other consumers, who use them to assess products and services before purchasing them (Filieri, 2016). Specifically, online consumer reviews are text-based declarations posted on websites that host consumer reviews (Filieri, McLeay et al., 2018). Voice assistants have been shown to provide benefits over and above those provided by e-WOM by giving consumers personalized product recommendations based on their needs, which they have inferred from their conversations with their users (Tabassum et al., 2019). As a result, academic research has emphasized the high importance of voice assistants in terms of the future of e-WOM for companies (e.g., hotels/restaurants) and their product promotion potential (Hernandez-Ortega & Ferreira, 2021; Klaus & Zaichkowsky, 2020).

The current study responds to the call for further empirical research on the influence of voice assistants on consumer behavior proposed by recent systematic literature reviews (e.g., W. M. Lim et al., 2022; Ling et al., 2021). These works mainly highlight factors influencing the consumer intention to use AI and voice assistants as well as their applications in marketing filed. Also, this research extends existing empirical works on voice assistants in the consumer behavior domain, which have mainly focused on analyzing consumers' perceptions and behaviors toward voice assistants (e.g., engagement and loyalty [Moriuchi, 2019], love [Hernandez-Ortega & Ferreira, 2021], or trust [Balakrishnan & Dwivedi, 2021; Pitardi & Marriott, 2021]), by drawing attention to the potential influence of voice assistants recommendations about other products/services on consumer choices.

Specifically, some prior literature review papers seem to suggest that AI-based devices such as virtual assistants may have a strong effect on consumers' choices, being able to alter their preferences as a result of AI-based interactions (e.g., Klaus & Zaichkowsky, 2020; Mariani et al., 2021). Using a voice assistant can be a unique experience, distinct from other recommendation-offering technologies (Lieberman & Schroeder, 2020). Voice assistants' ability to convey warmth, and to make their listeners feel in control, and competent (e.g., through the provision of immediate answers through natural language processing), enhance the perceived quality of their recommendations (Dellaert et al., 2020). Nevertheless, according to Bjork (1970), voice information subsists on a single temporal dimension, so that people have difficulties retaining vocal information in their short-term memories, while visual memory is more relied upon for information stored in our long-term memory. Klaus and Zaichkowsky (2020) adopted this concept to voice assistants, suggesting that, when people ask a voice assistant for a recommendation for a product/service, and they reject the first recommendation, the assistant makes a second, and a third, and so on. However, people are unlikely to ask for a 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 voice assistants make is, thus, usual. Therefore, Dellaert et al. (2020) suggested that voice assistants indirectly limit the amount of information provided to consumers. On the other hand, text-based recommendations (e.g., online consumer reviews) provide several options which can be simultaneously presented on a screen and remain frozen there for a span of time. Therefore, receiving information from online platforms leads consumers to retain their role as decision-makers (Klaus & Zaichkowsky, 2020). However, extant studies do not seem fully able to explain the influence of voice assistants' recommendations on consumers' perceptions and intentions or compare the influence they exert with that exerted by other recommendation sources, such as online consumer reviews. The previous research into voice assistants has focused on other aspects, such as their design and functional properties (e.g., Sciuto et al., 2018), their anthropomorphism and social functions (e.g., Schweitzer et al., 2019), customers' attitudes toward them (e.g., Brill et al., 2019) and the personalization-privacy paradox (e.g., Lau et al., 2018). While some comparative studies have been undertaken in this context, for example, synthetic versus the human voice (Chérif &

Lemoine, 2019), customer satisfaction in voice commerce versus e-commerce (Kraus, 2019), and voice mail versus e-email (Keil & Johnson, 2002), no studies have compared the effectiveness of text-based recommendations (online consumer reviews) and the voice-based recommendations provided by voice assistants.

Previous research has extensively examined the effectiveness of e-WOM reviews by assessing review credibility and usefulness (M. Y. Cheung et al., 2009; Filieri et al., 2020), perceived helpfulness (Filieri, 2015; Filieri, Hofacker et al., 2018), perceived competence (Y. Lim & Van Der Heide, 2015), relevance, factuality, source credibility, and ranking score (Filieri, McLeay et al., 2018), length, valence, argument quality, and content equivocality (Cheng & Ho, 2015; Filieri, 2015; Schindler & Bickart, 2012). Of these factors the prior research highlighted the vital roles of credibility and usefulness in the persuasiveness of e-WOM; they have both been found to influence consumers' intentions and behaviors (C. M. K. Cheung et al., 2008; M. Y. Cheung et al., 2009; Filieri, 2015; Viglia et al., 2016). In the online review context, credibility has been defined as the "consumers" perception that the information contained in a review is "believable, true, or factual" (M. Y. Cheung et al., 2009; p. 12). The usefulness of online reviews has been defined as "the degree to which consumers believe that online reviews would facilitate their purchase decision-making process" (Park & Lee, 2009; p. 334). Therefore, taking into account that these two factors are crucial in the determination of the influence of recommendations, it is proposed that the contribution of the present study to the literature is threefold. First, we compare the influence on consumer behavior of text-based recommendations received through online consumer reviews and through voice assistants' recommendations. Second, we analyze the mediating role of the key perceptions (credibility, usefulness) that users develop during the process. Third, the moderating effect of product type (search vs. experience) is examined to better understand if relationships vary based on whether a product or service is being recommended (Figure 1).

Our theoretical approach is based on media richness theory (MRT), which proposes that communication channels have affordances that influence consumers' perceptions and intentions. The theory was introduced by Daft and Lengel (1986) and was subsequently applied to the new media that emerged in the 1990s (e.g., email) and the 2000s (e.g., social media). The concept of media richness (Daft & Lengel, 1986) offers a theoretical framework for analyzing the possible advantages that consumers may derive from different forms of media.

Empirically, we performed two experimental studies. The first analyzed the influence of the recommendation mode employed (text vs. voice) on the users' key perceptions (credibility, usefulness); the mode used may affect consumers' behavioral intentions (i.e., intention to follow the recommendation, intention to recommend, and intention to purchase). The second experiment aimed to enhance the realism of the scenario by measuring actual behaviors, rather than intentions—and hence the external validity and generalizability of the results—following the design recommendations of Viglia et al. (2021). To confirm the influence of the recommendation mode (text vs. voice) on behavior, we presented the experimental participants with a situation in which they had to make choices, controlling for the apparent gender of the voice assistant (i.e., masculine vs. feminine voice).

The key result of the study is that voice assistants' recommendations are more effective than online consumer reviews in influencing consumer behaviors, both directly—Study 2—and indirectly (via credibility and usefulness)—Study 1. These findings give professionals a deep grasp of voice assistant technologies that they may use to their advantage in business strategies.

## 2 | THEORETICAL FRAMEWORK AND HYPOTHESES DEVELOPMENT

### 2.1 | MRT and the influence of recommendation modality on perceived credibility and usefulness

Communication channels have different attributes that affect consumers' perceptions and intentions. The most important is modality (Berger & Iyengar, 2013). MRT was originally posited to

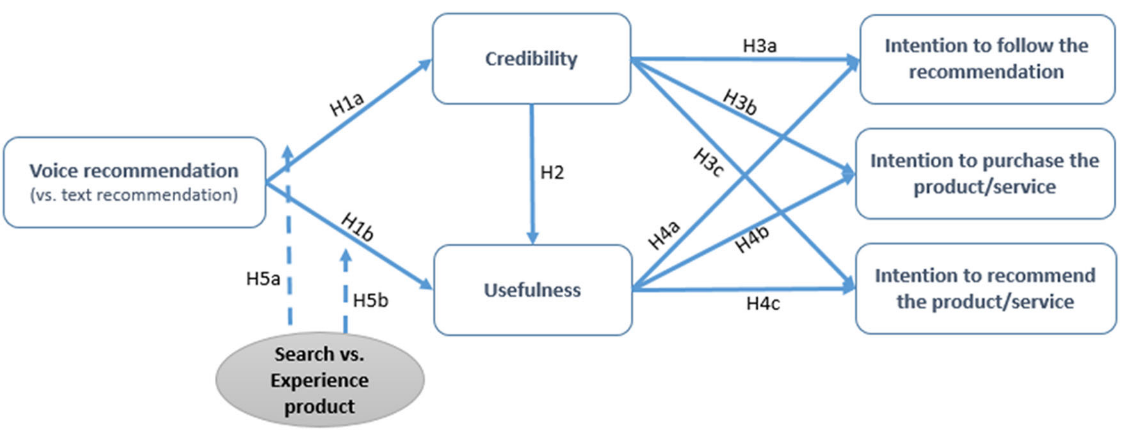



**FIGURE 1** Proposed conceptual model. Solid lines denote direct effects, dotted lines denote moderating effects.

explain the effects of different types of media on task performance. The theory's core proposition is that the more cues a communication channel features, that is, the "richer" the medium is, the more satisfying and effective it will be perceived (Caplan et al., 2014; Daft & Lengel, 1986). Face-to-face interaction has been classified as the "richest" way to communicate because it transmits verbal and nonverbal cues, which mitigate misunderstandings, whereas unaddressed documents (e.g., standard reports) have been described as the medium with the least communication richness (Campbell, 2006). Below we apply MRT to compare the influence of voice assistants' recommendations and e-WOM recommendations (in the form of text-based online reviews) on consumers' perceptions and intentions.

In general, AI-based devices (e.g., robots, virtual assistants) try to interact by using human-like features that elicit positive responses from users (Ahn et al., 2022; Belanche et al., 2021; Schepers et al., 2022). In particular, voice assistants use their voice function to relay information. This voice function is an important human-like characteristic that evokes a sense of social presence in the mind of consumers, which prompts them to interact with the voice assistant in the same way they would socially interact with humans (e.g., Rosenthal-von der Pütten et al., 2016). In addition, as individuals become comfortable in their conversations with voice assistants, they start to build rapport with the devices, just as they would in their personal relationships (Moriuchi, 2019; Rhee & Choi, 2020). Prior studies have shown that the voice feature leads users to personify voice assistants (Tassiello et al., 2021), and even consider them as friends or family members (J. Zhao & Patrick Rau, 2020). Similarly, several researchers have suggested that voice assistants make experiences more intimate, humanize interactions and enhance trust between the consumer and the service (Qiu & Benbasat, 2009). In addition, Ostrom et al. (2019) argued that voice assistants make consumers more effective, as they offer convenience and speed (Klaus & Zaichkowsky, 2020). According to Rosenthal-von der Pütten et al. (2019), consumers feel it is often easier and more convenient to use voice input than to type, as voice is regarded as faster. In addition, Rhee and Choi (2020) found that personalization is the main advantage of voice assistants. Voice assistants give recommendations based on consumers' histories, preferences, and habits, to which they have access through algorithm-based systems. Thus, consumers receive personalized recommendations which provide appropriate information, increasing the effectiveness of the recommendations which, consequently, facilitate their purchase decision-making processes. Invitational rhetoric is the degree to which a communication style encourages others to converse; a higher degree fosters mutual understanding (B. Liu & Sundar, 2018). Kontogiorgos et al. (2019) analyzed the effects of the invitational rhetoric in both chatbots and voice assistants' messages, and found that the latter's messages contained invitational rhetoric which had a beneficial effect on users' perceptions and behavioral outcomes.

On the other hand, in the context of text-based recommendations, various scholars have argued that many consumer reviews posted on online platforms fail to meet users' needs. Listeners are more attentive and responsive to devices with high nonverbal contingency and expressive narrative styles (e.g., in terms of pitch and tone [Kory Westlund et al., 2017]). Text-based recommendations contain less cues than voice-based recommendations, which can convey information with nonverbal cues such as voice tone, speed, pitch, volume, and emphasis (Kontogiorgos et al., 2019). For example, Stoll et al. (2016) and Spence (2019) found that consumers feel more uncertainty and expect fewer positive experiences when they read text-based recommendations. These findings align with the main MRT proposition, that is, when a technology exhibits human traits (e.g., voice) and elicits human-like interactions, people's responses to the technology will mirror social behaviors and they will respond to it consistent with social standards, as in their personal interactions (Moon & Nass, 1996). Therefore, voice assistants may be considered to be a rich communication channel (Rudovic et al., 2018).

Taking these points, and MRT, into account, their voice features, natural-language processing, and immediate feedback make voice assistants a rich communication channel, leading consumers to consider them as friends/conversational partners. As a result, a personal acquaintance and trusting relationship can develop (Pitardi & Marriott, 2021). The more familiarity the message recipient has with the sender (e.g., a friend), the more reliable the information in the message is regarded (Bampo et al., 2008; Keller, 2007). On the other hand, the multiple cues that voice assistants transmit increase the accuracy of the data they impart (e.g., detailed information about a product/service), which can alleviate uncertainty, resolve ambiguity and help consumers acquire the information they need. Hence, they may be perceived as more useful (Filieri, 2015). Therefore, we hypothesize that:

> H1. Voice recommendations (vs. text recommendations) generate higher levels of (a) perceived credibility and (b) perceived usefulness.

## 2.2 | The influence of recommendation credibility on the perceived usefulness of recommendations

Several works examining online reviews have stressed the importance of source credibility (e.g., Filieri, 2015; Lo & 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" (M. Y. Cheung et al., 2009; p. 12). In this respect, scholars usually agree that perceived credibility enhances the perceived helpfulness and effectiveness of information (Filieri, McLeay et al., 2018; 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 prepurchase 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:

> H2. The perceived credibility of a recommendation has a positive effect on its perceived usefulness.

## 2.3 | The influence of perceived credibility and usefulness on behavioral intentions

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

Scholars have demonstrated that perceived message credibility is one of the most important antecedents of recommendation adoption (M. Y. Cheung et al., 2009) and purchase intentions (Filieri, 2016). Credibility is determined early in the information persuasion process (Wathen & 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 & 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 & 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' behavioral intentions to share information on consumer online platforms (Filieri, 2015; Filieri et al., 2020; Ma & Chan, 2014). In sum, perceived credibility is an important factor in making recommendations more persuasive and for increasing consumers' behavioral intentions. As a consequence, we propose:

> H3. The perceived credibility of a recommendation has a positive effect on consumers' behavioral intentions: (a) to follow the recommendation; (b) to purchase the product/service; and (c) to recommend the product/service.

Similarly, Filieri (2015) and C. M. K. Cheung et al. (2008) suggested that usefulness is the primary factor in consumers' evaluations of recommendations and is an effective predictor of their intentions. In the online review context, when useful information is provided in a recommendation, this increases consumers' knowledge of, and familiarity with, the product/service (C. M. K. Cheung et al., 2008; Filieri, 2015). Hence, useful recommendations are particularly influential in consumers' decision-making as they affect their information adoption and purchase intentions (Filieri, Hafacker et al., 2018; Filieri, McLeay et al., 2018). Thus, only those reviews that their readers perceive as useful have been found to affect intention formation through the impression they create about the subject of the review (Purnawirawan et al., 2012). In addition, consumers have been shown to be more likely to share information contained in a review with others if they perceive the recommendations it contains to be useful (Park & Lee, 2009). Consumers share information, or form intention to recommend a product/service, because they want to help other people make good decisions about what they buy and/or avoid bad experiences (Chiu et al., 2009). Consequently:

> H4. The perceived usefulness of a recommendation has a positive effect on consumers' behavioral intentions: (a) to follow the recommendation; (b) to purchase the product/service; and (c) to recommend the product/service.

## 2.4 | The moderating effect of product type: search versus experience products

Nelson (1970) posited that the key difference between search and experience products is whether consumers can assess them before purchase. If a product's qualities can be determined before purchase (e.g., tangible products), it is classified as a search product; however, if a product's attributes cannot be determined until after the consumer buys and uses the product, it is classified as an experience product (e.g., a service) (Klein, 1998). Similarly, Weathers et al. (2007) categorized products into search and experience based on the degree to which consumers believe they must use them to assess their quality. The more one's senses are required to evaluate a product; the more experience features the product contains. On the other hand, the more one believes that information will suffice to assess a product, the more search features the product contains. Several academics have hypothesized that product type may influence how consumers evaluate recommendations (e.g., Jiménez & Mendoza, 2013; Zhang et al., 2014).

As aforementioned, information on the characteristics of search products is readily available (Hsieh et al., 2005), objective, easily comparable (Mudambi & Schuff, 2010) and discoverable without experiencing the product (P. Huang et al., 2009). In contrast, information about experience products is difficult and costly to obtain (Mudambi & Schuff, 2010), and consumers must use their senses more to assess them (Weathers et al., 2007). In addition, as consumers cannot completely evaluate experience goods until after consumption, the risk/uncertainty associated with the choice process is greater for experience products than for search products. Risk theory (Dowling & Staelin, 1994) posits that consumers look for more information when they perceive that the decision context involves greater risk. Therefore, the associated information processing requires more cognitive effort (P. Huang et al., 2009). On the other hand, when information is received from a rich media source, it tends to be easier to process, interpret and assimilate, which enables consumers to better evaluate it (Maity et al., 2018; Suh, 1999). Therefore, when they come from rich media sources, recommendations for experience products may be easier to evaluate; as a result, the influence of voice (vs. text) recommendations in terms of the development of perceptions of credibility and usefulness will be greater for experience than for search products (Figure 1). Hence, we propose our last hypotheses:

H5. The difference between the (a) perceived credibility and (b) perceived usefulness of voice and text recommendations will be greater for experience products than for search products.

# 3 | STUDY 1

## 3.1 | Methodology

### 3.1.1 | Experimental design and measures

To test the proposed model, we conducted a between-subjects factorial experiment design. Specifically, we manipulated modality (voice-recommendation vs. text-recommendation) and product type (search product vs. experience product), resulting in a two-by-two factorial design that combines two variables, each of which has two levels. The participants were randomly assigned to one of four scenarios. In the current market, several voice assistants are integrated into Bluetooth speakers, such as Amazon Echo (Alexa), and as software integrated into smart devices, for example, Apple Siri. In the present study we used Amazon Echo (Alexa), because it is the leading, global smart speaker, having a market share of 30%, and 70% in the United States (Statista, 2022). To simulate the experience of receiving a voice recommendation, we used a text-to-speech (TTS) demo version, accessible online at https://ttsdemo.com/. To control for the impact of vocal features (e.g., gender, pitch, speed), we used the same female voice character, with a preset standard vocal effect, for all the voice recommendations Two distinct product categories were chosen, a suitcase for the search product condition, and a dinner at a restaurant for the experience product condition.

Thereafter, the participants were asked to complete a questionnaire to allow the researchers to evaluate their perceptions of, and intentions developed based on, the recommendations received. The survey clearly identified the purpose of the research. Responses that were filled in very quickly or that failed screening questions, indicating that the participants had not paid attention to the questions, were excluded. In the text recommendation surveys, the participants could read the recommendation. For the voice recommendation surveys, the questionnaire provided a link to an audio file on which the participant (having pressed "play") could listen to the recommendation (see Appendixes A and B).

The variables credibility, usefulness and behavioral intentions were measured using multiple-item measurement scales on 7-point Likert-type response formats. The respondents rated the items from 1 ("strongly disagree") to 7 ("strongly agree"). The measurement scales were adapted from scales developed in the previous literature (see Table 3).

### 3.1.2 | Manipulation checks

Before the main experiment, a pretest was carried out to ensure the effectiveness of the manipulations. The pretest was conducted with 40 participants, 10 per condition. The treatment conditions were found to have been appropriately manipulated. The modality manipulation was successfully confirmed, with 98% of the participants verifying the text condition, and 99% the voice condition. The product type manipulation was also verified, 100% of the participants confirming the search product condition, and 92% the experience product condition (see Appendix C1). In addition, we controlled for realism (i.e., both real behaviors and intentions were measured), the level of consumer involvement (whether the product categories are high- or low-involvement), review characteristics (length, valence, and quality), and the participants' brand familiarity with the product/service. The measures for the realism scenario were taken from Bagozzi et al. (2016), and the measures for product/service involvement from Zaichkowsky (1985). These measures were recorded on seven-point Likert-type scales (1 = "strongly disagree"; 7 = "strongly agree"; see Appendix D). The measures of recommendation valence and length, review quality and brand familiarity were recorded on five-point Likert-type scales (1 = "Very low"; 5 = "Very high"). No statistical differences between the means were observed across the realism scenarios for user involvement, valence, length, recommendation quality, or brand familiarity with the product/service ($FR = 1.4$, $p > 0.1$; $FI = 2.53$, $p > 0.1$; $FV = 0.93$, $p > 0.1$; $FL = 1.30$, $p > 0.1$; $FQ = 1.17$, $p > 0.1$); this indicates that these variables are homogeneous in all the conditions (see Appendix C2).

### 3.1.3 | Product type

A suitcase was chosen as it is a necessary product that most people take on their travels. In addition, it can be used for a long time once purchased. Before purchasing a suitcase, people actively seek out and compare models and features. Conversely, a dinner at a restaurant is an experience product, the quality of which cannot be determined before interaction with the product (i.e., eating at the restaurant). Moreover, one's assessment of a restaurant's quality is influenced by one's tastes and personal interests, thus it is difficult to compare one establishment with another, or evaluate them without eating in them. In addition, the two products were chosen because they are generally in the same price range.

According to Filieri and McLeay (2014), e-WOM has a great influence on consumer purchasing decisions for high-involvement travel related products; consumers frequently spend significant time searching for information about high-involvement products so that they make the best choices (Zaichkowsky, 1986). Therefore, in the present study, we used high-involvement products. For the search product, the participants were encouraged to imagine they were purchasing a suitcase for a trip to meet their partners' parents for the first time, and that they wanted to highly impress their future in-laws. So, they should buy a new, appropriate suitcase. For the experience product the participants were asked to imagine that were looking for a restaurant to surprise their partner, where they would invite her/him to a romantic dinner to celebrate their anniversary. Thus, they needed to book a table (Table 1).

### 3.1.4 | Data collection and estimation procedure

The data collection took place during November 2021. The participants were US residents recruited through an online survey; we enlisted the assistance of a market research firm, Prolific, in the process. To take part, the participants had to have used voice assistants at least once; a qualifier sentence asked; "This survey is exclusively addressed to voice assistant users, so if you have used a voice assistant at least once, please answer this questionnaire truthfully." Some 130 voice assistant users were recruited to undertake the survey (>30 participants per scenario). Table 2 shows the main demographic characteristics of the sample.

The data collected were analyzed through partial least squares-structural equation modeling (PLS-SEM), with SMARTPLS 3.0 software, a method widely employed in recent studies (e.g., Hu et al., 2021; Ringle & Sarstedt, 2016). We selected the PLS-SEM approach because it has strong ability to model latent constructs under conditions of non-normality and places less restrictive demands on sample size and residual distribution (Chin, 1998), and because it is especially effective when a cause-effect model is exploratory in nature and reveals unique associations not previously examined in empirical studies (Hair et al., 2014). This matches our case, as we compare consumer perceptions and behavioral intentions in the context of voice versus text recommendations.

## 3.2 | Results

### 3.2.1 | Measurement model

To evaluate the dimensional structure of the scales we first examined the factor loadings to provide an initial assessment of the constructs' internal consistency. As shown in Table 3, the factor loadings in their respective constructions exceeded the 0.7 threshold (Henseler et al., 2009). The composite reliability (CR) method was used to assess the reliability of the measurements. Table 3 shows the CR values, which surpass the suggested limit of 0.7 (Hair et al., 2014). The Cronbach's $\alpha$ values, similarly, were above the recommended 0.7 level for all reflective constructs (Nunnally & Bernstein, 1994). Convergent

**TABLE 2** Demographic characteristics of the sample

| | Frequency | % |
|---|---|---|
| Gender | | |
| Male | 68 | 52.3 |
| Female | 62 | 47.7 |
| Age | | |
| 18–25 | 50 | 38.5 |
| 26–30 | 27 | 20.8 |
| 31–35 | 19 | 14.6 |
| 36–40 | 17 | 13.1 |
| 41–45 | 7 | 5.4 |
| 46–50 | 5 | 3.8 |
| 51–55 | 4 | 3.1 |
| 56–60 | 1 | 0.8 |
| Education level | | |
| High/secondary school diploma | 28 | 21.2 |
| Undergraduate degree | 76 | 58.5 |
| Graduate degree | 26 | 20.3 |
| Citizenship | | |
| USA | 122 | 93.8 |
| Other | 8 | 6.2 |

**TABLE 1** Description of the recommendations used in the research, based on product type

| Search product | Experience product |
|---|---|
| "Last week, I bought a C. K. L suitcase. I can honestly say the design of the C. K. L suitcase and its easy handling are great. The suitcase is very spacious and elegant. The size is perfect! With pockets and multicompartments for socks, chargers…etc. Regarding the wheel maneuverability, the suitcase has innovative 360° spinner wheels. It has an affordable price. | "Last week I went to Summer House restaurant. I can honestly say the location of the Summer House restaurant and the service you will receive are great. The restaurant is very spacious and cosy. The location is perfect! Within walking distance to downtown. Concerning the menu, Summer House restaurant offers delicious dishes and cocktails at very reasonable prices. |
| I highly recommend it! | I highly recommend it! |
| I rate it with 4.8 out of 5 stars!" | I rate it with 4.8 out of 5 stars!" |

**TABLE 3** Reliability and validity indices

| Construct | Factor loadings | Cronbach's α | CR | AVE |
|---|---|---|---|---|
| Usefulness (adapted from Venkatesh et al., 2003; and Chang et al., 2016). | | 0.956 | 0.968 | 0.884 |
| USF.1 I find the recommendation very helpful. | 0.957 | | | |
| USF.2 I find the recommendation very useful. | 0.955 | | | |
| USF.3 I find the recommendation very informative. | 0.909 | | | |
| USF.4 The recommendation gave me the information I needed. | 0.940 | | | |
| Credibility (adapted from Meyer, 1988; and Filieri, 2015). | | 0.947 | 0.962 | 0.862 |
| CRD.1 I find the recommendation fair. | 0.938 | | | |
| CRD.2 I find the recommendation accurate. | 0.894 | | | |
| CRD.3 I find the recommendation credible. | 0.946 | | | |
| CRD.4 The arguments in the recommendation are convincing. | 0.936 | | | |
| Intention to follow (adapted from Casaló et al., 2011; and M. Y. Cheung et al., 2009). | | 0.951 | 0.965 | 0.873 |
| IF.1 I feel comfortable behaving according to the recommendation I obtained from the voice assistant/online review. | 0.943 | | | |
| IF.2 I do NOT hesitate to take into account the recommendation obtained from the voice assistant/ online review. | 0.884 | | | |
| IF.3 I feel secure in following the recommendation obtained from the voice assistant/online review. | 0.966 | | | |
| IF.4 I will definitely follow the recommendation obtained from the voice assistant/online review. | 0.940 | | | |
| Intention to purchase (adapted from Filieri, McLeay et al., 2018). | | 0.920 | 0.950 | 0.863 |
| IP.1 It is very likely that I would buy/choose the recommended suitcase/restaurant. | 0.966 | | | |
| IP.2 I would definitely purchase/choose the recommended suitcase/restaurant. | 0.921 | | | |
| IP.3 I would consider purchasing/choosing the recommended suitcase/restaurant. | 0.899 | | | |
| Intention to recommend (adapted from Hosany & Witham, 2010). | | 0.917 | 0.948 | 0.860 |
| IR.1 I would recommend the suitcase/restaurant to friends and relatives. | 0.963 | | | |
| IR.2 I would say positive things about the suitcase/restaurant to other people. | 0.948 | | | |
| IR.3 I would seldom miss an opportunity to tell others about the suitcase/restaurant. | 0.868 | | | |
| Voice modality. | 1.000 | 1.000 | 1.000 | 1.000 |

Abbreviations: AVE, average variance extracted; CR, composite reliability.

validity was evaluated using average variance extracted (AVE), which should be greater than 0.5 (Fornell & Larcker, 1981). The results in Table 3 show this criterion was met. Finally, the results in Table 4 validate the discriminant validity, as the square roots of the AVEs of each construct were higher than their corresponding interconstruct correlations (Fornell & Larcker, 1981).

Finally, as we collected data using a questionnaire, common method variance (CMV) was assessed; CMV may arise when respondents fill out questionnaires very quickly, in a more or less automatic manner (Podsakoff et al., 2003). In addition to the recommended procedural steps taken during the survey design and administration process (e.g., the participants were assured of anonymity and confidentiality), a single factor Harman's test was performed to test for CMV. The results indicated that no one general factor accounted for the majority of the variance, as CMV accounted for less than 50% of the variance (Baumgartner et al., 2021).

**TABLE 4** Discriminant validity

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Credibility (1) | **0.929** | | | | | |
| Intention to follow (2) | 0.824 | **0.934** | | | | |
| Intention to purchase (3) | 0.796 | 0.882 | **0.929** | | | |
| Intention to recommend (4) | 0.706 | 0.800 | 0.835 | **0.927** | | |
| Usefulness (5) | 0.843 | 0.797 | 0.775 | 0.719 | **0.940** | |
| Modality (6) | 0.168 | 0.067 | 0.019 | −0.049 | 0.176 | **1.000** |

*Note*: Diagonal elements (in bold) are the squared roots of the AVEs (the variance shared between the constructs and their measures). The interconstruct correlations are the off-diagonal elements.

Abbreviation: AVE, average variance extracted.

## 3.3 | Structural model

To confirm the quality of the experimental design of the structural model, we performed the same manipulation checks as used in the pretest. The results were again satisfactory, the scenarios were clearly understood, as were the questionnaire items. Having confirmed the appropriateness of the manipulation checks and the reliability and validity of the measurement scales, we then used PLS to assess the research model. The path relationships and R2 values of the endogenous latent variables were analyzed, and the statistical significances of the path relationships were assessed using a bootstrapping process with 5000 subsamples (Temme et al., 2006). Figure 2 summarizes the findings.

As to the research model's explanatory power, we can partly account for the main endogenous variables: intention to follow the recommendation (R2 = 0.716), intention to purchase the recommended product/service (R2 = 0.671), and intention to recommend the product/service (R2 = 0.551). Based on Chin (1998), these findings suggest that the R2 values are substantial. In addition, the model explains more 70% of perceived usefulness and 3% of perceived credibility.

As to modality, voice recommendations had a direct, positive effect on credibility ($\beta = 0.259$, $p < 0.05$), but no direct effect on usefulness ($\beta = -0.017$, $p > 0.1$). This supports H1a, but not H1b. Perceived credibility had a strong, positive effect on perceived usefulness ($\beta = 0.838$, $p < 0.001$), supporting H2. In addition, perceived credibility exerted positive effects on behavioral intentions to follow the recommendation ($\beta = 0.525$, $p < 0.001$), to purchase the recommended product/service ($\beta = 0.495$, $p < 0.001$), and to recommend the product/service ($\beta = 0346$, $p < 0.001$). Thus, hypotheses H3a, H3b, and H3c were supported. Similarly, perceived usefulness positively influenced intention to follow the recommendation ($\beta = 0.354$, $p < 0.001$), intention to purchase the recommended product/service ($\beta = 0.357$, $p < 0.01$), and intention to recommend the product/service ($\beta = 0.427$, $p < 0.001$), supporting H4a, H4b, and H4c, respectively.

PLS-SEM was also used to analyze the moderating effect of product type on the influence of recommendation modality on credibility and usefulness. In line with the criteria proposed by Ringle et al. (2012) about dummy moderating variables, the present study used a two-stage approach, and followed the guidelines proposed by Cohen (1988) to perform the moderation analysis. H5 proposed that the difference between (a) perceived credibility and (b) perceived usefulness in terms of voice and text recommendations will be greater for experience products than for search products. However, the influence of the interaction term (consumer product type*-modality) on credibility ($\beta = -0.330$, $t = 1.008$, $p > 0.1$) and usefulness ($\beta = 0.208$, $t = 1.083$, $p > 0.1$, respectively) was not significant. Thus, product type did not exert a moderating effect, thus H5 is not supported. On the other hand, product type exerted a direct influence on perceived credibility ($\beta = 0.344$, $t = 3.032$, $p < 0.01$)—that is, greater credibility is ascribed when the recommendation is about a search product—but no similar effect was seen with usefulness ($\beta = -0.042$, $t = 0.560$, $p > 0.1$).

Finally, the results showed that credibility may mediate the effects of recommendation modality on usefulness, and both credibility and usefulness may mediate the effects of recommendation modality on behavioral intentions. Thus, we analyzed these potentially mediated relationships by calculating the bias-corrected and accelerated confidence intervals of the effects (Chin, 2010; X. Zhao et al., 2010). The effects were shown to be significant when the intervals excluded the value 0. Table 5 shows the results of the mediation analysis. Although the direct effect of recommendation modality on usefulness was not significant, it has a positive, indirect effect via credibility. In addition, it was shown that recommendation modality exerts significant, positive indirect effects on intentions to follow the recommendation and to purchase the recommended product, and a marginal, indirect effect on intention to recommend the product, via perceived credibility and usefulness. Taking all the results into account, voice-based recommendations seem to create better perceptions and higher behavioral intentions than text-based recommendations.

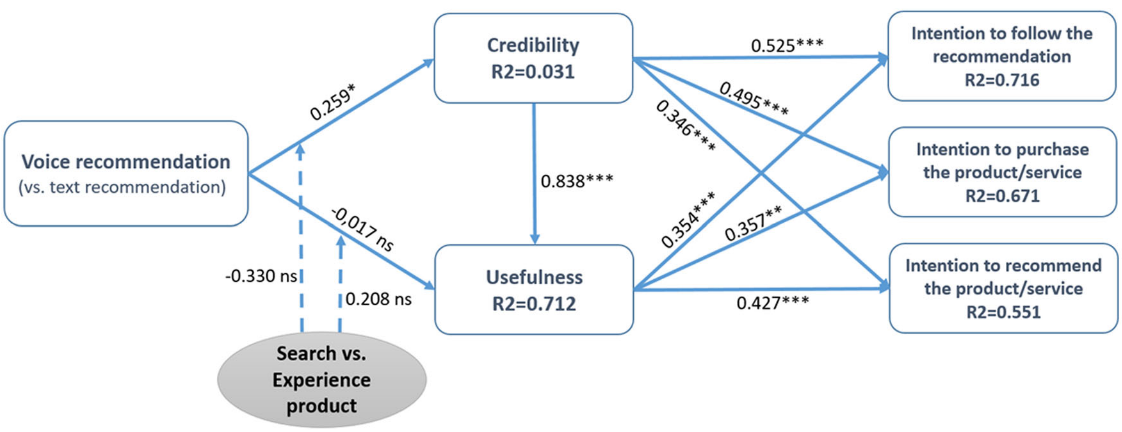



**FIGURE 2** Structural analysis of the research model: Direct effects. *$p < 0.05$; **$p < 0.01$; ***$p < 0.001$; ns: nonsignificant

TABLEE 5 Total indirect effects

| Effect | Mediator | Estimates | 95% bias-corrected and accelerated confidence interval | *t* | *p* |
|---|---|---|---|---|---|
| Modality (voice vs. text) → usefulness | Credibility | 0.217 | (0.021–0.406) | 2.192 | <0.05 |
| Modality (voice vs. text) → intention to follow | Credibility & usefulness | 0.207 | (0.005–0.411) | 2.004 | <0.05 |
| Modality (voice vs. text) → intention to purchase | Credibility & usefulness | 0.199 | (0.001–0.395) | 1.989 | <0.05 |
| Modality (voice vs. text) → intention to recommend | Credibility & usefulness | 0.175 | (−0.008 to 0.356) | 1.879 | <0.1 |

# 4 | STUDY 2

## 4.1 | Methodology

### 4.1.1 | Experimental design and measures

To improve the external validity and generalizability of the results, we conducted a second study to confirm that voice-based recommendations exert a greater influence on consumer behaviors than do text-based recommendations. Following Viglia et al. (2021) and Taylor et al. (2021), we presented participants with a situation in which they had to make choices, that is, whether to purchase a recommended product/service, and whether to recommend that product/service to other consumers. Thus, we aimed to examine the actual behaviors of participants toward the recommendations received.

This second study was also based on a between-subjects factorial experiment design. Specifically, a 2 (modality: voice vs. text) x 2 (product type: search vs. experience) x 2 (gender: male vs. female) factorial design was conducted. Thus, using the same modality and product type manipulations as in Study 1, we introduced gender as a control variable. Prior studies into online reviews have found that gender disclosure may affect consumers' perceptions of reviews (Ahn et al., 2022; Chevalier & Mayzlin, 2006), and even influence product sales (Duan et al., 2008). For the voice assistant scenarios, we manipulated the voice (masculine vs. feminine) using the same software as in Study 1. For the online review scenarios, we included information about the reviewer and, using female and male names, indicated whether the reviewer was male or female. Thereafter, in an online survey the participants were asked to complete a questionnaire in which they made their behavioral choices as regards the recommendations, that is, whether or not to follow the recommendation, purchase the recommended product/service and to recommend the product/service.

The items addressing the actual behavior of purchasing the recommended product/service were adapted from Viglia et al. (2021), Van Esch et al. (2021), and Mende et al. (2019), and the items for the actual behavior of recommending the product/service were adapted from Viglia et al. (2021) and Basil et al. (2006) (see Appendix E). Again, we excluded responses that completed the questionnaire very quickly and/or failed the attention checks.

### 4.1.2 | Manipulation checks

In this second study we checked whether the participants could identify gender (98% of participants confirmed the male gender condition, 100% confirmed the female gender condition), modality (99% of participants confirmed the text-based condition, 100% confirmed the voice-based condition), and product type (98% of participants confirmed the search product condition, and 97% confirmed the experience product condition; see Appendix F1). In addition, we controlled for realism, involvement, and review characteristics (length, valence quality, and brand familiarity of the reviewed product/service) using the same measures and scales as in Study 1. As to the realism scenario, there were no statistical differences in the means of user involvement, valence, length, quality of the recommendations, and brand familiarity (FR = 1.8, $p > 0.1$; FI = 2.46, $p > 0.1$; FV = 0.9, $p > 0.1$; FL = 1.44, $p > 0.1$; FQ = 1.24, $p > 0.1$), indicating that the variables were homogeneous in all conditions (see Appendix F2).

Finally, we checked the answers to the questions about actual behaviors by posing an additional question about each of the consumers' decisions. On the one hand, to verify the choice made to purchase the recommended product, the participants were asked to decide whether to purchase it, to look for other options or to keep the US85$ they had been given. On the other hand, to verify the choice made to recommend the product, we included an open question where the participants had to describe exactly what they would tell their families, friends, and acquaintances about the product. All the participants indicated they would recommend, and wrote positive things about, the product.

### 4.1.3 | Data collection and estimation procedure

The data collection took place during July 2022. The data were collected through an online survey questionnaire with a sample of 401 US-based voice assistant users (at least 50 per scenario). Prolific, a market research firm, was enlisted to assist in the process. As in Study 1, to participate the candidates had to have used voice assistants at least once previously. Table 6 displays the sample's demographic characteristics, which are similar to those of Study 1. The nature of the dependent variables, actual behaviors, dictates

TABLE 6 Demographic characteristics of the sample

| | Frequency | % |
|---|---|---|
| Gender | | |
| Male | 198 | 49.4 |
| Female | 193 | 48.1 |
| Prefer not to say | 10 | 2.5 |
| Age | | |
| 18–30 | 177 | 44.1 |
| 31–40 | 115 | 28.7 |
| 41–50 | 47 | 11.7 |
| 51–60 | 39 | 9.7 |
| Over 61 | 23 | 5.7 |
| Education level | | |
| Graduate degree | 78 | 19.5 |
| High/secondary school diploma | 119 | 29.7 |
| Primary school diploma | 4 | 1.0 |
| Undergraduate degree | 200 | 49.9 |
| Citizenship | | |
| USA | 360 | 89.8 |
| Other | 41 | 10.2 |

measurement through a single dichotomous (purchase or not purchase; recommend or not recommend) indicator. Thus, we codified purchase behaviors as follows: 1 = "Follow the recommendation and book the restaurant"; 0 = otherwise. Similarly, recommendation behavior was codified as follows: 1 = "Yes, I would say something positive"; 0 = Otherwise. Due to the dichotomous nature of the dependent measures, we conducted a logistic regression analysis (using SPSS v28 software) of the multivariate relationships between modality, gender, product type, and the actual behaviors of purchasing and recommending the product/service. This is consistent with recent works using logistic regression method to analyze experimental data (e.g., Agarwal et al., 2022; H. H. Liu & Chou, 2020).

## 4.2 | Results

Table 7 presents the results of the two logistic regressions, consumer choice (i.e., to purchase the product or not/recommend the product or not) being the dependent variable in each case. The findings of both logistic regressions show the effects of modality, gender, and product type on both purchase and recommendation behaviors. Voice (vs. text) modality, male (vs. female) gender, and search (vs. experience) products were positively associated with both behaviors. In other words, when the recommendation is about a search product, and provided by a male voice, there is a higher probability that people will purchase and recommend the product. Interestingly, these results

TABLE 7 Results of the logistic regression analysis

| | Dependent variables | | | |
|---|---|---|---|---|
| | To purchase: Yes/no | | To recommend: Yes/no | |
| Independent variables | β coefficient | Odds ratios | β coefficient | Odds ratios |
| Intercept | −1.847** | 0.158 | −0.313 | 0.731 |
| Modality (voice = 1) | 0.468** | 1.597 | 0.380* | 1.463 |
| Gender (male = 1) | 0.157* | 1.170 | 0.409* | 1.506 |
| Product type (search product = 1) | 1.045*** | 2.844 | 0.311* | 1.364 |

Abbreviation: ns, nonsignificant.
*<0.1
**$p < 0.01$; ***$p < 0.001$.

are consistent with the results of Study 1, which suggested that voice-based recommendations and search products attracted more positive perceptions and behavioral intentions. Similarly, the influence of recommendation modality (voice vs. text) was higher and more significant for purchase decisions than for recommendation decisions. This is also in line with the results of Study 1, which suggested that recommendation modality has a slightly higher influence—indirect via credibility and usefulness—on purchase intentions than it has on recommendation intentions.

# 5 | DISCUSSION

The results of the two experimental studies contribute to the general body of knowledge about e-WOM and voice assistants. The test of the comprehensive research model: (1) explains the effectiveness of voice (vs. text) recommendations for predicting consumer behaviors; (2) compares in which context (search vs. experience products) these recommendations are more effective; and (3) confirms that credibility and usefulness are key factors in the explanation of the effectiveness of voice recommendations and of text-based recommendations.

The first study evaluated the influence of the modality of the recommendation (text vs. voice) on users' key perceptions (credibility, usefulness), which subsequently may affect behavioral intentions related to the recommendation (i.e., intention to follow the recommendation, intention to recommend, and intention to purchase). In this respect, most of the proposed hypotheses were supported, and the key variables largely explained. The results confirmed that voice recommendations are perceived as more credible than text-based recommendations. These findings are consistent with the prior studies that suggested that voice messages transmit verbal, nonverbal, and social cues which convey effectiveness and credibility (Perloff, 1993; Sproull & Kiesler, 1986). In turn, perceived credibility is a key determinant of the usefulness of recommendations. When recommendations are perceived as credible, they provide good information that is likely to help consumers predict how an experience will turn out, which enhances the usefulness of the information. This finding is in line with previous works on consumer decision-making, specifically in the context of traveler's generated content platforms (e.g., Filieri, 2015) and social media platforms (Teng et al., 2014). In addition, the study results also suggested that voice (vs. text) recommendations influence usefulness via credibility. These findings are in line with previous research that supported the mediated role of credibility in predicting usefulness (McKnight & Kacmar, 2007; Saima & Khan, 2020).

The results also proved that both credibility and usefulness are key predictors of consumer behavioral intentions derived from recommendations. That is, the higher the credibility and usefulness of recommendations, the higher will be the consumer's intention to follow them, to make purchases and to recommend the product. Credibility and usefulness are widely studied consumer responses because of the impact they exert on product and brand evaluations (Craciun & Moore, 2019), and these effects have been confirmed by previous research in different contexts (e.g., M. Y. Cheung et al., 2009; Filieri, 2015; Filieri et al., 2015; Sussman & Siegal, 2003). On the one hand, review credibility is an important determinant that affects whether consumers are persuaded by a reviewer's opinions, as consumers want to avoid being manipulated by biased online reviews (Grewal et al., 2019). On the other hand, useful recommendations help consumers make the right purchase decisions. In addition, when consumers consider information about a given product/service to be useful and credible, they are more likely to recommend that product/service to their contacts and other consumers looking for similar information.

As to whether the influence of voice (vs. text) recommendations is more important for search than for experience products, the study discovered no interaction effect of recommendation modality and product type on perceived credibility or usefulness. These findings provide interesting insights into the role of product type on the effect of recommendation modality on the credibility and usefulness of recommendations, confirming that the effect of voice modality does not change based on whether a product is search or experience. On the other hand, it seems to have a direct effect on credibility, with recommendations, in general, being perceived as more credible with search products. This finding may be explained by perceived stability theory. The attributes of search products are more stable and homogeneous than the attributes of experience products (Hsieh et al., 2005), so recommendations for search products may be attributed to real, stable factors and, consequently, be considered as more credible.

The second study presented participants with a situation in which they had to make choices (i.e., to purchase the product or not, to recommend the product or not) based on the recommendation's modality (voice vs. text), product type (search vs. experience), with the gender of the voice assistant being controlled (masculine vs. feminine voice). It was shown that voice (vs. text) modality positively influenced the consumer's choice to purchase and recommend the product. This finding is in line with the communication clarity perspective (Grice, 1975), which suggests that the use of voice improves message clarity, helps listeners to focus on the ideas/proposals contained in the message and facilitates information exchange, which result in higher levels of effectiveness. In addition, this result is probably caused by the machine agent being perceived as human-like (e.g., possessing speaking/listening skills), as previous research has found that people develop more positive perceptions toward human-like robots (e.g., Eyssel & Hegel, 2012). Second, it was also seen that search products have a direct effect on both consumer choices, that is, whether or not to purchase and/or recommend. This is consistent with the results of the first study, as recommendations about search products are considered as more credible and may enhance purchasing and recommendation behaviors. Third, the results also showed that gender has a significant effect in predicting these consumer decisions. Focusing on voice recommendations, previous research has found that individuals are affected by gender stereotypes during their interactions with computers (Nass et al., 1997). While female voices may be perceived as warmer, and the industry trend is to use female rather than male voices (Tolmeijer et al., 2021), individuals perceive evaluations from computers with male voices as more valid than those from computers with female voices. This is especially important when consumers are judging a product's performance (e.g., suitcase/restaurant functions/performance, Ahn et al., 2022). This may be true in the context of the present study, as voice assistants are designed to offer individuals a useful and convenient way to search for product information/performance data (McLean & Osei-Frimpong, 2019).

## 5.1 | Theoretical implications

This research makes four main theoretical contributions. First, it contributes to the voice assistant and e-WOM literature by taking a first step toward understanding the influence of the voice recommendations made by voice assistants on consumer behaviors, in comparison to the influence of text recommendations on consumer behaviors (i.e., online consumer reviews). While voice assistants are a relatively new phenomenon, which is attracting considerable interest from academics and practitioners, little is known about their potential to affect consumer behaviors.

Specifically, the present study analyses the role of voice assistants in the consumer decision-making process by empirically testing the causal connection between recommendation modality (voice vs. text) and consumers' perceptions of credibility and usefulness, which in turn influence consumers' behavioral intentions (to follow the recommendation, to purchase and to recommend the product/service). The results suggested that recommendations received from voice assistants more strongly influence consumers' decisions than do text-based recommendations (e.g., online consumer reviews). By building a bridge between the literature on AI-based devices and e-WOM, this study highlights the power of voice technologies for increasing the effectiveness of product recommendations. Voice assistants can capture the consumer's preferences, humanize interactions, make recommendations more credible and useful, which leads to recommendation adoption.

Second, while previous researchers have applied MRT to organizational information (Daft & Lengel, 1986), emails (Schmitz & Fulk, 1991), websites (Patrakosol & Lee, 2013; mobile apps (Anandarajan et al., 2010), and social media (Xiao et al., 2021), the present study contributes to the MRT literature by applying it to an AI-based technology, voice assistants. More specifically, this research suggests that voice assistants are an AI-based technology able to interact using human-like cues (Chi et al., 2022). (Miller et al., 2013; Spence, 2019). Therefore, voice assistants can be regarded as a rich medium, as almost a face-to-face interpersonal interaction. Furthermore, the study contributes by supporting the proposal that the influence of E-WOM recommendations is affected by product type, that is, search vs experience (Park & Lee, 2009). We found no evidence of a moderating effect of product type on the influence of recommendation modality on credibility and usefulness; rather, this research found that recommendations about search products are perceived as more credible, and influence consumer decisions to a greater extent, than do recommendations about experience products.

Finally, the study showed that social psychology theory on gender stereotypes (in this context, that the perceived gender of a voice affects interpersonal conversations) can be applied to new domains, that is, we showed that gender voice affected AI–human interactions and consumers' behaviors based on voice assistants' recommendations. Although voice gender should continue to have an important influence in the design of voice assistants, little previous research has been undertaken in this field (e.g., Tolmeijer et al., 2021). In this respect, most virtual assistants convey gender-specific cues that can be classified as female (e.g., Feine et al., 2019). In turn, we found that male voices have greater influence on consumer behaviors, probably because of the research context. As stereotypical male (e.g., more assertive) and female (e.g., warmer) voices have different characteristics (Tolmeijer et al., 2021), their appropriateness may vary depending on the goals of the user-voice assistant interaction.

## 5.2 | Practical implications

As aforementioned, the main contribution of this study is the finding that, due to their greater perceived credibility and usefulness, voice assistants' recommendations have a stronger, more influential effect on consumer decision-making than do online consumer reviews (text-based recommendations). This finding highlights important points that should guide business managers (e.g., product managers, retail managers) and the designers of voice assistants.

The greater credibility ascribed to voice assistants' recommendations and its crucial role in shaping consumers' behaviors may lead product/retail managers to increase their use of voice technologies in their customer services and marketing communications (e.g., using voice assistants for launching/recommending new products). In addition, the research findings highlighted the important influence of perceived usefulness on consumer behaviors. Although voice assistant recommendations are perceived as more useful than online consumer reviews, practitioners should continue to focus on increasing the usefulness of the services provided by their virtual assistants. For example, supermarket/shop managers might think beyond the traditional role of voice assistants, that is, providing product recommendations, and use them to offer value-added services, such as providing recipes containing their brands, or even have them read out lists of ingredients to their users as they cook their food.

Furthermore, as the use of voice assistants proliferates, it becomes important for their designers to improve and innovate their voice technologies to increase the richness of the medium. With this aim, first, it is recommended they enhance their voice feature by introducing innovative technologies to convey human quirks (e.g., laughing, sneezing, sobbing) and carry fluctuations in tone when pronouncing words. Second, designers should develop new technologies to allow consumers to hold lengthy conversations. Designers, thus, should go beyond providing technologies that simply recommend, and develop means of offering near-human companionship throughout the purchase process. In addition, consumers tend to personalize their voice assistants when they give them useful recommendations (Capgemini, 2019). Therefore, it will become increasingly important for voice assistants to have personas and be more life-like. Furthermore, designers should solve accent and language problems by developing voice-enabled technologies that more readily recognize commands.

Finally, our findings suggest that practitioners should carefully consider the gender of voice assistants to ensure that they deliver the most effective and persuasive product recommendations. Specifically, and contrary to the industry mainstream, where most voice assistants are female (e.g., Feine et al., 2019), we found that a male voice was more influential. As aforementioned, masculine or feminine voices may be more appropriate based on the goal of the user-voice assistant interaction. Therefore, designers should not neglect male voices in voice assistant design. Similarly, our results suggested that voice assistants' recommendations are more effective for search products. Therefore, managers of this product type should be aware of the influence that voice assistants exert on their consumers.

## 5.3 | Limitations and further research

This research has limitations that open future research opportunities. First, the study focused on situational involvement, which it is temporary in nature as it disappears when the purchase is completed (Bloch, 1981). Therefore, future works might take into consideration long-term product involvement to assess if consumers' perceptions of the importance of the product over time influence the relationships proposed in this research. In addition, the data were collected from voice assistant users based only in the United States; however, several research works have noted the importance of incorporating cultural differences when analyzing AI-based technologies and consumer behaviors (P. H. Huang & Zhang, 2020). Thus, further studies might compare consumers' behaviors following AI-based voice assistant recommendations in different cultures, exploring, for example, potential differences between individualistic and collectivistic societies/countries. Finally, traditional psychology literature suggests that personality traits may significantly affect individuals' persuasion information processes (e.g., McCrae & Costa, 1987). Therefore, future research might examine how consumers' personality traits (e.g., the big five model) may affect their behavioral intentions toward voice assistants' recommendations.

## 6 | CONCLUSIONS

To the best of the authors' knowledge, this is the first empirical research to investigate the effect of voice assistants' recommendations on consumer behaviors, by comparing both voice recommendations made by voice assistants, and text recommendations made in online consumer reviews. So to do, this research applied MRT (Daft & Lengel, 1986) and carried out two experimental studies focused on behavioral intentions (Study 1) and consumers' decisions (Study 2). The major finding of the study is that voice assistants' recommendations are more effective than online consumer reviews in directly—Study 2—and indirectly influencing (mediating credibility and usefulness)—Study 1—consumer behaviors. The results of Study 1 confirmed, in the voice recommendation context, the important role of credibility and usefulness in shaping consumer behaviors, previously demonstrated in the online consumer review context. The results of Study 2 also showed that voice recommendations are more effective when delivered by a masculine voice. Finally, both studies suggested that recommendations for search products are regarded as more credible and effective than recommendations for experience products. These findings provide practitioners with a rich understanding of voice assistant technologies which they can use to their advantage in their business strategies.

### ACKNOWLEDGMENTS

This research was supported by the Spanish Ministry of Science and Innovation (PID2019-105468RB-I00) and the European Social Fund and the Government of Aragon (Group "METODO" S20_20R; LMP51_21 and pre-doctoral grant 2017-2021 C135/2017).

### CONFLICT OF INTEREST

The authors declare no conflict of interest.

### DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

### ORCID

*Carlos Flavián* http://orcid.org/0000-0001-7118-9013

### REFERENCES

Agarwal, J., Das, G., & Spence, M. T. (2022). Online group buying behavior: A study of experiential versus material purchases. *Psychology & Marketing*, *39*(10), 1946–1963.

Ahn, J., Kim, J., & Sung, Y. (2022). The effect of gender stereotypes on artificial intelligence recommendations. *Journal of Business Research*, *141*, 50–59.

Ajzen, I. (1991). The theory of planned behavior. *Organizational Behavior and Human Decision Processes*, *50*(2), 179–211.

Anandarajan, M., Zaman, M., Dai, Q., & Arinze, B. (2010). Generation Y adoption of instant messaging: An examination of the impact of social usefulness and media richness on use richness. *IEEE Transactions on Professional Communication*, *53*(2), 132–143.

Bagozzi, R. P., Belanche, D., Casaló, L. V., & Flavián, C. (2016). The role of anticipated emotions in purchase intentions. *Psychology & Marketing*, *33*(8), 629–645.

Balakrishnan, J., & Dwivedi, Y. K. (2021). Role of cognitive absorption in building user trust and experience. *Psychology & Marketing*, *38*(4), 643–668.

Bampo, M., Ewing, M. T., Mather, D. R., Stewart, D., & Wallace, M. (2008). The effects of the social structure of digital networks on viral marketing performance. *Information Systems Research*, *19*(3), 273–290.

Basil, D. Z., Ridgway, N. M., & Basil, M. D. (2006). Guilt appeals: The mediating effect of responsibility. *Psychology & Marketing*, *23*(12), 1035–1054.

Baumgartner, H., Weijters, B., & Pieters, R. (2021). The biasing effect of common method variance: Some clarifications. *Journal of the Academy of Marketing Science*, *49*(2), 221–235.

Belanche, D., Casaló, L. V., Schepers, J., & Flavián, C. (2021). Examining the effects of robots' physical appearance, warmth, and competence in frontline services: The humanness-value-loyalty model. *Psychology & Marketing*, *38*(12), 2357–2376. https://doi.org/10.1002/mar.21532

Berger, J., & Iyengar, R. (2013). Communication channels and word of mouth: How the medium shapes the message. *Journal of Consumer Research*, *40*(3), 567–579.

Bjork, R. A. (1970). Positive forgetting: The noninterference of items intentionally forgotten. *Journal of Verbal Learning and Verbal Behavior*, *9*(3), 255–268.

Bloch, P. H. (1981). An exploration into the scaling of consumers' involvement with a product class. ACR North American Advances.

Bräuer, P., & Mazarakis, A. (2022). "Alexa, can we design gamification without a screen?"—Implementing cooperative and competitive audio-gamification for intelligent virtual assistants. *Computers in Human Behavior*, *135*, 107362.

Brill, T. M., Munoz, L., & Miller, R. J. (2019). Siri, alexa, and other digital assistants: A study of customer satisfaction with artificial intelligence applications. *Journal of Marketing Management*, *35*(15–16), 1401–1436.

Campbell, J. (2006). Media richness, communication apprehension and participation in group videoconferencing. *Journal of Information, Information Technology & Organizations*, *1*, 89–96.

Cantallops, S. A., & Salvi, F. (2014). New consumer behavior: A review of research on eWOM and hotels. *International Journal of Hospitality Management*, *36*, 41–51.

Capgemini. (2019). Smart talk. How organizations and consumers are embracing voice and chat assistants. Capgemini Research Institute. https://www.capgemini.com/wp-content/uploads/2019/09/Report_Conversational-Interfaces-1.pdf

Caplan, S. E., Perse, E. M., & Gennaria, J. E. (2014). Computer-mediated technology and social interaction, *Communication technology and social change* (pp. 53–72). Routledge.

Casaló, L. V., Flavián, C., & Guinalíu, M. (2010). Determinants of the intention to participate in firm-hosted online travel communities and effects on consumer behavioral intentions. *Tourism Management*, *31*(6), 898–911.

Casaló, L. V., Flavián, C., & Guinalíu, M. (2011). Understanding the intention to follow the advice obtained in an online travel community. *Computers in Human Behavior*, *27*(2), 622–633.

Chang, Y., Wong, S. F., & Park, M. C. (2016). A three-tier ICT access model for intention to participate online: A comparison of developed and developing countries. *Information Development*, *32*(3), 226–242.

Chatterjee, P. (2001). *Online reviews: Do consumers use them? In NA—Advances in consumer research* (Vol. 28, pp. 129–133). Association for Consumer Research.

Cheng, Y. H., & Ho, H. Y. (2015). Social influence's impact on reader perceptions of online reviews. *Journal of Business Research*, *68*(4), 883–887.

Chérif, E., & Lemoine, J. F. (2019). Anthropomorphic virtual assistants and the reactions of Internet users: An experiment on the assistant's voice. *Recherche et Applications en Marketing (English Edition)*, *34*(1), 28–47.

Cheung, C. M. K., & Thadani, D. R. (2012). The impact of electronic word-of-mouth communication: A literature analysis and integrative model. *Decision Support Systems*, *54*(1), 461–470.

Cheung, C. M. K., Lee, M. K. O., & Rabjohn, N. (2008). The impact of electronic word-of-mouth: The adoption of online opinions in online customer communities. *Internet Research*, *18*(1), 229–247.

Cheung, M. Y., Luo, C., Sia, C. L., & Chen, H. (2009). Credibility of electronic word-of-mouth: Informational and normative determinants of on-line consumer recommendations. *International Journal of Electronic Commerce*, *13*(4), 9–38.

Chevalier, J. A., & Mayzlin, D. (2006). The effect of word of mouth on sales: Online book reviews. *Journal of Marketing Research*, *43*(3), 345–354.

Chin, W. W. (1998). Commentary: Issues and opinion on structural equation modeling. MIS quarterly, vii-xvi.

Chin, W. W. (2010). How to write up and report PLS analyses. In V. Esposito, W. W. Chin, J. Henseler, & H. Wang (Eds.), *Handbook of partial least squares* (pp. 655–690). Springer.

Chi, O. H., Gursoy, D., & Chi, C. G. (2022). Tourists' attitudes toward the use of artificially intelligent (AI) devices in tourism service delivery: Moderating role of service value seeking. *Journal of Travel Research*, *61*(1), 170–185.

Chiu, C. M., Chang, C. C., Cheng, H. L., & Fang, Y. H. (2009). Determinants of customer repurchase intention in online shopping. *Online Information Review*, *33*(4), 761–784.

Cohen, J. (1988). *Statistical power analysis for the behavioral sciences* (2nd ed.). Lawrence Erlbaum.

ComScore. (2021). As smart speakers evolve, so do consumers. Retrieved January 6, 2022, from https://www.comscore.com/Insights/Blog/As-Smart-Speakers-Evolve-So-Do-Consumers

Craciun, G., & Moore, K. (2019). Credibility of negative online product reviews: Reviewer gender, reputation and emotion effects. *Computers in Human Behavior*, *97*, 104–115.

Daft, R. L., & Lengel, R. H. (1986). Organizational information requirements, media richness and structural design. *Management Science*, *32*(5), 554–571.

Dellaert, B. G. C., Shu, S. B., Arentze, T. A., Baker, T., Diehl, K., Donkers, B., Fast, N. J., Häubl, G., Johnson, H., Karmarkar, U. R., Oppewal, H., Schmitt, B. H., Schroeder, J., Spiller, S. A., & Steffel, M. (2020). Consumer decisions with artificially intelligent voice assistants. *Marketing Letters*, *31*(4), 335–347.

Dowling, G. R., & Staelin, R. (1994). A model of perceived risk and intended risk-handling activity. *Journal of Consumer Research*, *21*(1), 119–134.

Duan, W., Gu, B., & Whinston, A. (2008). The dynamics of online word-of-mouth and product sales—An empirical investigation of the movie industry. *Journal of Retailing*, *84*(2), 233–242.

Van Esch, P., Cui, Y., & Jain, S. P. (2021). Self-efficacy and callousness in consumer judgments of AI-enabled checkouts. *Psychology & Marketing*, *38*(7), 1081–1100.

Eyssel, F., & Hegel, F. (2012). (S)he's got the look: Gender stereotyping of robots 1. *Journal of Applied Social Psychology*, *42*(9), 2213–2230.

Feine, J., Gnewuch, U., Morana, S., & Maedche, A. (2019). A taxonomy of social cues for conversational agents. *International Journal of Human-Computer Studies*, *132*, 138–161.

Filieri, R. (2015). What makes online reviews helpful? A diagnosticity-adoption framework to explain informational and normative influences in e-WOM. *Journal of Business Research*, *68*(6), 1261–1270.

Filieri, R. (2016). What makes an online consumer review trustworthy? *Annals of Tourism Research*, *58*, 46–64.

Filieri, R., & McLeay, F. (2014). E-WOM and accommodation: An analysis of the factors that influence travelers' adoption of information from online reviews. *Journal of Travel Research*, *53*(1), 44–57.

Filieri, R., Acikgoz, F., Ndou, V., & Dwivedi, Y. (2020). Is TripAdvisor still relevant? The influence of review credibility, review usefulness, and ease of use on consumers' continuance intention. *International Journal of Contemporary Hospitality Management*, *53*(1), 369–488.

Filieri, R., Alguezaui, S., & McLeay, F. (2015). Why do travelers trust TripAdvisor? Antecedents of trust towards consumer-generated media and its influence on recommendation adoption and word of mouth. *Tourism Management*, *51*, 174–185.

Filieri, R., Hofacker, C. F., & Alguezaui, S. (2018). What makes information in online consumer reviews diagnostic over time? The role of review relevancy, factuality, currency, source credibility and ranking score. *Computers in Human Behavior*, *80*, 122–131.

Filieri, R., McLeay, F., Tsui, B., & Lin, Z. (2018). Consumer perceptions of information helpfulness and determinants of purchase intention in online consumer reviews of services. *Information & Management*, *55*(8), 956–970.

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research*, *18*(1), 39–50.

Foster, M. E., & Oberlander, J. (2007). Corpus-based generation of head and eyebrow motion for an embodied conversational agent. *Language Resources and Evaluation*, *41*(3), 305–323.

Iribarren, M. (2021). Global digital traveler research report. https://www.travelport.com/company/media-center/press-releases/2018-11-13/travelers-say-technology-key-their-travel-experience

Grewal, L., Stephen, A. T., & Coleman, N. V. (2019). When posting about products on social media backfires: The negative effects of consumer identity signaling on product interest. *Journal of Marketing Research*, *56*(2), 197–210.

Grice, H. P. (1975). Logic and conversation. In P. Cole, & J. Morgan (Eds.), *Syntax and semantics: Vol. 3. Speech acts* (pp. 41–58). Seminar Press.

Grover, T., Rowan, K., Suh, J., McDuff, D., & Czerwinski, M. (2020). Design and evaluation of intelligent agent prototypes for assistance with focus and productivity at work. Proceedings of the 25th International Conference on Intelligent User Interfaces (390–400).

Hair, J. F., Jr., Sarstedt, M., Hopkins, L., & Kuppelwieser, V. G. (2014). Partial least squares structural equation modeling (PLS-SEM): *An emerging tool in business research. European Business Review*, *26*(2), 106–121. https://doi.org/10.1108/EBR-10-2013-0128

Hennig-Thurau, T., Gwinner, K. P., Walsh, G., & Gremler, D. D. (2004). Electronic word-of-mouth via consumer-opinion platforms: What motivates consumers to articulate themselves on the Internet? *Journal of Interactive Marketing*, *18*(1), 38–52.

Henseler, J., Ringle, C. M., & Sinkovics, R. R. (2009). The use of partial least squares path modeling in international marketing, *New challenges to international marketing*. Emerald Group Publishing Limited.

Hernandez-Ortega, B., & Ferreira, I. (2021). How smart experiences build service loyalty: The importance of consumer love for smart voice assistants. *Psychology & Marketing*, *38*(7), 1122–1139.

Hosany, S., & Witham, M. (2010). Dimensions of cruisers' experiences, satisfaction, and intention to recommend. *Journal of Travel Research*, *49*(3), 351–364.

Hsieh, Y. C., Chiu, H. C., & Chiang, M. Y. (2005). Maintaining a committed online customer: A study across search-experience-credence products. *Journal of Retailing*, *81*(1), 75–82.

Hu, H., Yang, Y., & Zhang, J. (2021). Avoiding panic during pandemics: COVID-19 and tourism-related businesses. *Tourism Management*, *86*, 104316.

Huang, P. H., & Zhang, Y. S. (2020). Media richness and adoption intention of voice assistants: A cross-cultural study. *International Journal of Multinational Corporation Strategy*, *3*(2), 108–129.

Huang, P., Lurie, N. H., & Mitra, S. (2009). Searching for experience on the web: An empirical examination of consumer behavior for search and experience goods. *Journal of Marketing*, *73*(2), 55–69.

Jiménez, F. R., & Mendoza, N. A. (2013). Too popular to ignore: The influence of online reviews on purchase intentions of search and experience products. *Journal of Interactive Marketing*, *27*(3), 226–235.

Kamins, M. A., Brand, M. J., Hoeke, S. A., & Moe, J. C. (1989). Two-sided versus one-sided celebrity endorsements: The impact on advertising effectiveness and credibility. *Journal of Advertising*, *18*(2), 4–10.

Keil, M., & Johnson, R. D. (2002). Feedback channels: Using social presence theory to compare voice mail to e-mail. *Journal of Information Systems Education*, *13*(4), 295.

Keller, E. (2007). Unleashing the power of word of mouth: Creating brand advocacy to drive growth. *Journal of Advertising Research*, *47*(4), 448–452.

Klaus, P., & Zaichkowsky, J. (2020). AI voice bots: A services marketing research agenda. *Journal of Services Marketing*, *34*(3), 389–398.

Klein, L. R. (1998). Evaluating the potential of interactive media through a new lens: Search versus experience goods. *Journal of Business Research*, *41*(3), 195–203.

Kontogiorgos, D., Pereira, A., Andersson, O., Koivisto, M., Gonzalez Rabal, E., Vartiainen, V., & Gustafson, J. (2019). The effects of anthropomorphism and non-verbal social behaviour in virtual assistants. In Proceedings of the 19th ACM International Conference on Intelligent Virtual Agents. 133–140.

Kory Westlund, J. M., Jeong, S., Park, H. W., Ronfard, S., Adhikari, A., Harris, P. L., DeSteno, D., & Breazeal, C. L. (2017). Flat vs. expressive storytelling: Young children's learning and retention of a social robot's narrative. *Frontiers in Human Neuroscience*, *11*, 295.

Kraus, D. (2019). *Factors influencing customer satisfaction: Differences between E-commerce and voice commerce*. Grin Verlag.

Lau, J., Zimmerman, B., & Schaub, F. (2018), Alexa, are you listening? Privacy perceptions, concerns and privacy-seeking behaviors with smart speakers, Proceedings of the ACM on Human-Computer Interaction, 2(CSCW), 1–31.

Lieberman, A., & Schroeder, J. (2020). Two social lives: How differences between online and offline interaction influence social outcomes. *Current Opinion in Psychology*, *31*, 16–21.

Lim, W. M., Kumar, S., Verma, S., & Chaturvedi, R. (2022). Alexa, what do we know about conversational commerce? Insights from a systematic literature review. *Psychology & Marketing*, *39*(6), 1129–1155.

Lim, Y., & Van Der Heide, B. (2015). Evaluating the wisdom of strangers: The perceived credibility of online consumer reviews on Yelp. *Journal of Computer-Mediated Communication*, *20*(1), 67–82.

Ling, E. C., Tussyadiah, I., Tuomi, A., Stienmetz, J., & Ioannou, A. (2021). Factors influencing users' adoption and use of conversational agents: A systematic review. *Psychology & Marketing*, *38*(7), 1031–1051. https://doi.org/10.1002/mar.21491

Lis, B., & Post, M. (2013). What's on TV? the impact of brand image and celebrity credibility on television consumption from an ingredient branding perspective. *International Journal on Media Management*, *15*(4), 229–244.

Liu, H. H., & Chou, H. Y. (2020). Payment formats and hedonic consumption. *Psychology & Marketing*, *37*(11), 1586–1600.

Liu, B., & Sundar, S. S. (2018). Should machines express sympathy and empathy? Experiments with a health advice chatbot. *Cyberpsychology, Behavior and Social Networking*, *21*(10), 625–636.

Lo, A. S., & Yao, S. S. (2019). What makes hotel online reviews credible? An investigation of the roles of reviewer expertise, review rating consistency and review valence. *International Journal of Contemporary Hospitality Management*, *11*(4), 228–241.

Maity, M., Dass, M., & Kumar, P. (2018). The impact of media richness on consumer information search and choice. *Journal of Business Research*, *87*, 36–45.

Mariani, M. M., Perez-Vega, R., & Wirtz, J. (2021). AI in marketing, consumer research and psychology: A systematic literature review and research agenda. *Psychology & Marketing*, *39*(4),755–776. https://doi.org/10.1002/mar.21619

Mather, D., Neuninger, R., & Duncan, T. (2016). Consumer's scepticism of wine awards: A study of consumers' use of wine awards. *Journal of Retailing and Consumer Services*, *35*, 98–105.

Ma, W. W. K., & Chan, A. (2014). Knowledge sharing and social media: Altruism, perceived online attachment motivation, and perceived online relationship commitment. *Computers in Human Behavior*, *39*, 51–58.

McCrae, R. R., & Costa, P. T. (1987). Validation of the five-factor model of personality across instruments and observers. *Journal of Personality and Social Psychology*, *52*(1), 81–90.

McKnight, D. H., & Kacmar, C. J. (2007). Factors and effects of information credibility. In Proceedings of the ninth international conference on Electronic commerce. 423–432.

McLean, G., & Osei-Frimpong, K. (2019). Hey alexa examine the variables influencing the use of artificial intelligent in-home voice assistants. *Computers in Human Behavior*, *99*, 28–37.

Mende, M., Scott, M. L., van Doorn, J., Grewal, D., & Shanks, I. (2019). Service robots rising: How humanoid robots influence service experiences and elicit compensatory consumer responses. *Journal of Marketing Research*, *56*(4), 535–556.

Meyer, P. (1988). Defining and measuring credibility of newspapers: Developing an index. *Journalism quarterly*, *65*(3), 567–574.

Miller, D. I., Talbot, V., Gagnon, M., & Messier, C. (2013). Administration of neuropsychological tests using interactive voice response technology in the elderly: Validation and limitations. *Frontiers in Neurology*, *4*, 107.

Moon, Y., & Nass, C. (1996). How "real" are computer personalities? Psychological responses to personality types in human-computer interaction. *Communication Research*, *23*(6), 651–674.

Moriuchi, E. (2019). Okay, *Grover* ogle! An empirical study on voice assistants on consumer engagement and loyalty. *Psychology & Marketing*, *36*(5), 489–501.

Mudambi, S. M., & Schuff, D. (2010). Research note: What makes a helpful online review? A study of customer reviews on Amazon. com. *MIS Quarterly*, *34*, 185–200.

Nass, C., Moon, Y., & Green, N. (1997). Are machines gender neutral? Gender-stereotypic responses to computers with voices. *Journal of Applied Social Psychology*, *27*(10), 864–876.

Nelson, P. (1970). Information and consumer behavior. *Journal of Political Economy*, *78*(2), 311–329.

Nunnally, J., & Bernstein, I. (1994). Psychometric theory. In S. Polger, & S. A. Thoma (Eds.), *Introduction to research in the health sciences*. Churchill Livingstone, McGraw Hill.

Ostrom, A. L., Fotheringham, D., & Bitner, M. J. (2019). Customer acceptance of AI in service encounters: Understanding antecedents and consequences, *Handbook of service science* (Vol. II, pp. 77–103). Springer. https://doi.org/10.1007/978-3-319-98512-1_5

Park, C., & Lee, T. M. (2009). Information direction, website reputation and eWOM effect: A moderating role of product type. *Journal of Business Research*, *62*(1), 61–67.

Patrakosol, B., & Lee, S. M. (2013). Information richness on service business websites. *Service Business*, *7*(2), 329–346.

Perloff, R. M. (1993). Third-person effect research 1983–1992: A review and synthesis. *International Journal of Public Opinion Research*, *5*(2), 167–184.

Petrock, V. (2020). *Voice assistant and smart speaker users 2020—Insider intelligence. Insider intelligence* Retrieved March 8, 2022, from https://www.insiderintelligence.com/content/voice-assistant-and-smart-speaker-users-2020

Petty, R. E., Briñol, P., & Tormala, Z. L. (2002). Thought confidence as a determinant of persuasion: The self-validation hypothesis. *Journal of Personality and Social Psychology*, *82*(5), 722–741.

Pitardi, V., & Marriott, H. R. (2021). Alexa, she's not human but… unveiling the drivers of consumers' trust in voice-based artificial intelligence. *Psychology & Marketing*, *38*(4), 626–642.

Pizzi, G., Scarpi, D., & Pantano, E. (2021). Artificial intelligence and the new forms of interaction: Who has the control when interacting with a chatbot? *Journal of Business Research*, *129*, 878–890.

Podsakoff, P. M., MacKenzie, S. B., Lee, J. Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. *Journal of Applied Psychology*, *88*(879), 879–903.

Purnawirawan, N., De Pelsmacker, P., & Dens, N. (2012). Balance and sequence in online reviews: How perceived usefulness affects attitudes and intentions. *Journal of Interactive Marketing*, *26*(4), 244–255.

Qiu, L., & Benbasat, I. (2009). Evaluating anthropomorphic product recommendation agents: A social relationship perspective to designing information systems. *Journal of Management Information Systems*, *25*(4), 145–182.

Rhee, C. E., & Choi, J. (2020). Effects of personalization and social role in voice shopping: An experimental study on product recommendation by a conversational voice agent. *Computers in Human Behavior*, *109*(1), 106359.

Ringle, C. M., Sarstedt, M., & Straub, D. W. (2012). Editor's comments: A critical look at the use of PLS-SEM in "MIS Quarterly". MIS quarterly, iii-xiv.

Ringle, C. M., & Sarstedt, M. (2016). Gain more insight from your PLS-SEM results: The importance-performance map analysis. *Industrial Management & Data Systems*, *56*, 897–909.

Rosenthal-von der Pütten, A. M., Straßmann, C., & Krämer, N. C. (2016). Robots or agents–neither helps you more or less during second language acquisition.In *prodeedings of the 16th International conference on intelligent virtual agents* (pp. 256–268). Springer, Cham.

Rosenthal-von der Pütten, A. M., Straßmann, C., Yaghoubzadeh, R., Kopp, S., & Krämer, N. C. (2019). Dominant and submissive nonverbal behavior of virtual agents and its effects on evaluation and negotiation outcome in different age groups. *Computers in Human Behavior*, *90*, 397–409.

Rudovic, O., Lee, J., Dai, M., Schuller, B., & Picard, R. W. (2018). Personalized machine learning for robot perception of affect and engagement in autism therapy. *Science Robotics*, *3*, 19.

Saima, I., & Khan, M. A. (2020). Effect of social media influencer marketing on consumers' purchase intention and the mediating role of credibility. *Journal of Promotion Management*, *27*(4), 503–523.

Schepers, J., Belanche, D., Casaló, L. V., & Flavián, C. (2022). How smart should a service robot be? *Journal of Service Research*, *25*(4), 565–582. https://doi.org/10.1177/10946705221107704

Schindler, R. M., & Bickart, B. (2012). Perceived helpfulness of online consumer reviews: The role of message content and style. *Journal of Consumer Behaviour*, *11*(3), 234–243.

Schmitz, J., & Fulk, J. (1991). Organizational colleagues, media richness, and electronic mail: A test of the social influence model of technology use. *Communication Research*, *18*(4), 487–523.

Schweitzer, F., Belk, R., Jordan, W., & Ortner, M. (2019). Servant, friend or master? The relationships users build with voice-controlled smart devices. *Journal of Marketing Management*, *35*(7-8), 693–715.

Sciuto, A., Saini, A., Forlizzi, J., & Hong, J. I. (2018). "Hey alexa, what's up?" A mixed-methods studies of in-home conversational agent usage. In Proceedings of the 2018 Designing Interactive Systems Conference. 857–868.

Spence, P. R. (2019). Searching for questions, original thoughts, or advancing theory: Human-machine communication. *Computers in Human Behavior*, *90*, 285–287.

Sproull, L., & Kiesler, S. (1986). Reducing social context cues: Electronic mail in organizational communication. *Management Science*, *32*(11), 1492–1512.

Statista. (2021). Number of digital voice assistants in use worldwide 2019–2024. Retrieved December 22, 2021, from https://www.statista.com/statistics/973815/worldwide-digital-voice-assistant-in-use/

Statista. (2022). Global smart speaker market share 2021. Statista. Retrieved January 12, 2022, from https://www.statista.com/statistics/792604/worldwide-smart-speaker-market-share/

Stoll, B., Edwards, C., & Edwards, A. (2016). "Why aren't you a sassy little thing": The effects of robot-enacted guilt trips on credibility and consensus in a negotiation. *Communication Studies*, *67*(5), 530–547.

Suh, K. S. (1999). Impact of communication medium on task performance and satisfaction: An examination of media-richness theory. *Information & Management*, *35*(5), 295–312.

Sussman, S. W., & Siegal, W. S. (2003). Informational influence in organizations: An integrated approach to knowledge adoption. *Information Systems Research*, *14*(1), 47–65.

Tabassum, M., Kosiński, T., Frik, A., Malkin, N., Wijesekera, P., Egelman, S., & Lipford, H. R. (2019). Investigating users' preferences and expectations for always-listening voice assistants. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies*, *3*(4), 1–23.

Tassiello, V., Tillotson, J. S., & Rome, A. S. (2021). "Alexa, order me a pizza!": *The mediating role of psychological power in the consumer–voice assistant interaction. Psychology & Marketing*, *38*(7), 1069–1080. https://doi.org/10.1002/mar.21488

Taylor, K. M., Hajmohammad, S., & Vachon, S. (2021). Activist engagement and industry-level change: Adoption of new practices by observing firms. *Industrial Marketing Management*, *92*, 295–306.

Temme, D., Kreis, H., & Hildebrandt, L. (2006). PLS path modeling: A software review (No. 2006, 084). SFB 649 discussion paper.

Teng, S., Khong, K. W., Goh, W. W., & Chong, A. Y. L. (2014). Examining the antecedents of persuasive eWOM messages in social media. *Online Information Review*, *17*(8), 1051–1077.

Tolmeijer, S., Zierau, N., Janson, A., Wahdatehagh, J. S., Leimeister, J. M. M., & Bernstein, A. (2021). Female by default?—Exploring the effect of voice assistant gender and pitch on trait and trust attribution. In extended abstracts of the 2021 CHI Conference on Human Factors in Computing Systems (pp. 1–7).

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS quarterly*, *27*, 425–478.

Verma, S., & Yadav, N. (2021). Past, present, and future of electronic word of mouth (EWOM). *Journal of Interactive Marketing*, *53*, 111–128.

Viglia, G., Minazzi, R., & Buhalis, D. (2016). The influence of e-word-of-mouth on hotel occupancy rate. *International Journal of Contemporary Hospitality Management*, *28*(9), 2035–2051.

Viglia, G., Zaefarian, G., & Ulqinaku, A. (2021). How to design good experiments in marketing: Types, examples, and methods. *Industrial Marketing Management*, *98*, 193–206.

Wathen, C. N., & Burkell, J. (2002). Believe it or not: Factors influencing credibility on the web. *Journal of the American Society for Information Science and Technology*, *53*(2), 134–144.

Weathers, D., Sharma, S., & Wood, S. L. (2007). Effects of online communication practices on consumer perceptions of performance uncertainty for search and experience goods. *Journal of Retailing*, *83*(4), 393–401.

Xiao, H., Zhang, Z., & Zhang, L. (2021). An investigation on information quality, media richness, and social media fatigue during the disruptions of COVID-19 pandemic. *Current Psychology*, *17*(2)1–12. https://doi.org/10.1007/s12144-021-02253-x

Zaichkowsky, J. L. (1985). Measuring the involvement construct. *Journal of Consumer Research*, *12*(3), 341–352.

Zaichkowsky, J. L. (1986). Conceptualizing involvement. *Journal of Advertising*, *15*(2), 4–34.

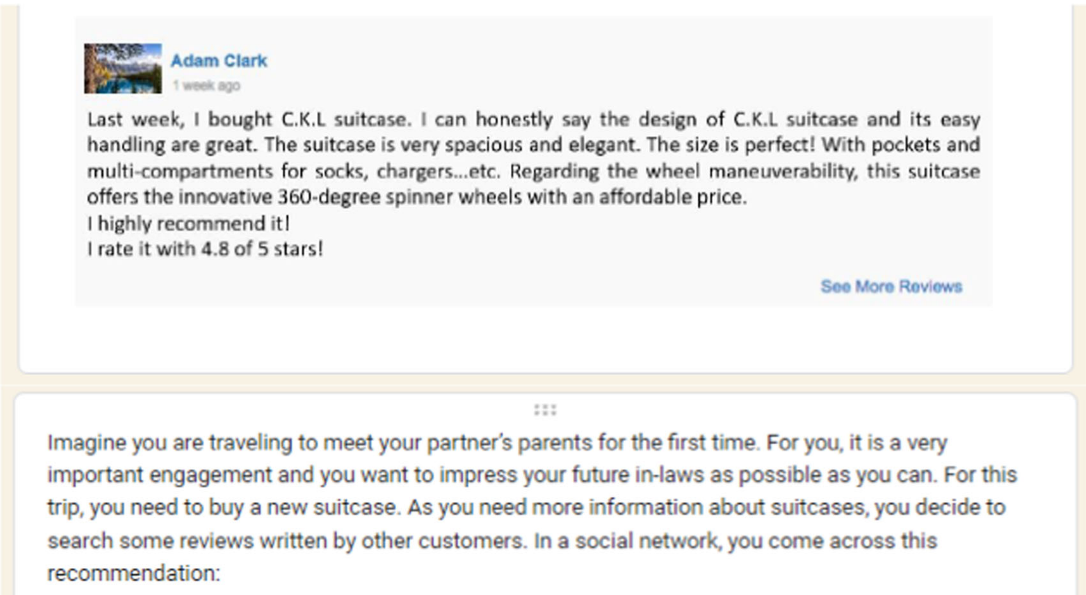
Zhang, H., Zhou, S., & Shen, B. (2014). Public trust: A comprehensive investigation on perceived media credibility in China. *Asian Journal of Communication*, *24*(2), 158–172.

Zhao, X., Lynch, J. G., & Chen, Q. (2010). Reconsidering Baron and Kenny: Myths and truths about mediation analysis. *Journal of Consumer Research*, *37*(2), 197–206.

Zhao, J., & Patrick Rau, P. L. (2020). Merging and synchronizing corporate and personal voice agents: Comparison of voice agents acting as a secretary and a housekeeper. *Computers in Human Behavior*, *108*, 106334.


**How to cite this article:** Flavián, C., Akdim, K., & Casaló, L. V. (2022). Effects of voice assistant recommendations on consumer behaviour. *Psychology & Marketing*, 1–19. https://doi.org/10.1002/mar.21765

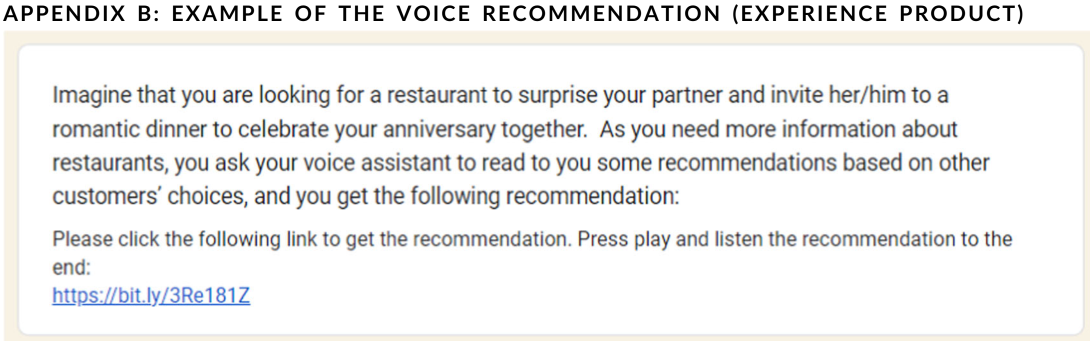
## APPENDIX A: EXAMPLE OF THE TEXT-BASED RECOMMENDATION (SEARCH PRODUCT)



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

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:

## APPENDIX B: EXAMPLE OF THE VOICE RECOMMENDATION (EXPERIENCE PRODUCT)



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 C1: MANIPULATION CHECKS OF THE STUDY 1 (PRETEST)

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

## APPENDIX C2: MANIPULATION CHECKS OF THE STUDY 1 (PRETEST)

| | Realism | Involvem-ent | 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 D: Realism and involvement items

| Construct |
|---|
| Realism (adapted from Bagozzi el al., 2016). |
| REAL 1. How likely the scenario would be realistic. |
| REAL 2. I How likely the scenario would be believable. |
| REAL 3. 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). |
| INVL 1. Imagining the situation, I would be very interested in the purchase decision. |
| INVL 2. 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. |

## APPENDIX E: ACTUAL BEHAVIOR ITEMS (STUDY 2)

| |
|---|
| Actual behavior to purchase the reviewed product (adapted from Mende et al., 2019; Van Esch et al., 2021; Viglia et al., 2021). |
| Please, make a decision based on the aforementioned recommendation and indicate your choice among the following options: |
| Follow the recommendation and book the restaurant. |
| Search for more recommendations. |
| Do nothing. |
| Now, imagine that you have 85$ available, and you have to decide what to do based on the aforementioned recommendation: |
| I will follow the recommendation and book the restaurant. |
| I will search for more recommendations. |
| I won't follow the recommendation and keep the 85$. |
| Actual behavior to recommend the recommended product (adapted from Basil et al., 2006; Viglia et al., 2021). |
| After reading the recommendation, would you tell your family, friends, and your acquaintances, about the service: |
| Yes, I would say something positive. |
| Yes, I would say something negative. |
| Yes, I would say something neutral. |
| I would say nothing. |
| Please, write what would you exactly tell your family, friends, and your acquaintances about the product: ______________________________________________________ |

(Continues)

## APPENDIX F1: MANIPULATION CHECKS OF THE STUDY 2

| Modality % | | Product type % | | Gender % | |
|---|---|---|---|---|---|
| Voice | Text | Search product | Experience product | Male | Female |
| 98 | 99 | 100 | 96 | 98 | 100 |

## APPENDIX F2: MANIPULATION CHECKS OF THE STUDY 2

| | Realism | Involvement | Valence | Length | Quality | Brand familiarity |
|---|---|---|---|---|---|---|
| *F* | 1.8 | 2.46 | 0.90 | 1.44 | 1.24 | 1.24 |
| *p* Value | 0.33 | 0.12 | 0.45 | 0.20 | 0.42 | 0.56 |