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**Exploring the role of personality, trust, and privacy in customer experience performance during voice shopping: Evidence from SEM and fuzzy set qualitative comparative analysis**

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# **Exploring the role of personality, trust, and privacy in customer experience performance during voice shopping: Evidence from SEM and fuzzy set qualitative comparative analysis**

## **Abstract**

Voice shopping is becoming increasingly popular among consumers due to the ubiquitous presence of artificial intelligence (AI)-based voice assistants in our daily lives. This study explores how personality, trust, privacy concerns, and prior experiences affect customer experience performance perceptions and the combinations of these factors that lead to high customer experience performance. Goldberg's Big Five Factors of personality, a contextualized theory of reasoned action (TRA-privacy), and recent literature on customer experience are used to develop and propose a conceptual research model. The model was tested using survey data from 224 US-based voice shoppers. The data were analyzed using partial least squares structural equation modeling (PLS-SEM) and fuzzy-set qualitative comparative analysis (fsQCA). PLS-SEM revealed that trust and privacy concerns mediate the relationship between personality (agreeableness, emotional instability, and conscientiousness) and voice shoppers' perceptions of customer experience performance. FsQCA reveals the combinations of these factors that lead to high perceptions of customer experience performance. This study contributes to voice shopping literature, which is a relatively understudied area of e-commerce research yet an increasingly popular shopping method.

**Keywords:** Voice shopping, personality, trust, privacy, prior experience, customer experience, smart speaker, personalization, artificial intelligence.

## 1. Introduction

Consumers increasingly expect to use digital platforms to obtain instant, frictionless, and memorable experiences during online shopping (Behrenbeck et al., 2015; Williams et al., 2020). Consequently, firms are constantly developing strategies to satisfy their customers' experiential needs through the latest technologies adopted by consumers (Fanderl et al., 2019; Lim et al., 2020). One strategy that many firms are currently using to stand out from the competition is by providing voice shopping services (Arnett et al., 2018; Fiona, 2017; Kinsella & Mutchier, 2019). The term *voice shopping* today mostly describes the use of artificial intelligence (AI)-based voice assistants like Amazon's Alexa and Google's Google Assistant to shop online. In the US alone, one in five consumers has performed voice shopping through this shopping channel, which is already worth over 1.8 billion USD (Kinsella & Mutchler, 2018a). This has led to calls for studies that explain how to improve individual customer experiences when using voice assistants through personalization (Davenport et al., 2020; de Barcelos Silva et al., 2020; Duan et al., 2019; Dwivedi et al., 2020). Prior research has established the importance of personalization in customer experience, especially when using AI-enabled technologies (Ameen et al., 2021; Tyrväinen et al., 2020; von Briel, 2018). It is also known that consumer personality is a key determinant of personalization in e-commerce (Kazeminia et al., 2019; Kim et al., 2015; Moon, 2002). Yet, no study investigates how/if personality affects customer experience during voice shopping in particular.

Understanding this phenomenon in the specific context of voice shopping is important not just for comparative reasons with other shopping channels but also because voice shopping has its specificities. For example, speech has been associated with personality traits like impulsive sensation seeking and aggression (Guidi et al., 2019). It has also been associated with emotions that determine customer satisfaction in voice commerce environments due to additional information contained in voice pitch and tone (Chang & Jang, 2009). Such data cannot be obtained from text-based channels like websites, giving voice shopping platforms the ability to provide personalized services by analyzing both text and voice signals. Also, trust and privacy play a central role in adopting AI-based voice assistants (Burbach et al., 2019; Liao et al., 2019; McLean & Osei-Frimpong, 2019). The personalization/privacy paradox makes it challenging for customers to obtain personalized services that will meet their experiential needs without trading off some of their privacy rights (Cloarec, 2020; Dwivedi et al., 2020; Lee & Rha, 2016). In voice shopping, this challenge is even more critical than in other e-commerce channels, given that voice shopping devices are usually "always listening" devices, exposing consumers to significant privacy concerns. Furthermore, trust mediates the relationship between personalization and AI-enabled customer experience because trust in the AI context also involves trusting the intentions of AI and its processes (Ameen et al., 2021). In other e-commerce channels, intentions and processes are predefined whereas AI-based voice assistants are expected to learn, understand, adapt, and evolve (Kaplan & Haenlein, 2019). Thus, trusting the vendor, voice

assistant service provider, and AI algorithms could affect the personalization of voice shopping services depending on how much the consumer is willing to share (even unconsciously) through voice shopping devices. All these specificities of voice shopping incite the need to investigate the relationship between personality and customer experience in the specific context of voice shopping.

This paper explores *how personality, trust, privacy concerns, and prior experiences affect consumer perceptions and lead to high customer experience performance*. It seeks to answer two main research questions: (i) how do personality, trust, privacy concerns, and prior experience affect consumer perceptions of customer experience performance? (ii) which configurations of these factors lead to high customer experience performance? This study is theoretically grounded in Goldberg's Big Five personality factors (Goldberg, 1990), a contextualized theory of reasoned action (TRA-privacy), and recent literature on customer experience. Using an online survey involving 224 US-based voice shoppers shows the relationships between personality, privacy concerns, trust, prior experience with smart speakers, and customer experience performance. Understanding the relationships between these concepts is essential for addressing personalization issues during the design and implementation of voice shopping services. Specifically, it reveals which personalities are more concerned about trust and privacy and the combinations that lead to high customer experience performance.

The rest of the paper presents a literature review of customer experience performance, voice shopping, and personality, discusses the theoretical framework and model development, followed by the methodology, results, discussion, and conclusions.

## **2. Literature review**

### **2.1. Customer experience performance**

Customer experience is holistically conceptualized as a multidimensional construct that characterizes a customer's cognitive, emotional, behavioral, sensorial, and social responses to service delivery processes (Hsu & Tsou, 2011; Lemon & Verhoef, 2016; Shi et al., 2020; Verhoef et al., 2009). It encompasses the total experience of the customer throughout the customer journey (Laming & Mason, 2014; Verhoef et al., 2009). Although measuring customer experience is critical for decision making, scholars and practitioners started measuring the overall customer experience only recently. Consequently, there is, to date, no well-established customer experience measurement scale or approach (Lemon & Verhoef, 2016; Morgeson et al., 2015). Customer satisfaction and Net Promoter Score (NPS) are currently the most popular approaches used to measure customer experience (Klie, 2013; Level 3 Communications, 2010; Santander UK, 2014). However, customer satisfaction only captures the customer's emotional state resulting from the customer's interaction with a platform or business (Verhoef, 2003). Thus, customer feedback metrics that focus on a specific dimension of customer experience are not strong predictors of customer experience performance, thus calling for the development of stronger measurement scales (Lemke et al., 2011; Lemon & Verhoef, 2016).

While some researchers have attempted to conceptualize customer experience and to evaluate its impact on shopping intentions (Hsu & Tsou, 2011; Shi et al., 2020), others have investigated tools that can help firms comprehensively measure their overall customer experience performance (Kuppelwieser & Klaus, 2020; Scheidt & Chung, 2019; Sperkova, 2019). Some are also investigating the antecedents of customer experience (Foroudi et al., 2018; Hsu & Tsou, 2011; McLean & Wilson, 2016) and how to best manage the customer experience in this era of big data (Grewal et al., 2009; Holmlund et al., 2020; Witell et al., 2020). Others have explored the mediating role of customer experience in relation to utilitarian/hedonic attributes of a product and brand equity, social interaction, convenience, and customer satisfaction (Sheng & Teo, 2012; Srivastava & Kaul, 2014).

In online contexts, customer experience is centered around information technology (IT) access and design, customer support, customer service, and fulfillment in relation to product quality, price, description, and delivery time (Stanworth et al., 2015). Online customer experience is influenced by a web page's verbal and visual design elements (Bleier et al., 2019). Depending on the product type and brand trustworthiness, this experience could influence purchase decisions. Perceived utilitarian and hedonic benefits have been found to influence customer satisfaction with online social network services (Hsu et al., 2014). While web design quality enjoyment and web service quality influence customer satisfaction, these relationships are moderated by websites' interactivity (Ku & Chen, 2015).

In the context of mobile commerce, customer experience is an important factor for the improvement of customer conversion and repurchase intention (Chopdar & Balakrishnan, 2020; Kaatz et al., 2019; Wagner et al., 2020). Perceived enjoyment and ubiquity directly affect customer satisfaction, and perceived enjoyment is influenced by two-way communication, responsiveness, and synchronicity of the mobile commerce platform (Chopdar & Balakrishnan, 2020; Yang & Lee, 2017). Utilitarian factors of technology, ease of use, convenience, and customization influence enjoyment, while the perceived amount of time spent on a shopping activity using mobile applications influences the customer's shopping experience (McLean, Al-Nabhani, & Wilson, 2018). Also, perceived visual complexities negatively affect satisfaction with customer experience, and this relationship is mediated by perceived psychological cost (time, effort, and visual crowdedness) (Sohn et al., 2017). Furthermore, customers with good customer experience in terms of interactional justice tend to complain less than others when they face an issue with a vendor (Wu, 2013).

## **2.2. Voice shopping**

The extant literature shows that AI continues to disrupt business models and foster digital transformation. Smart speakers are the fastest-growing AI-based consumer technology since the smartphone (Simms, 2019). Business leaders are actively thinking about how they can be leveraged to improve sales and their customers' shopping experiences. The two most important characteristics of voice shopping are ease of use and personalization (Rowe, 2019; While et al., 2018). Personalization

and the social role of conversational voice agents influence consumers' attitudes towards recommendations made by these agents during voice shopping. Thus, more personalized recommendations and a more socially-friendly design of voice shopping services have become necessary (Qiu & Benbasat, 2008; Rhee & Choi, 2020; Yuan & Dennis, 2019). Customers are increasingly doing voice shopping because of the convenience expectations of this shopping channel, especially regarding faster and frictionless shopping (Klaus & Zaichkowsky, 2020; Reisinger, 2018). They expect this channel to provide faster and more efficient shopping services, including repurchasing items, hands-free online shopping, shopping reminders, and timely recommendations (Moriuchi, 2019; While et al., 2018).

However, a major downside of voice shopping remains privacy concerns since voice shopping services are offered through “always listening” devices meant to facilitate the provision of personalized services (Cloarec, 2020; Kinsella & Mutchler, 2018b). Nevertheless, the constantly growing number of voice shoppers indicates that the convenience voice shopping brings to the customer experience largely outweighs privacy concerns (While et al., 2018). Also, it is relatively difficult to browse and discover new shopping possibilities during voice shopping. This explains why voice shopping is more adapted for repurchase activities since the consumer does not have to go through the cognitive effort required to browse and purchase new items (Simms, 2019). Some authors have also revealed security flaws in voice shopping systems (Lei et al., 2017). For businesses, voice shopping is perceived as an excellent way to convert leads to sales (Simms, 2019) and improve customer loyalty (Moriuchi, 2019). Nevertheless, this channel brings about several challenges regarding data ownership, commissions for payment services, and competition with smart speaker companies since they also provide voice shopping services (Simms, 2019).

There are debates about the importance of consumer trust in firms' services through voice assistants (Klaus & Zaichkowsky, 2020). Consumer trust in voice shopping as well as in the voice shopping service provider (e.g., Amazon) significantly affects customer experience and adoption of voice shopping platforms (Klaus & Zaichkowsky, 2020). Trust is built by the interaction quality between the consumer and the voice assistant, especially through the assistant's quality of responses and recommendations (Li & Karahanna, 2015; Nasirian et al., 2017). The social perception of voice assistants also affects consumer trust in voice assistants and leads to a para-social relationship between voice assistants and voice shoppers (Hu et al., 2019; Whang, 2018). However, consumers hardly trust the integrity and choices of voice assistants, although some managers strongly believe voice assistants would win consumer trust compared to other technologies (Mari, Mandelli, & Algesheimer, 2020).

### **2.3. Artificial intelligence and personality**

Several researchers are working on embedding personality and enhancing social interactions between AI systems and their environments (Rodić et al., 2015). Voice personality could influence the

acceptance and continued use of social AI systems, especially for elderly people (Rodić et al., 2016; Shareef et al., 2021). Furthermore, people generally prefer female extraverted voices in social AI systems, and it is important to consider individual preferences during design (Loideain & Adams, 2020). Such studies have created the need for research that can help assess, understand, and apply individual differences in adaptation to AI technologies that manifest social agency capabilities (Chang et al., 2018; Matthews et al., 2020). On the other hand, peoples' personality traits have been used to train AI algorithms that help explain human behaviors like gambling (Cerasa et al., 2018), cyberbullying (Sánchez-Medina et al., 2020), and desirability (Fatahi & Moradi, 2016). They have also been used to train AI algorithms for candidate recruitment (Lee & Ahn, 2020) and predict peoples' reactions to tweets (Gallo et al., 2020) based on personality analyses. Furthermore, some studies suggest that the way people interact with AI is different from the way they do with other humans. Although people tend to be more open, agreeable, extraverted, conscientious, and self-disclosing with humans than with AI (Mou & Xu, 2017), extraverts are more likely to delegate decision making to AI than introverts, and conscientious people tend to prioritize performance over convenience (Goldbach et al., 2019).

Personality traits influence consumers' preferences and online shopping behaviors and experiences (Anaza, 2014; Bosnjak et al., 2007; Marbach et al., 2016; Wu & Ke, 2015). For example, the Big Five traits (neuroticism, conscientiousness, extraversion, openness, and agreeableness) influence impulsive and compulsive online shopping behaviors (Gohary & Hanzaae, 2014; Olsen et al., 2016; Turkyilmaz et al., 2015). They also influence self-reported happiness and non-grocery shopping (Goldsmith, 2016). Furthermore, extraversion and conscientiousness have been shown to influence consumers' willingness to pay (Ufer et al., 2019). Meanwhile, aggressiveness and altruism have significant impacts on consumers' complaining attitudes and behaviors (Souiden et al., 2019).

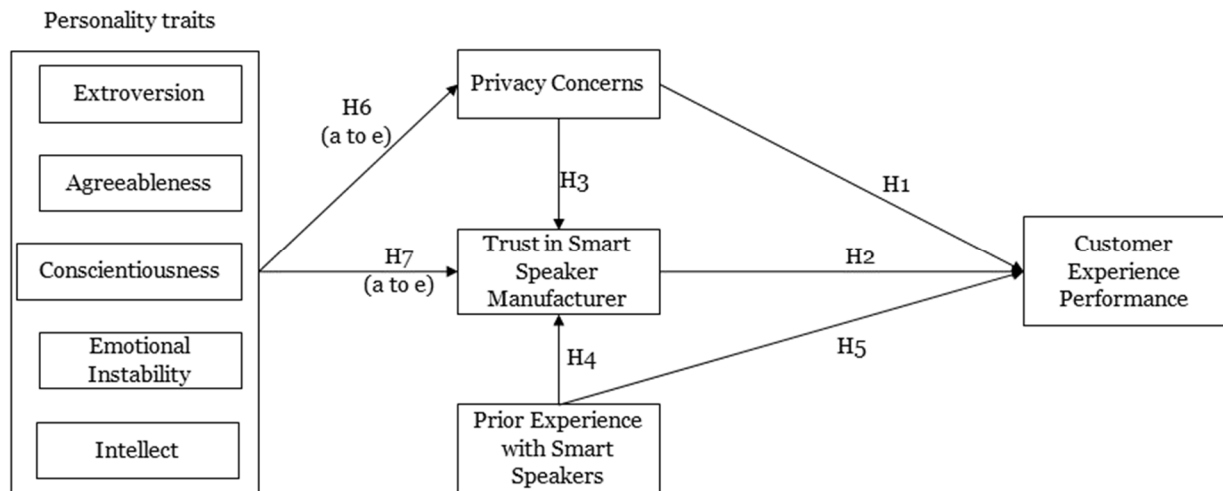
This review reveals the conspicuous absence of personality studies in the context of voice shopping despite the importance of personalization and perceptions of ease of use for the customer experience of voice shoppers. Therefore, this study seeks to fill this research gap by investigating the relationship between personality traits and perceptions of customer experience performance in the context of voice shopping.

### **3. Theoretical framework and model development**

This study is theoretically founded on the Big Five personality traits (Goldberg, 1990) and TRA-privacy (Bansal et al., 2016), which contextualizes TRA. The Big Five factors are a well-established set of personality traits that have been extensively used in personality research to understand how individual differences affect human behavior (Cui, 2017; Gohary & Hanzaae, 2014; Goldsmith, 2016). It has also been extensively used in information systems (IS) research to explain human-computer interactions (Chen et al., 2015; Maier et al., 2020; Venkatesh et al., 2014). TRA-privacy is a



contextualized trust theory that argues that “*personality types and privacy concerns are critical factors impacting trust and the willingness to disclose personal information*” (Bansal et al., 2016, p.1). As highlighted in the literature review, privacy concerns are a major issue in voice shopping. Thus, TRA-privacy could help explain how personality relates to customer experience in voice shopping contexts since benefiting from the full voice shopping experience requires the willingness to disclose personal information. Based on the aforementioned theories, Figure 1 presents a research model to explain customer experience performance.



**Figure 1. Research Model**

### 3.1. Privacy concerns, trust, and prior experience with smart speakers

Privacy concerns refer to worries individuals have about the control they have over the use of the personal information they share with organizations (Yun et al., 2019). On web platforms, publishers are often challenged by the decision to trade between price and privacy in their attempt to make profits. Platform owners sometimes tend to violate the privacy of their customers to offer cheaper services by monetizing customer data, thus justifying the rising concerns about information disclosure and online privacy expressed by consumers (Gopal et al., 2018; Piotrowicz & Cuthbertson, 2014). Smart speakers provide access to voice shopping services that are not created and managed by smart speaker companies (like Amazon or Google) but by other third-party companies providing voice shopping services. The question is, will the data be used by the smart speaker company or the third-party company, and how? Therefore, although the services provided by third parties create value for their customers, this comes at the cost of concerns regarding information sharing and disclosure between the manufacturer and third parties.

However, in the context of mobile apps, app value reduces the cost of privacy trade-offs, especially regarding permitting apps to access personal data (Gu et al., 2017; Wottrich et al., 2018). Therefore, depending on the voice shopping service's perceived value, the privacy-concerned user may not be

willing to grant the voice shopping service access to their personal information. This would limit the service's ability to provide the customer with the best possible voice shopping experience. Also, user interfaces that positively affect consumers make them significantly underestimate privacy concerns (Kehr et al., 2015). Given that convenience is the main reason consumers like using smart speakers for voice shopping, this shopping interface's convenience could make customers underestimate privacy concerns. However, suppose the consumer has to read or say personal information out loud during voice shopping interactions. In that case, this may create discomfort, especially in public spaces (Easwara Moorthy & Vu, 2015), thereby reducing the customer experience performance. Moreover, voice shopping involves granting access to a lot of personal information, leading to transactional privacy concerns and even intrusiveness feelings (Choi & Land, 2016; Krafft et al., 2017). This could influence the shopper's customer experience, which would explain why perceived privacy risk negatively affects the use of in-home voice assistants (de Barcelos Silva et al., 2020; Hadian et al., 2019; McLean & Osei-Frimpong, 2019). These arguments led us to the following hypothesis:

*Hypothesis 1 (H1): Privacy concerns will have a negative effect on customer experience performance during voice shopping with smart speakers.*

Trust is defined as the belief that one party will not take advantage of the other's relative weakness but can rather depend on them to fulfill their commitments (Gefen et al., 2003). Smart speaker owners are always in a position of relative weakness since these devices are always listening for instructions from the user and collecting user information at the same time. Bansal et al. (2016) define a sensitive context as “an environment in which individuals' sensitive information is collected, stored, and communicated as a matter of routine business activity” (p.4). This is precisely the case with smart speakers since people will naturally not censor everything they say at home simply because they own a smart speaker. Moreover, plugging/unplugging the smart speaker each time we want/don't want to use it just because of privacy concerns will defeat the purpose of convenience for which these devices were made. Thus, smart speaker owners are bound to trust that the smart speaker manufacturers will not misuse their data. This suggests that trust plays an important role in the perceived customer experience performance. Previous studies show that trusting beliefs – the belief that firms are interested in and care about the wellbeing of their customers, positively influences word-of-mouth and purchase intentions (Mikalef et al., 2017; Mikalef et al., 2017; Pappas et al., 2017). This implies customers who experience positive trust beliefs most likely had good enough experiences to incite their intention to purchase from a given company and to encourage others to do the same. Furthermore, one could argue that trust is related to customer experience as trust can reduce the cognitive effort required to pay attention to details, especially when the voice assistant is perceived as easy to learn and operate (Lemon & Verhoef, 2016; Shareef et al., 2021). Therefore, we hypothesize that:

*Hypothesis 2 (H2): Trust in the smart speaker manufacturer will have a positive effect on customer experience performance during voice shopping with smart speakers.*

Although consumers could end up trusting platform owners with their private information, they have less trust in third-party companies seeking their information through these platforms (Kelly et al., 2017). This implies that customers doing voice shopping with smart speakers may not be willing to trust a third-party service provider with their personal/financial information. However, without sharing this information with the third-party, they will not be able to use all or part of the voice shopping services. Consequently, this lack of trust could negatively affect their experience with the voice shopping service since they would not fully enjoy it. This suggests that trust mediates the relationship between customer experience performance and privacy concerns. Therefore, we hypothesize that:

*Hypothesis 3 (H3): The effect of privacy concerns on customer experience performance during voice shopping with smart speakers will be mediated by the trust customers have in their smart speaker manufacturer.*

A consumer's impression may change depending on the person's perceived history of success or failure with a particular experience (Avnet et al., 2012). Previous studies show that the prior experience of a consumer with a company influences trust in the company's website (Kumar et al., 2018; Shi & Chow, 2015). Also, in sensitive contexts like financial services markets, prior experience with information exchange is found to influence customer trust (Lindh et al., 2016). Similarly, we argue that when voice shopping with smart speakers, experience with smart speakers influences the way the smart speaker company is trusted. If the past experiences in using smart speakers were good, then it is more likely that the satisfied user would trust the smart speaker company to deliver good voice shopping services. In other words, the trust built in the manufacturer while using the smart speaker in the past would be extended to the voice shopping services provided through the smart speaker. Therefore, we hypothesize that:

*Hypothesis 4 (H4): Prior experience with smart speakers will have a positive effect on the trust customers have in their smart speaker manufacturer.*

People are found to avoid internet ads based on their negative prior experience with other internet ads and vice versa (Seyedghorban et al., 2016). Similarly, consumer perceptions of other smart speaker services would influence their evaluation of the experience with voice shopping services. This study argues that if smart speaker users have positive prior experiences with other smart speaker services, they will likely use this as a baseline to evaluate their voice shopping experiences. Therefore, the following hypothesis is made:

*Hypothesis 5 (H5): Prior experience with smart speakers will have a positive effect on customer experience performance during voice shopping with smart speakers.*

### 3.2. Personality

According to TRA-privacy, personality differences affect trust and privacy concerns because personality traits are related to people's information behaviors (Bansal et al., 2016). We resorted to Goldberg's Big Five factors (extraversion, agreeableness, emotional instability, conscientiousness, and intellect) (Goldberg, 1990) to identify the personality traits that play a role in customer experience performance how they operate.

*Extraversion* is a personality trait that describes people who are playful, expressive, talkative, brave, optimistic, and spontaneous (Goldberg, 1990). People with this personality are more likely to engage in social orientation activities (interpersonal relations) because they are more people-oriented. They are willing not only to pay more for products just to encourage local producers (Ufer et al., 2019) but to delegate tasks to AI algorithms (Goldbach et al., 2019). They also tend to show higher life satisfaction, happiness, and hedonic shopping habits (Goldsmith, 2016). However, higher extraversion is positively associated with higher utilitarian shopping values and negatively associated with impulsive online buying (Gohary & Hanzae, 2014). Furthermore, extraversion is negatively associated with privacy concerns and positively associated with trust in environments that require information disclosure online (Bansal et al., 2016). Knowing that extraverts enjoy social interactions and are more willing to delegate tasks to AI algorithms, they would be less wary about privacy concerns and more inclined to trust the algorithms behind smart speakers. As a result, we hypothesize that:

*Hypothesis 6a (H6a): extraversion will negatively affect privacy concerns.*

*Hypothesis 7a (H7a): extraversion will positively affect trust.*

*Agreeableness* is a personality trait that describes people who are cooperative, friendly, emphatic, lenient, courteous, generous, flexible, warm, natural, and with strong moral values (Goldberg, 1990). This personality trait is positively correlated with happiness, hedonic shopping habits (Goldsmith, 2016), online impulse buying (Turkyilmaz et al., 2015), internet addiction (Leong et al., 2019), high utilitarian values, and knowledge sharing attitudes (Cui, 2017). It is also positively associated with privacy concerns and trust online because it is perceived as immoral for manufacturers or third parties to invade their privacy (Bansal et al., 2016). However, because of their friendliness, leniency, and hedonic shopping habits, people with this trait may decide to trust these companies despite their privacy concerns because they look forward to enjoying the pleasure of voice shopping. Therefore, we formulate the following hypotheses:

*Hypothesis 6b (H6b): Agreeableness will positively affect privacy concerns.*

*Hypothesis 7b (H7b): Agreeableness will positively affect trust.*

*Emotional instability or neuroticism* is a personality trait that describes people who are insecure, fearful, emotional, gullible, and intrusive (Goldberg, 1990). This personality trait negatively affects impulsive online buying (Turkyilmaz et al., 2015). Given their anxious nature and low confidence in their decisions, people with this personality trait tend to easily engage in compulsive buying behaviors (Gohary & Hanzae, 2014). This shows that they do not trust their instincts. Also, disclosing their personal information makes them nervous and anxious, especially in sensitive contexts (Bansal et al., 2016). We believe the fear, anxiety, and insecurity they feel will make them scared to share and entrust their personal information through smart speakers. Therefore, we hypothesize that:

*Hypothesis 6c (H6c): Emotional instability will positively affect privacy concerns.*

*Hypothesis 7c (H7c): Emotional instability will negatively affect trust.*

*Conscientiousness* is a personality trait that describes people who are organized, efficient, dependable, precise, conventional, persistent, cautious, punctual, decisive, and predictable (Goldberg, 1990). Conscientious individuals make decisions based on the information they have. Perceptions of strong moral values and ethics positively influence their trust and decision to commit to an action. Such people are willing to pay more to derive utilitarian value from a product or service, especially if the company seems dependable and trustworthy (Gohary & Hanzae, 2014; Ufer et al., 2019). Furthermore, they are more likely to trust brands that they perceive as trying to improve their services and better meet customer needs (Rajavi et al., 2019). Nevertheless, their careful and responsible nature makes them avoid unnecessary risks (Ufer et al., 2019), which also explains why this personality trait is positively associated with privacy concerns (Junglas et al., 2008; Korzaan & Boswell, 2008). Voice shopping requires sharing an extensive amount of personal information to benefit from the full experience it offers fully. We argue that conscientious individuals would acquire as much information as possible on the primary and secondary uses of the data collected. This would enable them to decide whether or not it is worth the risk in terms of customer experience improvements. Since they are very meticulous, it is expected that more conscientious individuals will have greater privacy concerns than less conscientious ones. Also, conscientious individuals are more likely to trust voice shopping services provided through smart speakers that are perceived to better serve customer needs and to have trustworthy user agreements. This leads us to hypothesize that:

*Hypothesis 6d (H6d): Conscientiousness will positively affect privacy concerns.*

*Hypothesis 7d (H7d): Conscientiousness will positively affect trust.*

*Intellect* or openness to experience is a personality trait that describes people who are insightful, creative, and curious (Goldberg, 1990). This personality trait is positively associated with non-grocery shopping habits because it is a highly experiential activity and people with this personality trait like new experiences (Goldsmith, 2016). It also is positively associated with higher utilitarian shopping

values (Gohary & Hanzae, 2014), impulsive online buying (Turkyilmaz et al., 2015), and social commerce adoption intentions (Aydın, 2019) for the same reasons. Individuals with this personality trait are more willing to disclose their personal information when using technology (Pizzi & Scarpi, 2020). Voice shopping is a very new practice that is gaining popularity. Therefore, we argue that the stronger this personality trait is in an individual, the more likely they are to disclose their personal information to experience voice shopping fully. Their open-mindedness and curiosity would overshadow their privacy concerns and will make them trust the process although their rationality would enable them to understand the risks involved fully. Therefore, we hypothesize that:

*Hypothesis 6e (H6e): Intellect will negatively affect privacy concerns.*

*Hypothesis 7e (H7e): Intellect will positively affect trust.*

## **4. Methodology**

### **4.1. Survey administration and data collection**

We used an online questionnaire-based survey to collect data. We chose this approach because, in exploratory and predictive research settings, it is a well-established approach that is easily replicable and generalizable (Mikalef et al., 2020). All scales used for the survey were adapted from previous studies. Given that customer experience performance has no well-established set of measurement items (Lemon & Verhoef, 2016; Morgeson et al., 2015), we adapted a performance impact scale from Aldholay et al., (2018). We chose this scale because it attempts to holistically capture performance impact expectations of consumers who use technology services (Isaac et al., 2017; Isaac et al., 2019; MD Main Uddin et al., 2019). We did a pretest and a pilot test to verify the psychometric properties of our measurement instrument. The pretest was conducted to test the understandability of the instrument, which was a 7-point-Likert scale questionnaire. Thus, 20 random graduate students from our university were asked to fill in and provide feedback on the instructions, wordings, length, and clarity. As expected, we did not have any negative feedback as the scales that we used had already been validated in existing studies.

The pilot test was used to verify the reliability and validity of items used to measure each construct. This test was conducted on our study's target population, that is, US citizens with voice shopping experience through smart speakers. We used a platform called Prolific<sup>1</sup> to recruit research participants. This platform helps researchers recruit survey participants and collect reliable data (Jeong et al., 2019; Peer et al., 2017). We used this platform because: (i) it has a strict participant recruitment procedure; (ii) it ensures the privacy of participants; and (iii), it gave us more screening options, thereby enabling access to better-quality participants. The pilot test was conducted using 50 responses. All construct reliability and validity test scores, including Cronbach's alpha, average variance extracted (AVE), and

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<sup>1</sup> <https://www.prolific.co/>

Fornell-Larcker test, were deemed acceptable (Hair Jr. et al., 2017). The results of the pilot test enabled us to validate the questionnaire and pursue our study.

The validated questionnaire was sent to target participants through the *Prolific* platform. The participants of this main data collection phase did not take part in the pilot test. The data collection process took place in February 2020. Out of the 243 responses obtained, 224 were validated and retained for further analysis. To mitigate any effects of common method bias in this study, we did the following (Podsakoff et al., 2003): (i) informed participants that the survey was completely anonymized, data collected will be used strictly for academic research, and there are no wrong or right answers; (ii) questionnaires were administered online, and questions were randomized; (iii) participants were informed on attention checks to keep them focus throughout the process. After data collection, Harman's single factor test showed that no single factor solution emerged from the factor analysis, and the maximum variance explained by any one factor was 31.2%. This is below the critical threshold of 50% (Podsakoff et al., 2003). Thus, data analysis was pursued without fear of errors induced by common method bias. [Table 1](#) presents a description of our sample.

**Table 1. Description of the study sample**

<b>Characteristic</b>	<b>Sample (N=224)</b>
<i>Type of smart speaker used</i>	
Amazon Echo	150
Google Home	54
Both	20
<i>Years of Experience with smart speakers</i>	
Less than a year	17
1 year	45
2 years	91
3-5 years	64
Over 5 years	7
<i>Age (in years)</i>	
Below 21	6
21-40	149
41-55	52
56-74	16
Over 74	1
<i>Gender</i>	
Female	99
Male	124
Prefer not to say	0
Transgender	1
<i>Annual household income (in USD)</i>	
Less than 10K	5

10K-50K	52
50K-100K	109
100K-150K	42
Over 150K	16

#### 4.2. PLS-SEM

First of all, we used partial least squares structural equation modeling for data analysis (PLS-SEM) (Hair et al., 2014; Hair Jr et al., 2016). A well-established approach in IS and marketing research allows researchers to quantitatively and reliably assess causal relationships between multiple independent and dependent variables simultaneously (Chen et al., 2020; Gu et al., 2019; Mikalef et al., 2020). This approach involves two main stages: (i) assess the measurement model wherein the reliability and validity of the model's measurement constructs are verified; and (ii) assess the structural model wherein the hypotheses of the model are tested. We completed our data analysis using SmartPLS software version 3.3.2.

The measurement model was assessed through the computation of the values of item loadings, Cronbach's alpha, composite reliability, average variance extracted (AVE), Fornell-Larcker criteria, and the heterotrait-monotrait ratio of correlations (HTMT) (Hair Jr. et al., 2017). The ultimate goal was to validate the quality of our scale. Item loadings, Cronbach's alpha, and composite reliability values were expected to be above the 0.70 thresholds to support item and construct reliability; AVE values have to be above the 0.50 threshold to support convergent validity; to validate discriminant validity, HTMT has to be below 0.85 and the square root of the AVE for each construct should be greater than the correlation involving the constructs (Fornell-Larcker criterion).

The structural model was assessed by reporting the path coefficients and their significance levels. The paths' significance was evaluated using p-values obtained by running a bootstrap analysis with 5000 subsamples to verify the stability of the results obtained (Hair Jr. et al., 2017). Mediation analysis was also conducted to determine if the impact of personality traits on customer experience performance was direct or mediated. We used the R-square ( $R^2$ ) value to determine the predictivity of our model. In IS and marketing studies,  $R^2$  values of 0.75, 0.50, or 0.25 are generally described as substantial, moderate, or weak, respectively. However, consumer behavior studies targeting customer satisfaction issues tend to accept  $R^2$  values of 0.20 as substantial (Hair Jr. et al., 2017).

#### 4.3. FsQCA

Fuzzy-set Qualitative Comparative Analysis (FsQCA) is a qualitative-quantitative method used to analyze multiple cases that explain a given phenomenon in complex situations (Ragin, 2009). This method has been applied to explore several configurations of factors that explain consumer behavior in general (Fang et al., 2016; Pappas et al., 2016; Pappas et al., 2020) and customer experience during online shopping in particular (Foroudi et al., 2016; Pappas et al., 2017; Pekovic & Rolland, 2020). The



approach complements conventional quantitative methods which are incapable of revealing causal complexity between variables, which is a crucial aspect of social science research (Ragin & Pennings, 2005). Thus, several times, it has been used to complement the findings of research models initially analyzed using SEM (Fang et al., 2016; Xie & Tsai, 2020; Yueh et al., 2016). Combining these approaches helps researchers overcome the overly simplistic nature of hypotheses tested using regression methods and identify sufficiently new and unique findings regarding complex issues analyzed (Russo & Confente, 2019; Woodside, 2014). Thus, this study uses fsQCA to explore the mechanisms underlying consumer perceptions of high customer experience performance during voice shopping which were not revealed using PLS-SEM. Specifically, we investigate the configurations of personality, privacy, trust, and prior experience that lead to high customer experience performance.

To perform fsQCA, the interval scale variables were transformed into fuzzy sets. To do so, the variables need to be calibrated to determine the configurations that would lead to high customer experience performance. Calibration scores typically range from 0 (non-membership) to 1 (full membership) and a crossover point of 0.5 representing maximum ambiguity regarding the membership (Ragin, 2009). Using the fsQCA software for calibration, the recommended breakpoints for full membership, non-membership, and crossover points are 0.95, 0.05, and 0.5 respectively for full-set membership, full-set non-membership are 0.95 and 0.05 respectively (Ragin et al., 2008). To calibrate the variables, summated measures were created by summing items measuring each construct (X. Hu et al., 2016; Tho & Trang, 2015).

The calibrated fuzzy sets were analyzed using the truth table algorithm in fsQCA software (Ragin et al., 2008). This procedure involves creating a truth table based on the fuzzy data to select the configurations to analyze, followed by specifying the causal conditions and outcomes to minimize. Since this study has over 100 samples, only configurations with minimum frequencies of 3 were used for analysis. Configurations selected in this study (consistency) captured at least 80% of the cases, representing the extent to which a causal solution leads to an outcome (Ragin et al., 2008). Combinations that meet this consistency threshold explain the outcome to be determined (high customer experience performance). Solution consistency was used to measure the extent to all the solutions implemented systematically lead high customer experience performance (Mikalef & Krogstie, 2020). The empirical relevance of each solution was determined by calculating the raw, unique, and solution coverage (Ragin, 2006, 2009). Raw coverage measures the proportion of membership in the outcome explained by each term in the solution. Unique coverage measures the proportion of memberships in the outcome explained solely by each solution term. Solution coverage measures the proportion of memberships in the outcome that is explained by the complete solution (Mikalef & Krogstie, 2020; Ragin et al., 2008).

## 5. Results

### 5.1. Measurement model analysis

All the reliability and validity measurements met the threshold values. Cronbach's alpha and composite reliability values were above the threshold of 0.70. All item loadings were above the 0.7 thresholds except one and the item was dropped from the study. AVE values were also above the threshold of 0.50. Thus, the items and construct reliability and validity measures were verified (Table 2).

**Table 2. Construct definitions and results of the measurement model**

Measures	Item loadings
Customer experience performance ( $\alpha=0.945$ , $CR=0.953$ , $AVE=0.669$ ) <i>The degree to which customers appreciate the physical and emotional experiences occurring through their interactions with a product and/or service offering of a brand from point of first direct, conscious contact, through the total journey to the post-consumption stage</i> (Aldholay et al., 2018; Laming & Mason, 2014).	
<b>My smart speaker helps me to accomplish my shopping tasks more quickly.</b>	0.836
<b>My smart speaker makes it easier to complete my shopping tasks.</b>	0.796
<b>My smart speaker helps me save money when it comes to shopping tasks.</b>	0.801
<b>My smart speaker improves my shopping performance.</b>	0.875
<b>My smart speaker enhances my shopping effectiveness.</b>	0.867
<b>My smart speaker helps me review and eliminate errors in my shopping tasks.</b>	0.799
<b>My smart speaker helps me to meet my future shopping target.</b>	0.867
<b>My smart speaker helps me acquire new shopping knowledge.</b>	0.755
<b>My smart speaker helps me acquire new shopping skills.</b>	0.797
<b>My smart speaker helps me to come up with innovative shopping ideas.</b>	0.776
Privacy concerns ( $\alpha=0.897$ , $CR=0.936$ , $AVE=0.830$ ) <i>The fear an individual has about control over the use of personal information they share with organizations</i> (Bansal et al., 2016; Yun et al., 2019).	
<b>My financial/personal information will not be abused at all once submitted through my smart speaker.</b>	0.926
<b>My financial/personal information will not be compromised at all once submitted through my smart speaker.</b>	0.938
<b>My extent of concern regarding the misuse of my financial/personal information submitted through my smart speaker is very low.</b>	0.867
Trust ( $\alpha=0.937$ , $CR=0.955$ , $AVE=0.842$ ) <i>The belief that one party will not take advantage of the relative weakness of the other but can rather depend on them to fulfill their commitments</i> (Gefen et al., 2003; Pavlou & Gefen, 2004).	
<b>I believe that my smart speaker company is honest</b>	0.914
<b>I believe that my smart speaker company is trustworthy</b>	0.920
<b>I believe that my smart speaker company is dependable</b>	0.914
<b>I believe that my smart speaker company is reliable</b>	0.921
Prior experience ( $\alpha=0.952$ , $CR=0.969$ , $AVE=0.912$ ) <i>The knowledge users acquired from using smart speakers in the past</i> (Bansal et al., 2016; Taylor & Todd, 1995).	
<b>I have found my smart speaker very useful this far</b>	0.947
<b>I have benefited many times from using my smart speaker</b>	0.966
<b>I have had numerous positive encounters with my smart speaker</b>	0.951
Personality traits <i>Personality characteristics that describe the relatively stable behavioral dispositions of people</i> (Bansal et al., 2016; Srivastava et al., 2015).	
<b>Extraversion (I...)</b> ( $\alpha=0.897$ , $CR=0.923$ , $AVE=0.705$ )	

<b>Am the life of the party</b>	0.802
<b>Feel comfortable around people</b>	0.856
<b>Start conversations</b>	0.851
<b>Talk to many different people at parties</b>	0.861
<b>Don't mind being the center of attention</b>	0.827
<i>Agreeableness (I...)</i> ( $\alpha=0.874$ , CR=0.910, AVE=0.718)	
<b>Sympathize with others' feelings</b>	0.801
<b>Have a soft heart</b>	0.846
<b>Take time out for others</b>	0.883
<b>Feel others' emotions</b>	0.856
<i>Emotional instability (I...)</i> ( $\alpha=0.930$ , CR=0.946, AVE=0.779)	
<b>Get stressed out easily</b>	0.914
<b>Am easily disturbed</b>	0.820
<b>Get upset easily</b>	0.919
<b>Change mood a lot</b>	0.877
<b>Get irritated easily</b>	0.878
<i>Conscientiousness (I...)</i> ( $\alpha=0.788$ , CR=0.876, AVE=0.701)	
<b>Am always prepared</b>	0.794
<b>Pay attention to details</b>	0.733
<b>Get chores done right away</b>	0.840
<b>Like order</b>	0.812
<b>Follow a schedule</b>	0.794
<i>Intellect (I...)</i> ( $\alpha=0.724$ , CR=0.834, AVE=0.629)	
<b>Am quick to understand things</b>	0.868
<b>Spend time reflecting on things (dropped)</b>	0.650
<b>Am full of ideas</b>	0.843

Legend:  $\alpha$ =Cronbach's alpha, CR=composite reliability, AVE=average variance extracted

The square root of each construct's AVE is greater than its highest correlation with other constructs thus establishing discriminant validity of the latent variables based on the Fornell-Larcker criterion (Table 3). Also, discriminant validity is established since the HTMT pairs of latent variables are all below the threshold of 0.85 (Table 4).

**Table 3. Discriminant validity (Fornell-Larcker criterion)<sup>2</sup>**

	Agreeableness	Conscientiousness	Customer experience	Emotional instability	Extraversion	Intellect	Prior experience	Trust	Privacy concern
Agreeableness	0.847								
Conscientiousness	0.290	0.838							
Customer experience	0.328	0.191	0.818						
Emotional instability	0.001	-0.081	-0.126	0.882					
Extraversion	0.267	0.198	0.149	-0.388	0.840				
Intellect	0.376	0.402	0.169	-0.074	0.339	0.793			
Prior experience	0.265	0.154	0.524	-0.029	0.102	0.160	0.955		
Trust	0.315	0.247	0.382	-0.156	0.216	0.198	0.414	0.917	
Privacy concern	0.082	0.077	0.326	-0.145	0.087	0.050	0.411	0.496	0.911

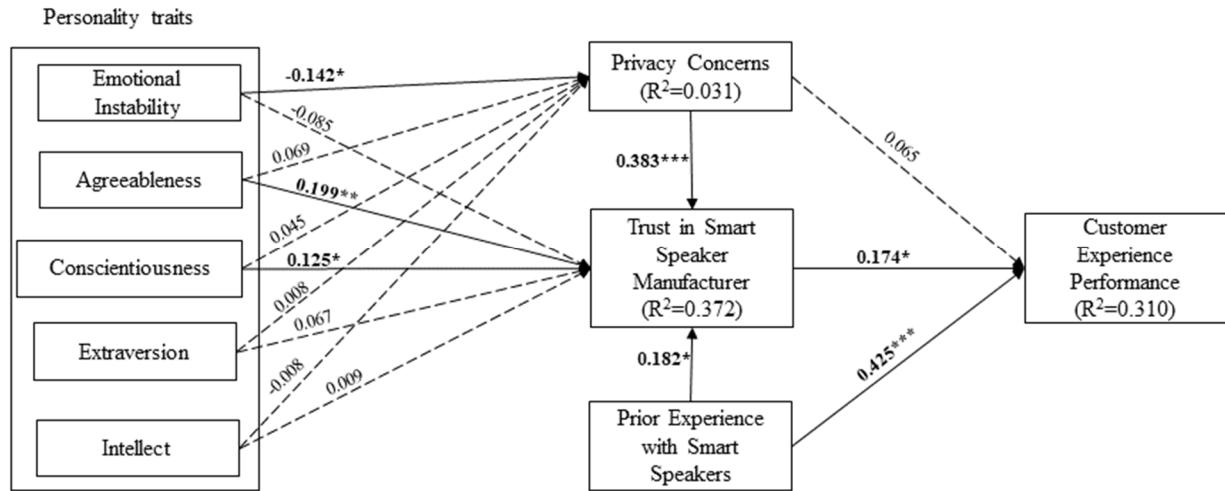
**Table 4. Heterotrait-monotrait ratio of correlations (HTMT)<sup>2</sup>**

	Agreeableness	Conscientiousness	Customer experience	Emotional instability	Extraversion	Intellect	Prior experience	Trust	Privacy concern
Agreeableness									
Conscientiousness	0.381								
Customer experience	0.340	0.224							
Emotional instability	0.071	0.110	0.130						
Extraversion	0.288	0.236	0.162	0.419					
Intellect	0.504	0.570	0.203	0.188	0.381				
Prior experience	0.281	0.206	0.545	0.038	0.103	0.221			
Trust	0.321	0.301	0.404	0.159	0.222	0.216	0.438		
Privacy concern	0.087	0.107	0.350	0.148	0.100	0.081	0.444	0.540	

<sup>2</sup> Correlations and square root of AVE values on the diagonal.

## 5.2. Structural model

Figure 2 summarizes our structural model obtained from PLS analysis with the path coefficients, their significance levels and the variance of the dependent variables explained by the model ( $R^2$ ).



**Figure 2. Results of the structural model. ( $p < 0.05$  \*.  $p < 0.01$  \*\*.  $p < 0.001$ \*\*\*)**

Our model explains 31% of the variance in customer experience performance, 37% of the variance in trust in the smart speaker company, and 3% of the variance in privacy concerns. To test the model fit, we computed the standardized root mean square residual (SRMR) value, which is the difference between the sample covariance matrix and the model covariance matrix. The acceptable cutoff SRMR value for PLS path models is 0.08 (Henseler, Hubona, & Ray, 2016). Thus, the SRMR value of 0.055 obtained in this study means that the model fit criterion is met. Table 5 summarizes the hypotheses tested and their significance. The hypotheses in bold indicate significant paths while the others indicate non-significant paths.

**Table 5. Hypotheses and their significance**

Hypothesis	Path Coefficients ( $\beta$ )	p-values	
H1	privacy concern -> Customer experience	0.065	0.372
<b>H2</b>	<b>Trust -&gt; Customer experience</b>	<b>0.174</b>	<b>0.014</b>
<b>H3</b>	<b>privacy concern -&gt; Trust</b>	<b>0.383</b>	<b>0.000</b>
<b>H4</b>	<b>Prior experience -&gt; Trust</b>	<b>0.182</b>	<b>0.013</b>
<b>H5</b>	<b>Prior experience -&gt; Customer experience</b>	<b>0.425</b>	<b>0.000</b>
H6a	Extraversion -> privacy concern	0.008	0.930
H7a	Extraversion -> Trust	0.067	0.282
H6b	Agreeableness -> privacy concern	0.069	0.339
<b>H7b</b>	<b>Agreeableness -&gt; Trust</b>	<b>0.199</b>	<b>0.004</b>
<b>H6c</b>	<b>Emotional instability -&gt; privacy concern</b>	<b>-0.142</b>	<b>0.025</b>
H7c	Emotional instability -> Trust	-0.085	0.201
H6d	Conscientiousness -> privacy concern	0.045	0.548
<b>H7d</b>	<b>Conscientiousness -&gt; Trust</b>	<b>0.125</b>	<b>0.048</b>

H6e	Intellect -> privacy concern	-0.008	0.927
H7e	Intellect -> Trust	0.009	0.910

H1 was not validated, thus indicating that privacy concerns do not directly influence customer experience performance during voice shopping with smart speakers. However, the validation of H2 indicates that trust in the smart speaker manufacturer influences customer experience performance during voice shopping with smart speakers. Furthermore, H3 was validated indicating that the effect of privacy concerns on customer experience performance during voice shopping with smart speakers is mediated by the trust customers have in their smart speaker manufacturer. The validation of H4 and H5 confirms that prior experience with smart speakers influences the trust customers have in their smart speaker manufacturers and also has a direct effect on the perceptions of customer experience performance during voice shopping with smart speakers.

Regarding personality and trust, agreeableness is positively associated with trust (H7b). However, only conscientiousness was positively associated with trust, as opposed to what was predicted by H7d. No other personality trait had a significant effect on trust. Meanwhile, emotional instability had a negative effect on privacy concerns (H6c). Extraversion and intellect have no significant effects on either trust or privacy concerns.

### 5.3. Mediation analysis

Agreeableness has a direct significant effect on customer experience performance ( $\beta = 0.044$ ;  $p = 0.048$ ) and trust ( $\beta = 0.226$ ;  $p = 0.000$ ). It also has a total indirect effect on customer experience ( $\beta = 0.044$ ;  $p = 0.048$ ) and a specific indirect effect on customer experience (Agreeableness -> Trust -> Customer experience;  $\beta = 0.035$ ;  $p = 0.049$ ). This indicates a complementary (partial mediation) between agreeableness and customer experience performance. Conscientiousness was found to have a direct significant effect on trust ( $\beta = 0.142$ ;  $p = 0.034$ ) only. In other words, there is an indirect-only (full) mediation between conscientiousness and customer experience performance. Emotional instability has a direct significant effect on both privacy concerns ( $\beta = -0.142$ ;  $p = 0.025$ ). and trust ( $\beta = -0.140$ ;  $p = 0.032$ ). It also has a total indirect effect on trust ( $\beta = -0.054$ ;  $p = 0.032$ ). This effect on trust is mediated by privacy concerns (Emotional instability -> privacy concern -> Trust:  $\beta = -0.054$ ;  $p = 0.032$ ). This indicates an indirect-only (full mediation) between conscientiousness and customer experience performance. Privacy concerns has a total indirect effect on customer experience ( $\beta = 0.066$ ;  $p = 0.026$ ). Its effect on customer experience is shown to be mediated by trust (Privacy Concern -> Trust -> Customer experience:  $\beta = 0.066$ ;  $p = 0.026$ ). This shows a complementary (partial) mediation between privacy concerns and customer experience performance.

#### 5.4. Results of Fuzzy set analysis

Table 6 presents the coverage and consistency of the three combinations that sufficiently explain high customer experience performance. The black circles indicate the variable's presence, the hollow circles indicate its absence, and the blank cells indicate that the specific variable is not considered in the solution.

**Table 6. Main configurations for high customer experience performance**

Configuration	Solutions		
	1	2	3
Extraversion		●	●
Agreeableness	●	●	●
Conscientiousness	●	●	●
Emotional instability		○	○
Intellect	●	●	●
Privacy concerns		○	○
Trust	●		●
Prior experience	●	●	
Consistency	0.930	0.968	0.958
Raw coverage	0.808	0.436	0.429
Unique coverage	0.390	0.018	0.011
Solution coverage	0.837		
Solution consistency	0.914		

*Legend: The black circles = presence of the variable; hollow circles = absence of the variable; blank = not considered in the solution.*

The existence of multiple sufficient configurations for customer experience performance indicates equifinality (Fiss, 2011). The findings indicate an overall solution coverage of 0.837 and an overall solution consistency of 0.914. This shows that the three configurations cover a substantial proportion of the outcome. Solution 1 demonstrates high levels of consistency (0.930) and explains a substantial number of cases (coverage = 0.808), thus representing the best solution for high customer experience performance. This means that the presence of agreeableness, conscientiousness, intellect, trust, and prior smart speaker experience are key conditions for high customer experience performance. Solution 2 is also highly consistent (0.968) and has significant coverage (0.436). This means that the presence of extraversion, agreeableness, conscientiousness, and intellect, and the absence of emotional instability and privacy concerns would lead to high customer experience performance. Solution 3 also shows very high consistency (0.958) and has significant coverage (0.429). This solution set is similar to solution 2 besides the fact that the presence of trust substitutes the presence of prior experience.

## 6. Discussion

The purpose of this paper was to explore how personality, trust, privacy concerns, and prior experiences affect customer experience performance perceptions and the combinations of these factors that lead to high customer experience performance. The results obtained from SEM-PLS and fsQCA confirm the effects of each factor investigated on customer experience performance and identify the configurations that lead to high customer experience performance. Overall, these findings are in line with the existing literature in other online shopping contexts (Bansal et al., 2016; Seyedghorban et al., 2016; Wang & Herrando, 2019; Webber et al., 2012). Surprisingly, privacy concerns had no direct effect on customer experience performance (H1). This implies that in voice shopping contexts, privacy concerns do not affect the total experience of the customer throughout the customer journey. These findings are in line with recent research that shows that information privacy concerns have an almost zero significance on the satisfaction of customers who use AI-based voice assistants (Brill et al., 2019). This may be because exposure to privacy risks is needed to benefit from voice shopping experiences. Therefore, consumers who engage in voice shopping inherently accept the privacy costs associated with using voice shopping. Thus, consumers who use voice shopping services could have already factored privacy concerns into their trust beliefs (H3). To them, trust includes trusting the companies with the privacy of their data (Hossain & Dwivedi, 2014). This implies that privacy concerns may significantly affect intention to use and actual use of voice shopping services rather than customer experience performance. This is a plausible explanation because the results show that trust mediates the relationship between privacy concerns and customer experience performance. Another possibility is that younger generations (about 70% of the participants of this study) are less wary of sharing their personal information online as they are accustomed to this practice (Piotrowicz & Cuthbertson, 2014). Therefore, the desire to experience voice shopping and the convenience of this shopping method largely outweighs their privacy concerns (Kelly et al., 2017; While et al., 2018). As hypothesized, trust has a significant positive effect on customer experience performance (H2). Thus, the belief that the smart speaker company is interested in and cares about the wellbeing of its users will positively influence customer experience performance. Its mediating effect on privacy concerns shows that customers trust that the smart speaker company will not allow their data to be misused, allowing them to share their personal information comfortably. Furthermore, voice shopping is not always the first encounter customers have with smart speakers. The results show that prior experience with smart speakers positively affects consumer trust (H4) and customer experience performance (H5). This implies that the trust and experiences acquired by the smart speaker user with other services would be extended or used as the baseline to evaluate voice shopping experiences.

Regarding personalities, extraversion has no significant effect on trust or privacy (H6a and H7a). This implies that this personality trait alone is not concerned about privacy or trust. While agreeableness has no significant effect on privacy concerns (H6b), it has a significant positive effect on trust (H7b).



This implies that although agreeable people are lenient, their strong moral values would make them seek evidence of privacy measures taken to protect their data in order to build trust (Bansal et al., 2016; McCarthy, Wood, & Holmes, 2017). They would be able to experience voice shopping only after trust is established. Emotional instability has a significant effect on privacy concerns (H6c) but no significant effect on trust (H7c). This shows that the hysterical nature of people with this personality trait makes them very concerned about privacy irrespective of any trust efforts made by the smart speaker company (Bansal et al., 2016; McCarthy et al., 2017). Meanwhile, conscientiousness has no significant effect on privacy concerns (H6d) but a significant effect on trust (H7d). As hypothesized, the rigorous nature of people with this personality trait would allow them to build trust based on actions made by the company to better serve customers' needs and to have trustworthy user agreements. This personality also factors its privacy concerns into trust beliefs. Finally, intellect, just like extraversion, has no significant effect on trust or privacy (H6e and H7e). This implies that this personality trait alone is not concerned about privacy or trust (Bansal et al., 2016; McCarthy et al., 2017).

Nevertheless, the fsQCA reveals three configurations that can lead to high customer experience performance. Based on the value of its unique coverage, solution 1 it represents the largest proportion of cases. This solution indicates that the presence of agreeableness, conscientiousness, and intellect personality traits as well as the presence of trust and prior experience would lead to high customer experience performance. This implies that a single individual with these three personality traits who has prior experience with smart speakers and who trusts the smart speaker company will have high customer experience performance. This solution validates the SEM results (H2-H5, H7b, H7d) and includes H7e. It confirms the possibility that privacy concerns have been factored into the trust beliefs of voice shoppers. It also demonstrates the importance of the experience consumers have during their initial contact with smart speakers before using voice shopping services. This is in line with recent research showing that consumers discontinued the use of their voice assistants because they developed negative beliefs related to its abilities and value in performing certain tasks (Trajkova & Martin-Hammond, 2020). Thus, if voice shopping is not the first experience consumers have with smart speakers, their initial contact can create biases before they get to use voice shopping services. Therefore, this study shows that tailoring voice shopping services to the personality traits and prior experiences of customers lead to greater customer experience performance compared to a "one-size-fits-all" approach.

### **6.1. Implications for research**

This study shows that personality differences affect individual perceptions of customer experience performance during voice shopping. In an environment where personalization is central to customer adoption and decision making (Gutierrez et al., 2019; Zhu et al., 2017; Zhu & Kanjanamekanant, 2020), we believe it is important to understand the personality-AI relationship as well as how it affects

customer experience performance expectations. Voice shopping using smart speakers is a very new context within which relatively few studies have been conducted. Yet, it is a shopping channel with great potential for highly personalized services and requires customers to entrust a lot of personal information to smart speaker companies and voice shopping service providers. Therefore, this study could serve as a starting point for understanding this phenomenon in voice shopping contexts. While the hype around voice assistants and voice shopping continues growing, the underlying factors that make them so appealing for online shoppers remain largely unexplored, especially in IS research.

This study makes three main contributions to AI and personality research in IS. First, it identifies the critical role of personality, trust, and privacy concerns during voice shopping and the combinations of these factors that lead to high customer experience. More precisely, the findings show that a consumer who possesses agreeableness, conscientiousness, and intellect personality traits is expected to have high customer experience performance when combined with the presence of prior experience and trust; the absence of both emotional instability and privacy concerns lead to high customer experience performance; the presence of trust plays a key role in increasing customer experience performance. This implies that consumer trust is not the only important factor regarding customer experience with AI-based voice technologies used by firms to provide services to their customers (Klaus & Zaichkowsky, 2020). Individual personality differences also play a critical role in modern-day online shopping contexts (Choden et al., 2019; Kang & Johnson, 2015; Yoon & Occeña, 2015). Therefore, we contribute to the body of knowledge on the interplay between personality, privacy, and trust in e-commerce environments (Masele & Matama, 2020; Yoon & Occeña, 2015), specifically in the voice shopping environment.

Second, this study uses an innovative approach to explain customer experience performance and its relationship with other dimensions within the complex voice shopping scenario. In e-commerce contexts, scenarios are often complex and unique since consumers can easily switch from one e-marketplace to another, especially with the availability of new shopping channels like voice assistants (Russo & Confente, 2019). Thus, regression-based methods like PLS-SEM oversimplify the relationship between variables in e-commerce contexts (Pappas et al., 2020; Ragin, 2006). This study uses fsQCA to capture the most complex relationships between customer experience, privacy concerns, trust, and prior experience. Thus, this study contributes to research by revealing specific combinations of these factors that lead to high customer experience performance, thereby contributing to theory development. Furthermore, this study complements other studies that have demonstrated the relevance of combining SEM and fsQCA in explaining complex phenomena in social science research (Fang et al., 2016; Xie & Tsai, 2020; Yueh et al., 2016).

Third, this study contributes to research seeking to explain consumer behavior differences when shopping through smart devices and virtual assistants (Klaus & Zaichkowsky, 2020; Pillai et al., 2020;

Tong et al., 2020). Thus, we contribute to calls for more research on the behaviors of consumers using smart devices and virtual assistants for shopping. Our findings can be used to investigate similar contexts like voice shopping using smartphones and even compare the differences in results. Furthermore, customer experience has been identified as one of the key performance indicators of customer service performance in firms that seek to gain competitive advantages by delivering superior customer services (Lycett & Radwan, 2019; Scheidt & Chung, 2019). We contribute to research on customer experience performance by using a scale different from customer satisfaction to capture perceptions of overall customer experience (Lemon & Verhoef, 2016; Shin, 2017). This scale is more encompassing and captures customer experience beyond mere satisfaction measured from an emotional perspective. Specifically, we show that performance scales can contribute to understanding the overall perceptions of customer experiences. Thus, researchers can further develop, adapt, and assess the ability of other performance scales to better explain customer experience performance.

Fourth, we demonstrate not only TRA-privacy's ability to support research in highly information-sensitive contexts but also the importance of context during theory development and implementation (Bansal et al., 2016). By applying this theory in the context of voice shopping, we validate its relevance and potential to support other studies geared towards personality, trust, and privacy in e-commerce environments. Furthermore, more studies are needed to bring personality into the scenes of IS research (Bansal et al., 2016; Matthews et al., 2020) as AI becomes more present in the lives of consumers. Thus, this study contributes to personality research which is highly solicited to understand individual differences and how they affect consumer adoption of AI (Dwivedi et al., 2019; Matthews et al., 2020).

## **6.2. Implications for practice**

Rapidly changing consumer needs have led to a growing interest in how businesses can stand out from the competition by providing top-notch online omnichannel shopping services (Ameen et al., 2021; Shi et al., 2020). This study provides useful implications for managers and practitioners seeking to exploit the potential of voice shopping services for competitive advantage. As voice assistants become increasingly popular (Steinhoff et al., 2019; Tong et al., 2020), firms need to meet rising customer experience expectations by providing safer and more personalized customer services through such channels (Russo & Confente, 2019). Our study contributes to ongoing discussions by showing that understanding individual personality differences can enable businesses that provide voice shopping services to generate insights that can help them provide more personalized and enhanced customer experiences. We discuss five main implications of our study for practice. First, we highlight that personality plays an important role in consumer-oriented AI services like voice shopping. Personality affects privacy concerns and trust relationships of customers during voice shopping. Therefore, during personalization efforts, managers need to develop and tailor their strategies to the personality of their customers. More attention should be given to customers with agreeableness, emotional instability, and

conscientiousness personality traits. Managers could use self-evaluation questions or gamification to acquire information on personality from customers without making them feel invaded (Triantoro et al., 2019).

Second, we enlighten managers on the key factors to consider during their efforts towards personalizing voice shopping services. Managers need to understand the personality of their customers who use voice shopping services because this could have significant impacts on their marketing and sales strategies. Categorizing customers by personality when offering voice shopping services through smart speakers implies meeting consumer expectations concerning seamless shopping experiences as this will create better customer experiences. Businesses often associate positive customer experiences with increased sales and improved customer loyalty and encourage making enhancing customer experience part of business culture. Therefore, enhancing customer experience performance means ensuring retention, referrals, cross-sales, and other behaviors that can yield tangible results in terms of profitability (Collins-Taylor, 2016; Holmlund et al., 2020; Witell et al., 2020).

Third, we suggest that in the voice shopping context, organizations should include trust in the smart speaker company and prior experience with smart speakers into their customer experience performance toolkits, while taking into account customer personality. A recent marketing report based on US companies (Moorman, 2019) shows a continuous rise of AI in marketing, especially for personalization, consumer insights, and targeting decisions. Marketing leaders expect to prioritize excellent customer services although they perceive their customer experience performance as low compared to their competitors. This is mainly because of their limited ability to design, deliver, and monitor the customer experience. Our study shows that measuring trust and prior experience with using smart speakers could support the design, delivery, and monitoring of customer experience performance. Customer (dis)confirmation of perceived performance influences customer satisfaction and confidence in their expectations (Lin & Lekhawipat, 2016). Thus, if customers appreciate the added value of the experience provided by voice shopping services, this could increase their levels of advocacy and repurchase intentions as is the case with other shopping channels (Dowling et al., 2020). Also, trust will make customers more comfortable with disclosing their personal information during voice shopping, allowing them to fully appreciate the experience provided by the voice shopping service. Therefore, the challenge is how to get consumers to the stage where they can strategically control the information that they share through their smart speakers to reduce vulnerabilities. This could include adding more features in the smart speaker's app that the user could use to control and monitor the use of personal data.

Fourth, understanding customers' personality traits could help marketers design and deliver more personalized voice shopping services to their customers while considering its effects on their privacy concerns and trust perceptions. Since customer experience is more affective in nature, its outcome can

either make the customer a promoter or a detractor. We recommend that voice shopping service providers should systematically measure customer experience performance after each purchase and incentivize the consumers to participate in such evaluations if necessary. Instead of rating each experience individually, managers could rather make consumers rate their actual experience compared to the previous one and if possible, compared to their expectations. This will enable the managers to take proactive actions towards planning continuous service improvements.

Fifth, our study also has implications for smart speaker manufacturers. Given the correlation between service relevance, perceived ease of use and customer experience performance (Fairhurst, 2013; Visinescu et al., 2015), smart speaker companies should make sure that all the services offered through their platform are relevant and easy for the user to understand. Managers should expect personality to influence variations in customer experience performance during voice shopping due to trust in the smart speaker manufacturer. This can be used as a decision criterion for retail companies to choose the smart speaker company for their voice shopping service. Retail organizations can also conduct a simple survey to find out from their customers who own smart speakers which one they prefer and why. Questions should focus on the trust relationships the customers have with their smart speaker manufacturer and their current experiences with the smart speakers.

Furthermore, smart speaker manufacturers play a key role in building consumer trust and alleviating privacy concerns regarding the use of smart speakers for voice shopping. No matter how impressive voice shopping services are, customers need to trust the voice shopping service to deliver the expected experience. If customers had a tough time interacting with the smart speaker in the past or has had a bad privacy experience with smart speakers, they would not trust the voice shopping service to be any different. If retail organizations notice that their customers prefer one smart speaker company over the other, this will logically influence their partnership decisions. We showed that customers' trust and privacy concerns are tied to the smart speaker company. Therefore, it is equally important for these companies to understand different personalities and learn how they can leverage this to build trust and reduce privacy concerns. They could do this by analyzing data collected during interactions between the speaker and its user and use this information to support arguments when negotiation deals with third parties regarding voice shopping services. Smart speaker companies could also audit the quality of services provided through their smart speakers because it could play a role in the image of the smart speaker. If users notice that third parties provide bad services through a smart speaker, they may not be able to tell the difference and assume it is the smart speaker manufacturer that is bad, thus reducing their propensity to trust future services provided through the speaker. Therefore, the stakes are as high for the smart speaker companies as they are for the voice shopping service providers.

### **6.3. Limitations and future research**

This study has some limitations which provide opportunities for future research. First, our data were collected only from US-based participants for consistency. This limits generalizability because cultural and environmental factors may influence trust and privacy concerns. For example, privacy-personality relationships may be different in European countries due to the General Data Protection Regulation (GDPR) which may make citizens feel more protected when sharing their data through voice shopping devices. Therefore, further research could be conducted in other contexts like in Europe, Africa, and Asia to determine if similar results are obtained. Second, our hypotheses were tested using self-reported data from participants through a crowdsourcing platform. Although we put considerable effort into screening participants and inciting them to respond as objectively as possible, we acknowledge that there might still be biases in responses as we had no way to confirm that the participants were actually US-based or that they had ever used a smart speaker for shopping as they claimed. Thus, future research could have an experimental design where participants are invited to actively take part in a voice shopping exercise before evaluating their experiences. Future research should also consider a longitudinal approach to investigating customer experience with voice shopping as consumer experiences might change as privacy concerns and trust beliefs might evolve with time. Lastly, we did not restrict our respondents to any particular type of voice assistant, smart speaker, product, or service purchased. Thus, future research should examine each of these aspects to provide a deeper understanding of customer experience performance in voice shopping contexts.

## **7. Conclusions**

This study explored how personality, trust, privacy concerns, and prior experience with smart speakers affect customer experience performance and the combinations of these factors that lead to high customer experience performance. It was highly motivated by the growing interest of business scholars and practitioners in the adoption and use of AI in e-commerce environments. The study reveals that the belief that the smart speaker company is interested in and cares about the wellbeing of its users, especially regarding privacy, will strongly influence customer experience performance. This trust and experience significantly depend on the experiences and trust beliefs developed due to past experiences with smart speakers. Consumers with a high sense of curiosity and strong moral values who perceive the smart speaker company's efforts to protect the privacy of its customers and better serve their needs will have high customer experience performance. This research contributes to research by showing the relationships and combinations of factors that lead to high customer experience performance in the voice shopping context. It also shows managers and practitioners how to improve personalized voice shopping experiences. Hopefully, these contributions would incite researchers to further explore how voice assistants could be used to enhance the shopping experiences of consumers and help businesses provide better voice shopping services.

## 8. References

- Aldholay, A., Isaac, O., Abdullah, Z., Abdulsalam, R., & Al-Shibami, A. H. (2018). An extension of Delone and McLean IS success model with self-efficacy: Online learning usage in Yemen. *International Journal of Information and Learning Technology*, 35(4), 285–304. <https://doi.org/10.1108/IJILT-11-2017-0116>
- Ameen, N., Tarhini, A., Reppel, A., & Anand, A. (2021). Customer experiences in the age of artificial intelligence. *Computers in Human Behavior*, 114, 106548. <https://doi.org/10.1016/j.chb.2020.106548>
- Ameen, N., Tarhini, A., Shah, M. H., & Nusair, K. (2021). A cross cultural study of gender differences in omnichannel retailing contexts. *Journal of Retailing and Consumer Services*, 58, 102265. <https://doi.org/https://doi.org/10.1016/j.jretconser.2020.102265>
- Anaza, N. A. (2014). Personality Antecedents of Customer Citizenship Behaviors in Online Shopping Situations. *Psychology and Marketing*, 31(4), 251–263. <https://doi.org/10.1002/mar.20692>
- Arnett, J., Goldfinch, B., & Chinta, R. (2018). Multi-dimensional nature of innovation at Amazon. *International Journal of Business Innovation and Research*, 15(1), 1–13. <https://doi.org/10.1504/IJBIR.2018.088461>
- Avnet, T., Pham, M. T., & Stephen, A. T. (2012). Consumers' Trust in Feelings as Information. *Journal of Consumer Research*, 39(4), 720–735. <https://doi.org/10.1086/664978>
- Aydın, G. (2019). Do Personality Traits and Shopping Motivations Affect Social Commerce Adoption Intentions? Evidence from an Emerging Market. *Journal of Internet Commerce*, 18(4), 428–467. Retrieved from <http://10.0.4.56/15332861.2019.1668659>
- Bansal, G., Zahedi, F. M., & Gefen, D. (2016). Do context and personality matter? Trust and privacy concerns in disclosing private information online. *Information and Management*, 53(1), 1–21. <https://doi.org/10.1016/j.im.2015.08.001>
- Behrenbeck, K., Peter, B., Peter, C., Rugholm, J., Frank, S., Wachinger, T., & Zocchi, A. (2015). Perspectives on retail and consumer goods. In *Perspectives on retail and consumer goods*. Retrieved from [https://www.mckinsey.com/~media/McKinsey/Industries/Retail/Our Insights/Perspectives on retail and consumer goods Number 7/Perspectives-on-Retail-and-Consumer-Goods\\_Issue-7.ashx](https://www.mckinsey.com/~media/McKinsey/Industries/Retail/Our%20Insights/Perspectives%20on%20retail%20and%20consumer%20goods%20Number%207/Perspectives-on-Retail-and-Consumer-Goods_Issue-7.ashx)
- Bleier, A., Harmeling, C. M., & Palmatier, R. W. (2019). Creating effective online customer experiences. *Journal of Marketing*, 83(2), 98–119. <https://doi.org/10.1177/0022242918809930>
- Bosnjak, M., Galesic, M., & Tuten, T. (2007). Personality determinants of online shopping: Explaining online purchase intentions using a hierarchical approach. *Journal of Business Research*, 60(6), 597–605. <https://doi.org/10.1016/j.jbusres.2006.06.008>
- 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. <https://doi.org/10.1080/0267257X.2019.1687571>
- Burbach, L., Halbach, P., Plettenberg, N., Nakayama, J., Ziefle, M., & Valdez, A. C. (2019). “Hey, Siri”, “Ok, Google”, “Alexa”. Acceptance-Relevant Factors of Virtual Voice-Assistants. *2019 IEEE International Professional Communication Conference (ProComm)*, 101–111. IEEE.
- Cerasa, A., Lofaro, D., Cavedini, P., Martino, I., Bruni, A., Sarica, A., ... Quattrone, A. (2018). Personality biomarkers of pathological gambling: A machine learning study. *Journal of Neuroscience Methods*, 294, 7–14. <https://doi.org/10.1016/j.jneumeth.2017.10.023>

- Chang, R. C. S., Lu, H. P., & Yang, P. (2018). Stereotypes or golden rules? Exploring likable voice traits of social robots as active aging companions for tech-savvy baby boomers in Taiwan. *Computers in Human Behavior*, *84*, 194–210. <https://doi.org/10.1016/j.chb.2018.02.025>
- Chang, S. E., & Jang, Y. T. (2009). Assessing customer satisfaction in a V-commerce environment. *Journal of Organizational Computing and Electronic Commerce*, *19*(1), 30–49. <https://doi.org/10.1080/10919390802605083>
- Chen, J. V., Widjaja, A. E., & Yen, D. C. (2015). Need for Affiliation, Need for Popularity, Self-Esteem, and the Moderating Effect of Big Five Personality Traits Affecting Individuals' Self-Disclosure on Facebook. *International Journal of Human-Computer Interaction*, *31*(11), 815–831. Retrieved from <http://10.0.4.56/10447318.2015.1067479>
- Chen, X., Ma, J., Wei, J., & Yang, S. (2020). The role of perceived integration in WeChat usages for seeking information and sharing comments: A social capital perspective. *Information and Management*, 103280. <https://doi.org/10.1016/j.im.2020.103280>
- Choden, K., Bagchi, K. K., Udo, G. J., & Kirs, P. J. (2019). The influence of individual values on internet use: A multinational study. *International Journal of Information Management*, *46*, 198–209. <https://doi.org/10.1016/j.ijinfomgt.2018.12.010>
- Choi, B. C. F., & Land, L. (2016). The effects of general privacy concerns and transactional privacy concerns on Facebook apps usage. *Information and Management*, *53*(7), 868–877. <https://doi.org/10.1016/j.im.2016.02.003>
- Chopdar, P. K., & Balakrishnan, J. (2020). Consumers response towards mobile commerce applications: S-O-R approach. *International Journal of Information Management*, *53*, 102106. <https://doi.org/10.1016/j.ijinfomgt.2020.102106>
- Cloarec, J. (2020). The personalization–privacy paradox in the attention economy. *Technological Forecasting and Social Change*, *161*, 120299. <https://doi.org/https://doi.org/10.1016/j.techfore.2020.120299>
- Collins-Taylor, C. (2016). The Evolving Behaviors of Empowered Consumers. *Teller Vision*, (1469), 2–3.
- Cui, X. (2017). In- and extra-role knowledge sharing among information technology professionals: The five-factor model perspective. *International Journal of Information Management*, *37*(5), 380–389. <https://doi.org/10.1016/j.ijinfomgt.2017.04.011>
- Davenport, T., Guha, A., Grewal, D., & Bressgott, T. (2020). How artificial intelligence will change the future of marketing. *Journal of the Academy of Marketing Science*, *48*(1), 24–42. <https://doi.org/10.1007/s11747-019-00696-0>
- de Barcelos Silva, A., Gomes, M. M., da Costa, C. A., da Rosa Righi, R., Barbosa, J. L. V., Pessin, G., ... Federizzi, G. (2020). Intelligent personal assistants: A systematic literature review. *Expert Systems with Applications*, *147*, 113193. <https://doi.org/https://doi.org/10.1016/j.eswa.2020.113193>
- Dowling, K., Guhl, D., Klapper, D., Spann, M., Stich, L., & Yegoryan, N. (2020). Behavioral biases in marketing. *Journal of the Academy of Marketing Science*, *48*(3), 449–477. <https://doi.org/10.1007/s11747-019-00699-x>
- Duan, Y., Edwards, J. S., & Dwivedi, Y. K. (2019). Artificial intelligence for decision making in the era of Big Data – evolution, challenges and research agenda. *International Journal of Information Management*, *48*, 63–71. <https://doi.org/10.1016/j.ijinfomgt.2019.01.021>
- Dwivedi, Y. K., Hughes, L., Ismagilova, E., Aarts, G., Coombs, C., Crick, T., ... Williams, M. D.



- (2019). Artificial Intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy. *International Journal of Information Management*. <https://doi.org/10.1016/j.ijinfomgt.2019.08.002>
- Dwivedi, Y. K., Ismagilova, E., Hughes, D. L., Carlson, J., Filieri, R., Jacobson, J., ... Wang, Y. (2020). Setting the future of digital and social media marketing research: Perspectives and research propositions. *International Journal of Information Management*, 102168. <https://doi.org/10.1016/j.ijinfomgt.2020.102168>
- Easwara Moorthy, A., & Vu, K. P. L. (2015). Privacy Concerns for Use of Voice Activated Personal Assistant in the Public Space. *International Journal of Human-Computer Interaction*, 31(4), 307–335. <https://doi.org/10.1080/10447318.2014.986642>
- Fairhurst, M. (2013). Collision Course. *Canadian Underwriter*, 80(5), 58–61.
- Fanderl, H., Matthey, A., Pratsch, S., & Stöber, J. (2019). Driving the automotive customer experience towards the age of mobility. *McKinsey & Company*, 1. Retrieved from <https://www.mckinsey.com/industries/automotive-and-assembly/our-insights/driving-the-automotive-customer-experience-toward-the-age-of-mobility>
- Fang, J., Shao, Y., & Wen, C. (2016). Transactional quality, relational quality, and consumer e-loyalty: Evidence from SEM and fsQCA. *International Journal of Information Management*, 36(6, Part B), 1205–1217. <https://doi.org/https://doi.org/10.1016/j.ijinfomgt.2016.08.006>
- Fatahi, S., & Moradi, H. (2016). A fuzzy cognitive map model to calculate a user's desirability based on personality in e-learning environments. *Computers in Human Behavior*, 63, 272–281. <https://doi.org/10.1016/j.chb.2016.05.041>
- Fiona, G. (2017). Asda parent introduces voice shopping technology. *DIY Week*, 2.
- Fiss, P. C. (2011). Building better causal theories: A fuzzy set approach to typologies in organization research. *Academy of Management Journal*, 54(2), 393–420. <https://doi.org/10.5465/AMJ.2011.60263120>
- Foroudi, P., Gupta, S., Sivarajah, U., & Broderick, A. (2018). Investigating the effects of smart technology on customer dynamics and customer experience. *Computers in Human Behavior*, 80, 271–282. <https://doi.org/https://doi.org/10.1016/j.chb.2017.11.014>
- Foroudi, P., Jin, Z., Gupta, S., Melewar, T. C., & Foroudi, M. M. (2016). Influence of innovation capability and customer experience on reputation and loyalty. *Journal of Business Research*, 69(11), 4882–4889. <https://doi.org/https://doi.org/10.1016/j.jbusres.2016.04.047>
- Gallo, F. R., Simari, G. I., Martinez, M. V., & Falappa, M. A. (2020). Predicting user reactions to Twitter feed content based on personality type and social cues. *Future Generation Computer Systems*, 110, 918–930. <https://doi.org/10.1016/j.future.2019.10.044>
- Gefen, D., Karahanna, E., & Straub, D. W. (2003). Trust and tam in online shopping: AN integrated model. *MIS Quarterly: Management Information Systems*, 27(1), 51–90. <https://doi.org/10.2307/30036519>
- Gohary, A., & Hanzae, K. H. (2014). Personality Traits as Predictors of Shopping Motivations and Behaviors: A Canonical Correlation Analysis. *Arab Economic and Business Journal*, 9(2), 166–174. <https://doi.org/10.1016/j.aebj.2014.10.001>
- Goldbach, C., Kayar, D., Pitz, T., & Sickmann, J. (2019). Transferring decisions to an algorithm: A simple route choice experiment. *Transportation Research Part F: Traffic Psychology and Behaviour*, 65, 402–417. <https://doi.org/10.1016/j.trf.2019.08.011>

- Goldberg, L. R. (1990). An alternative" description of personality": the big-five factor structure. *Journal of Personality and Social Psychology*, 59(6), 1216.
- Goldsmith, R. (2016). The Big Five, happiness, and shopping. *Journal of Retailing and Consumer Services*, 31, 52–61. <https://doi.org/10.1016/j.jretconser.2016.03.007>
- Gopal, R. D., Hidaji, H., Patterson, R. A., Rolland, E., & Zhdanov, D. (2018). How much to share with third parties? User privacy concerns and website dilemmas. *MIS Quarterly: Management Information Systems*, 42(1), 143–163. <https://doi.org/10.25300/MISQ/2018/13839>
- Grewal, D., Levy, M., & Kumar, V. (2009). Customer Experience Management in Retailing: An Organizing Framework. *Journal of Retailing*, 85(1), 1–14. <https://doi.org/https://doi.org/10.1016/j.jretai.2009.01.001>
- Gu, D., Deng, S., Zheng, Q., Liang, C., & Wu, J. (2019). Impacts of case-based health knowledge system in hospital management: The mediating role of group effectiveness. *Information and Management*, 56(8), 103162. <https://doi.org/10.1016/j.im.2019.04.005>
- Gu, J., Xu, Y. (Calvin), Xu, H., Zhang, C., & Ling, H. (2017). Privacy concerns for mobile app download: An elaboration likelihood model perspective. *Decision Support Systems*, 94, 19–28. <https://doi.org/10.1016/j.dss.2016.10.002>
- Guidi, A., Gentili, C., Scilingo, E. P., & Vanello, N. (2019). Analysis of speech features and personality traits. *Biomedical Signal Processing and Control*, 51, 1–7. <https://doi.org/10.1016/j.bspc.2019.01.027>
- Gutierrez, A., O’Leary, S., Rana, N. P., Dwivedi, Y. K., & Calle, T. (2019). Using privacy calculus theory to explore entrepreneurial directions in mobile location-based advertising: Identifying intrusiveness as the critical risk factor. *Computers in Human Behavior*, 95, 295–306. <https://doi.org/10.1016/j.chb.2018.09.015>
- Hadian, M., Altuwaiyan, T., Liang, X., & Li, W. (2019). Privacy-preserving voice-based search over mHealth data. *Smart Health*, 12, 24–34. <https://doi.org/https://doi.org/10.1016/j.smhl.2018.04.001>
- Hair, J. F., 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>
- Hair Jr., Joe F., Matthews, L. M., Matthews, R. L., & Sarstedt, M. (2017). PLS-SEM or CB-SEM: updated guidelines on which method to use. *International Journal of Multivariate Data Analysis*, 1(2), 107. <https://doi.org/10.1504/ijmda.2017.10008574>
- Hair Jr, Joseph F, Hult, G. T. M., Ringle, C., & Sarstedt, M. (2016). *A primer on partial least squares structural equation modeling (PLS-SEM)*. Sage publications.
- Henseler, J., Hubona, G., & Ray, P. A. (2016). Using PLS path modeling in new technology research: Updated guidelines. *Industrial Management and Data Systems*, 116(1), 2–20. <https://doi.org/10.1108/IMDS-09-2015-0382>
- Holmlund, M., Van Vaerenbergh, Y., Ciuchita, R., Ravald, A., Sarantopoulos, P., Ordenes, F. V., & Zaki, M. (2020). Customer experience management in the age of big data analytics: A strategic framework. *Journal of Business Research*, 116, 356–365. <https://doi.org/https://doi.org/10.1016/j.jbusres.2020.01.022>
- Hossain, M. A., & Dwivedi, Y. K. (2014). What improves citizens’ privacy perceptions toward RFID technology? A cross-country investigation using mixed method approach. *International Journal of Information Management*, 34(6), 711–719.

<https://doi.org/https://doi.org/10.1016/j.ijinfomgt.2014.07.002>

- Hsu, H. Y., & Tsou, H.-T. (2011). Understanding customer experiences in online blog environments. *International Journal of Information Management*, 31(6), 510–523. <https://doi.org/https://doi.org/10.1016/j.ijinfomgt.2011.05.003>
- Hsu, J. S., Lin, T. C., & Tsai, J. (2014). Does confirmation always matter? Extending confirmation-based theories. *Behaviour and Information Technology*, 33(11), 1219–1230. <https://doi.org/10.1080/0144929X.2013.857431>
- Hu, P., Wang, K., & Liu, J. (2019). Speaking and listening: Mismatched human-like conversation qualities undermine social Perception and Trust in AI-based voice assistants. *Proceedings of the 23rd Pacific Asia Conference on Information Systems: Secure ICT Platform for the 4th Industrial Revolution, PACIS 2019*.
- Hu, X., Huang, Q., Zhong, X., Davison, R. M., & Zhao, D. (2016). The influence of peer characteristics and technical features of a social shopping website on a consumer's purchase intention. *International Journal of Information Management*, 36(6), 1218–1230. <https://doi.org/10.1016/j.ijinfomgt.2016.08.005>
- Isaac, O., Abdullah, Z., Ramayah, T., & Mutahar, A. M. (2017). Internet usage, user satisfaction, task-technology fit, and performance impact among public sector employees in Yemen. *International Journal of Information and Learning Technology*, 34(3), 210–241. <https://doi.org/10.1108/IJILT-11-2016-0051>
- Isaac, O., Aldholay, A., Abdullah, Z., & Ramayah, T. (2019). Online learning usage within Yemeni higher education: The role of compatibility and task-technology fit as mediating variables in the IS success model. *Computers & Education*, 136, 113–129. <https://doi.org/https://doi.org/10.1016/j.compedu.2019.02.012>
- Jeong, M., Zo, H., Lee, C. H., & Ceran, Y. (2019). Feeling displeasure from online social media postings: A study using cognitive dissonance theory. *Computers in Human Behavior*, 97, 231–240. <https://doi.org/https://doi.org/10.1016/j.chb.2019.02.021>
- Junglas, I. A., Johnson, N. A., & Spitzmüller, C. (2008). Personality traits and concern for privacy: An empirical study in the context of location-based services. *European Journal of Information Systems*, 17(4), 387–402. <https://doi.org/10.1057/ejis.2008.29>
- Kaatz, C., Brock, C., & Figura, L. (2019). Are you still online or are you already mobile? – Predicting the path to successful conversions across different devices. *Journal of Retailing and Consumer Services*, 50, 10–21. <https://doi.org/https://doi.org/10.1016/j.jretconser.2019.04.005>
- Kang, J. Y. M., & Johnson, K. K. P. (2015). F-Commerce platform for apparel online social shopping: Testing a Mowen's 3M model. *International Journal of Information Management*, 35(6), 691–701. <https://doi.org/10.1016/j.ijinfomgt.2015.07.004>
- Kaplan, A., & Haenlein, M. (2019). Siri, Siri, in my hand: Who's the fairest in the land? On the interpretations, illustrations, and implications of artificial intelligence. *Business Horizons*, 62(1), 15–25. <https://doi.org/https://doi.org/10.1016/j.bushor.2018.08.004>
- Kazemini, A., Kaedi, M., & Ganji, B. (2019). Personality-Based Personalization of Online Store Features Using Genetic Programming: Analysis and Experiment. *Journal of Theoretical & Applied Electronic Commerce Research*, 14(1), 16–29. Retrieved from <http://10.0.15.227/S0718-18762019000100103>
- Kehr, F., Kowatsch, T., Wentzel, D., & Fleisch, E. (2015). Blissfully ignorant: The effects of general privacy concerns, general institutional trust, and affect in the privacy calculus. *Information Systems Journal*, 25(6), 607–635. <https://doi.org/10.1111/isj.12062>

- Kelly, L., Kerr, G., & Drennan, J. (2017). Privacy concerns on social networking sites: a longitudinal study. *Journal of Marketing Management*, 33(17–18), 1465–1489. <https://doi.org/10.1080/0267257X.2017.1400994>
- Kim, C., Li, W., & Kim, D. J. (2015). An Empirical Analysis of Factors Influencing M-Shopping Use. *International Journal of Human-Computer Interaction*, 31(12), 974–994. <https://doi.org/10.1080/10447318.2015.1085717>
- Kinsella, B., & Mutchier, A. (2019). *Smart Speaker Consumer Adoption Report March 2019 Giving Voice To a Revolution U.S.* Retrieved from [https://voicebot.ai/wp-content/uploads/2019/03/smart\\_speaker\\_consumer\\_adoption\\_report\\_2019.pdf](https://voicebot.ai/wp-content/uploads/2019/03/smart_speaker_consumer_adoption_report_2019.pdf)
- Kinsella, B., & Mutchler, A. (2018a). *Voice assistant consumer adoption report November 2018.* Retrieved from <https://voicebot.ai/wp-content/uploads/2019/01/voice-assistant-consumer-adoption-report-2018-voicebot.pdf>
- Kinsella, B., & Mutchler, A. (2018b). Voice Shopping: Consumer Adoption Report. In *Voicebot.ai*. Retrieved from <https://voicebot.ai/wp-content/uploads/2018/06/voice-shopping-consumer-adoption-report-june-2018-voicebot-voysis.pdf%0D%0A>
- Klaus, P., & Zaichkowsky, J. (2020). AI voice bots: a services marketing research agenda. *Journal of Services Marketing*, 34(3), 389–398. <https://doi.org/10.1108/JSM-01-2019-0043>
- Klie, L. (2013). Which Interaction Channels Are Most Popular? - CRM Magazine. *CRM Magazine*, 17(9), 12. Retrieved from <http://www.destinationcrm.com/Articles/Columns-Departments/Insight/Which-Interaction-Channels-Are-Most-Popular-91537.aspx>
- Korzaan, M. L., & Boswell, K. T. (2008). The influence of personality traits and information privacy concerns on behavioral intentions. *Journal of Computer Information Systems*, 48(4), 15–24. <https://doi.org/10.1080/08874417.2008.11646031>
- Krafft, M., Arden, C. M., & Verhoef, P. C. (2017). Permission Marketing and Privacy Concerns — Why Do Customers (Not) Grant Permissions? *Journal of Interactive Marketing*, 39, 39–54. <https://doi.org/10.1016/j.intmar.2017.03.001>
- Ku, E. C. S., & Chen, C. Der. (2015). Cultivating travellers' revisit intention to e-tourism service: The moderating effect of website interactivity. *Behaviour and Information Technology*, 34(5), 465–478. <https://doi.org/10.1080/0144929X.2014.978376>
- Kumar, S., Kumar, P., & Bhasker, B. (2018). Interplay between trust, information privacy concerns and behavioural intention of users on online social networks. *Behaviour and Information Technology*, 37(6), 622–633. <https://doi.org/10.1080/0144929X.2018.1470671>
- Kuppelwieser, V. G., & Klaus, P. (2020). Measuring customer experience quality: The EXQ scale revisited. *Journal of Business Research*. <https://doi.org/https://doi.org/10.1016/j.jbusres.2020.01.042>
- Laming, C., & Mason, K. (2014). Customer experience - An analysis of the concept and its performance in airline brands. *Research in Transportation Business and Management*, 10, 15–25. <https://doi.org/10.1016/j.rtbm.2014.05.004>
- Lee, D. S., & Ahn, C. K. (2020). Industrial human resource management optimization based on skills and characteristics. *Computers and Industrial Engineering*, 144, 106463. <https://doi.org/10.1016/j.cie.2020.106463>
- Lee, J. M., & Rha, J. Y. (2016). Personalization-privacy paradox and consumer conflict with the use of location-based mobile commerce. *Computers in Human Behavior*, 63, 453–462. <https://doi.org/10.1016/j.chb.2016.05.056>

- Lei, X., Tu, G.-H., Liu, A. X., Ali, K., Li, C.-Y., & Xie, T. (2017). The Insecurity of Home Digital Voice Assistants -- Amazon Alexa as a Case Study. *ArXiv Preprint ArXiv:1712.03327*. Retrieved from <http://arxiv.org/abs/1712.03327>
- Lemke, F., Clark, M., & Wilson, H. (2011). Customer experience quality: an exploration in business and consumer contexts using repertory grid technique. *Journal of the Academy of Marketing Science*, 39(6), 846–869. <https://doi.org/10.1007/s11747-010-0219-0>
- Lemon, K. N., & Verhoef, P. C. (2016). Understanding customer experience throughout the customer journey. *Journal of Marketing*, 80(6), 69–96. <https://doi.org/10.1509/jm.15.0420>
- Leong, L. Y., Hew, T. S., Ooi, K. B., Lee, V. H., & Hew, J. J. (2019). A hybrid SEM-neural network analysis of social media addiction. *Expert Systems with Applications*, 133, 296–316. <https://doi.org/10.1016/j.eswa.2019.05.024>
- Level 3 Communications. (2010). Level 3 Communications, Inc. Annual Report. In *Reportal Company Reports*. Acquisdata Inc.
- Li, S. S., & Karahanna, E. (2015). Online recommendation systems in a B2C E-commerce context: A review and future directions. *Journal of the Association for Information Systems*, 16(2), 72–107. <https://doi.org/10.17705/1jais.00389>
- Liao, Y., Vitak, J., Kumar, P., Zimmer, M., & Kritikos, K. (2019). Understanding the Role of Privacy and Trust in Intelligent Personal Assistant Adoption. *Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, 11420 LNCS, 102–113. [https://doi.org/10.1007/978-3-030-15742-5\\_9](https://doi.org/10.1007/978-3-030-15742-5_9)
- Lim, L. G., Tuli, K. R., & Grewal, R. (2020). Customer Satisfaction and Its Impact on the Future Costs of Selling. *Journal of Marketing*, 84(4), 23–44. Retrieved from <http://10.0.4.153/0022242920923307>
- Lin, C., & Lekhawipat, W. (2016). How Customer Expectations Become Adjusted After Purchase. *International Journal of Electronic Commerce*, 20(4), 443–469. <https://doi.org/10.1080/10864415.2016.1171973>
- Lindh, C., Thilenius, P., & Hadjikhani, A. (2016). Distrust online in the financial services market: The relevance of experiential knowledge and information exchange. *Journal of Customer Behaviour*, 15(2), 173–191. <https://doi.org/10.1362/147539216x14594362873776>
- Loideain, N. N., & Adams, R. (2020). From Alexa to Siri and the GDPR: The gendering of Virtual Personal Assistants and the role of Data Protection Impact Assessments. *Computer Law & Security Review*, 36, 105366. <https://doi.org/https://doi.org/10.1016/j.clsr.2019.105366>
- Lycett, M., & Radwan, O. (2019). Developing a Quality of Experience (QoE) model for Web Applications. *Information Systems Journal*, 29(1), 175–199. <https://doi.org/10.1111/isj.12192>
- Maier, C., Mattke, J., Pflügner, K., & Weitzel, T. (2020). Smartphone use while driving: A fuzzy-set qualitative comparative analysis of personality profiles influencing frequent high-risk smartphone use while driving in Germany. *International Journal of Information Management*, 55, 102207. <https://doi.org/https://doi.org/10.1016/j.ijinfomgt.2020.102207>
- Marbach, J., Lages, C. R., & Nunan, D. (2016). Who are you and what do you value? Investigating the role of personality traits and customer-perceived value in online customer engagement. *Journal of Marketing Management*, 32(5–6), 502–525. <https://doi.org/10.1080/0267257X.2015.1128472>
- Mari, A., Mandelli, A., & Algesheimer, R. (2020). The evolution of marketing in the context of voice commerce: A managerial perspective. *Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, 12204 LNCS, 405–

425. [https://doi.org/10.1007/978-3-030-50341-3\\_32](https://doi.org/10.1007/978-3-030-50341-3_32)

- Masele, J. J., & Matama, R. (2020). Individual consumers' trust in B2C automobile e-commerce in Tanzania: Assessment of the influence of web design and consumer personality. *Electronic Journal of Information Systems in Developing Countries*, 86(1), e12115. <https://doi.org/10.1002/isd.12115>
- Matthews, G., Hancock, P. A., Lin, J., Panganiban, A. R., Reinerman-Jones, L. E., Szalma, J. L., & Wohleber, R. W. (2020). Evolution and revolution: Personality research for the coming world of robots, artificial intelligence, and autonomous systems. *Personality and Individual Differences*, 109969. <https://doi.org/10.1016/j.paid.2020.109969>
- McCarthy, M. H., Wood, J. V, & Holmes, J. G. (2017). Dispositional Pathways to Trust: Self-Esteem and Agreeableness Interact to Predict Trust and Negative Emotional Disclosure. *Journal of Personality & Social Psychology*, 113(1), 95–116. Retrieved from <http://10.0.4.13/pspi0000093>
- McLean, G., Al-Nabhani, K., & Wilson, A. (2018). Developing a Mobile Applications Customer Experience Model (MACE)- Implications for Retailers. *Journal of Business Research*, 85, 325–336. <https://doi.org/10.1016/j.jbusres.2018.01.018>
- 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. <https://doi.org/10.1016/j.chb.2019.05.009>
- McLean, G., & Wilson, A. (2016). Evolving the online customer experience ... is there a role for online customer support? *Computers in Human Behavior*, 60, 602–610. <https://doi.org/https://doi.org/10.1016/j.chb.2016.02.084>
- MD Main Uddin, Isaac, O., Alrajawy, I., & Maram, M. A. (2019). Do User Satisfaction and Actual Usage of Online Learning Impact Students Performance? *International Journal of Management and Human Science (IJMHS)*, 3(2), 60–67.
- Mikalef, P., & Krogstie, J. (2020). Examining the interplay between big data analytics and contextual factors in driving process innovation capabilities. *European Journal of Information Systems*, 29(3), 260–287. <https://doi.org/10.1080/0960085X.2020.1740618>
- Mikalef, P., Krogstie, J., Pappas, I. O., & Pavlou, P. (2020). Exploring the relationship between big data analytics capability and competitive performance: The mediating roles of dynamic and operational capabilities. *Information and Management*, 57(2), 103169. <https://doi.org/10.1016/j.im.2019.05.004>
- Mikalef, P., Pappas, I. O., & Giannakos, M. N. (2017). Value co-creation and purchase intention in social commerce: The enabling role of word-of-mouth and trust. *AMCIS 2017 - America's Conference on Information Systems: A Tradition of Innovation, 2017-Augus*.
- Mikalef, P., Pappas, I. O., Giannakos, M. N., & Sharma, K. (2017). Determining consumer engagement in word-of-mouth: Trust and network ties in a social commerce setting. *Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, 10595 LNCS, 351–362. [https://doi.org/10.1007/978-3-319-68557-1\\_31](https://doi.org/10.1007/978-3-319-68557-1_31)
- Moon, Y. (2002). Personalization and personality: Some effects of customizing message style based on consumer personality. *Journal of Consumer Psychology*, 12(4), 313–325. <https://doi.org/10.1207/15327660260382351>
- Moorman, C. (2019). August 2019 CMO Survey: Hiring, AI on the Rise. *Marketing News*, 53(9), 6–7. Retrieved from <https://www.ama.org/marketing-news/august-2019-cmo-survey-hiring-ai-on-the-rise/>

- Morgeson, F. V., Sharma, P. N., & Hult, G. T. M. (2015). Cross-national differences in consumer satisfaction: Mobile services in emerging and developed markets. *Journal of International Marketing*, 23(2), 1–24. <https://doi.org/10.1509/jim.14.0127>
- Moriuchi, E. (2019). Okay, Google!: An empirical study on voice assistants on consumer engagement and loyalty. *Psychology and Marketing*, 36(5), 489–501. <https://doi.org/10.1002/mar.21192>
- Mou, Y., & Xu, K. (2017). The media inequality: Comparing the initial human-human and human-AI social interactions. *Computers in Human Behavior*, 72, 432–440. <https://doi.org/10.1016/j.chb.2017.02.067>
- Nasirian, F., Ahmadian, M., & Lee, O. K. D. (2017). AI-based voice assistant systems: Evaluating from the interaction and trust perspectives. *AMCIS 2017 - America's Conference on Information Systems: A Tradition of Innovation, 2017-Augus.*
- Olsen, S. O., Tudoran, A. A., Honkanen, P., & Verplanken, B. (2016). Differences and Similarities between Impulse Buying and Variety Seeking: A Personality-based Perspective. *Psychology and Marketing*, 33(1), 36–47. <https://doi.org/10.1002/mar.20853>
- Pappas, I. O., Kourouthanassis, P. E., Giannakos, M. N., & Chrissikopoulos, V. (2016). Explaining online shopping behavior with fsQCA: The role of cognitive and affective perceptions. *Journal of Business Research*, 69(2), 794–803. <https://doi.org/10.1016/j.jbusres.2015.07.010>
- Pappas, I. O., Kourouthanassis, P. E., Giannakos, M. N., & Lekakos, G. (2017). The interplay of online shopping motivations and experiential factors on personalized e-commerce: A complexity theory approach. *Telematics and Informatics*, 34(5), 730–742. <https://doi.org/https://doi.org/10.1016/j.tele.2016.08.021>
- Pappas, I. O., Mikalef, P., Giannakos, M. N., & Pavlou, P. A. (2017). Value co-creation and trust in social commerce: An fsQCA approach. *Proceedings of the 25th European Conference on Information Systems, ECIS 2017*, 2153–2168.
- Pappas, I. O., Papavlasopoulou, S., Mikalef, P., & Giannakos, M. N. (2020). Identifying the combinations of motivations and emotions for creating satisfied users in SNSs: An fsQCA approach. *International Journal of Information Management*, 53, 102128. <https://doi.org/10.1016/j.ijinfomgt.2020.102128>
- Pavlou, P. A., & Gefen, D. (2004). Building effective online marketplaces with institution-based trust. *Information Systems Research*, 15(1), 37–59. <https://doi.org/10.1287/isre.1040.0015>
- Peer, E., Brandimarte, L., Samat, S., & Acquisti, A. (2017). Beyond the Turk: Alternative platforms for crowdsourcing behavioral research. *Journal of Experimental Social Psychology*, 70, 153–163. <https://doi.org/10.1016/j.jesp.2017.01.006>
- Pekovic, S., & Rolland, S. (2020). Recipes for achieving customer loyalty: A qualitative comparative analysis of the dimensions of customer experience. *Journal of Retailing and Consumer Services*, 56, 102171. <https://doi.org/https://doi.org/10.1016/j.jretconser.2020.102171>
- Pillai, R., Sivathanu, B., & Dwivedi, Y. K. (2020). Shopping intention at AI-powered automated retail stores (AIPARS). *Journal of Retailing and Consumer Services*, 57, 102207. <https://doi.org/https://doi.org/10.1016/j.jretconser.2020.102207>
- Piotrowicz, W., & Cuthbertson, R. (2014). Introduction to the special issue information technology in retail: Toward omnichannel retailing. *International Journal of Electronic Commerce*, 18(4), 5–16. <https://doi.org/10.2753/JEC1086-4415180400>
- Pizzi, G., & Scarpi, D. (2020). Privacy threats with retail technologies: A consumer perspective. *Journal of Retailing and Consumer Services*, 56, 102160.

<https://doi.org/10.1016/j.jretconser.2020.102160>

- 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*(5), 879–903. <https://doi.org/10.1037/0021-9010.88.5.879>
- Qiu, L., & Benbasat, I. (2008). Evaluating anthropomorphic product recommendation agents: A social relationship perspective to designing information systems. *Journal of Management Information Systems, 25*(4), 145–182. <https://doi.org/10.2753/MIS0742-1222250405>
- Ragin, C. C. (2006). Set relations in social research: Evaluating their consistency and coverage. *Political Analysis, 14*(3), 291–310. <https://doi.org/10.1093/pan/mpj019>
- Ragin, C. C. (2009). *Redesigning social inquiry: Fuzzy sets and beyond*. <https://doi.org/10.7208/chicago/9780226702797.001.0001>
- Ragin, C. C., Drass, K., & Davey, S. (2008). User's Guide to Fuzzy-Set / Qualitative Comparative Analysis. *University of Arizona, 87*, 1–87.
- Ragin, C. C., & Pennings, P. (2005). Fuzzy sets and social research. *Sociological Methods and Research, 33*(4), 423–430. <https://doi.org/10.1177/0049124105274499>
- Rajavi, K., Kushwaha, T., & Steenkamp, J. B. E. M. (2019). In Brands We Trust? A Multicategory, Multicountry Investigation of Sensitivity of Consumers' Trust in Brands to Marketing-Mix Activities. *Journal of Consumer Research, 46*(4), 651–670. <https://doi.org/10.1093/jcr/ucz026>
- Reisinger, D. (2018). Amazon Says Alexa Voice Shopping Tripled During 2018 Holiday Season. *Fortune.Com, N.PAG-N.PAG*.
- 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*, 106359. <https://doi.org/10.1016/j.chb.2020.106359>
- Rodić, A., Jovanović, M., Stevanović, I., Karan, B., & Potkonjak, V. (2015). Building technology platform aimed to develop service robot with embedded personality and enhanced communication with social environment. *Digital Communications and Networks, 1*(2), 112–124. <https://doi.org/10.1016/j.dcan.2015.03.002>
- Rodić, A., Vujović, M., Stevanović, I., & Jovanović, M. (2016). Development of human-centered social robot with embedded personality for elderly care. In *Mechanisms and Machine Science* (Vol. 39, pp. 233–247). [https://doi.org/10.1007/978-3-319-30674-2\\_18](https://doi.org/10.1007/978-3-319-30674-2_18)
- Rowe, S. Del. (2019). Voice Assistants Are Changing Shopping--Are You Ready? *Speech Technology Magazine, 24*(2), 9. Retrieved from <https://www.speechtechmag.com/Articles/ReadArticle.aspx?ArticleID=131582>
- Russo, I., & Confente, I. (2019). From dataset to qualitative comparative analysis (QCA)—Challenges and tricky points: A research note on contrarian case analysis and data calibration. *Australasian Marketing Journal, 27*(2), 129–135. <https://doi.org/10.1016/j.ausmj.2018.11.001>
- Sánchez-Medina, A. J., Galván-Sánchez, I., & Fernández-Monroy, M. (2020). Applying artificial intelligence to explore sexual cyberbullying behaviour. *Heliyon, 6*(1), e03218. <https://doi.org/10.1016/j.heliyon.2020.e03218>
- Santander UK. (2014). MarketLine Company Profile: Santander UK plc. In *Santander UK plc MarketLine Company Profile*. MarketLine, a Progressive Digital Media business.
- Scheidt, S., & Chung, Q. B. (2019). Making a case for speech analytics to improve customer service



- quality: Vision, implementation, and evaluation. *International Journal of Information Management*, 45, 223–232. <https://doi.org/https://doi.org/10.1016/j.ijinfomgt.2018.01.002>
- Syedghorban, Z., Tahernejad, H., & Matanda, M. J. (2016). Reinquiry into advertising avoidance on the internet: A conceptual replication and extension. *Journal of Advertising*, 45(1), 120–129. <https://doi.org/10.1080/00913367.2015.1085819>
- Shareef, M. A., Kumar, V., Dwivedi, Y. K., Kumar, U., Akram, M. S., & Raman, R. (2021). A new health care system enabled by machine intelligence: Elderly people's trust or losing self control. *Technological Forecasting and Social Change*, 162, 120334. <https://doi.org/10.1016/j.techfore.2020.120334>
- Sheng, M. L., & Teo, T. S. H. (2012). Product attributes and brand equity in the mobile domain: The mediating role of customer experience. *International Journal of Information Management*, 32(2), 139–146. <https://doi.org/https://doi.org/10.1016/j.ijinfomgt.2011.11.017>
- Shi, S., & Chow, W. S. (2015). Trust development and transfer in social commerce: Prior experience as moderator. *Industrial Management and Data Systems*, 115(7), 1182–1203. <https://doi.org/10.1108/IMDS-01-2015-0019>
- Shi, S., Wang, Y., Chen, X., & Zhang, Q. (2020). Conceptualization of omnichannel customer experience and its impact on shopping intention: A mixed-method approach. *International Journal of Information Management*, 50, 325–336. <https://doi.org/https://doi.org/10.1016/j.ijinfomgt.2019.09.001>
- Shin, D. H. (2017). Conceptualizing and measuring quality of experience of the internet of things: Exploring how quality is perceived by users. *Information and Management*, 54(8), 998–1011. <https://doi.org/10.1016/j.im.2017.02.006>
- Simms, K. (2019). How Voice Assistants Could Change the Way We Shop. *Harvard Business Review*, may, 2–7. Retrieved from <https://hbr.org/2019/05/how-voice-assistants-could-change-the-way-we-shop>
- Sohn, S., Seegebarth, B., & Moritz, M. (2017). The Impact of Perceived Visual Complexity of Mobile Online Shops on User's Satisfaction. *Psychology and Marketing*, 34(2), 195–214. <https://doi.org/10.1002/mar.20983>
- Souden, N., Ladhari, R., & Natarajan, R. (2019). Personality traits and complaining behaviors: A focus on Japanese consumers. *Psychology and Marketing*, 36(4), 363–375. <https://doi.org/10.1002/mar.21184>
- Sperkova, L. (2019). Integration of textual VoC into a CX data model for business intelligence use in B2C. *Journal of Intelligence Studies in Business*, 9(3), 39–55. <https://doi.org/10.37380/jisib.v9i3.514>
- Srivastava, M., & Kaul, D. (2014). Social interaction, convenience and customer satisfaction: The mediating effect of customer experience. *Journal of Retailing and Consumer Services*, 21(6), 1028–1037. <https://doi.org/https://doi.org/10.1016/j.jretconser.2014.04.007>
- Srivastava, S. C., Chandra, S., & Shirish, A. (2015). Technostress creators and job outcomes: Theorising the moderating influence of personality traits. *Information Systems Journal*, 25(4), 355–401. <https://doi.org/10.1111/isj.12067>
- Stanworth, J. O., Warden, C. A., & Hsu, R. S. (2015). The voice of the Chinese customer: Facilitating ecommerce encounters. *International Journal of Market Research*, 57(3), 459–481. <https://doi.org/10.2501/IJMR-2015-037>
- Steinhoff, L., Arli, D., Weaven, S., & Kozlenkova, I. V. (2019). Online relationship marketing.

- Journal of the Academy of Marketing Science*, 47(3), 369–393. <https://doi.org/10.1007/s11747-018-0621-6>
- Taylor, S., & Todd, P. (1995). Assessing IT usage: The role of prior experience. *MIS Quarterly: Management Information Systems*, 19(4), 561–568. <https://doi.org/10.2307/249633>
- Tho, N. D., & Trang, N. T. M. (2015). Can knowledge be transferred from business schools to business organizations through in-service training students? SEM and fsQCA findings. *Journal of Business Research*, 68(6), 1332–1340. <https://doi.org/https://doi.org/10.1016/j.jbusres.2014.12.003>
- Tong, S., Luo, X., & Xu, B. (2020). Personalized mobile marketing strategies. *Journal of the Academy of Marketing Science*, 48(1), 64–78. <https://doi.org/10.1007/s11747-019-00693-3>
- Trajkova, M., & Martin-Hammond, A. (2020). “alexa is a Toy”: Exploring Older Adults’ Reasons for Using, Limiting, and Abandoning Echo. *Conference on Human Factors in Computing Systems - Proceedings*, 1–13. <https://doi.org/10.1145/3313831.3376760>
- Triantoro, T., Gopal, R., Benbunan-Fich, R., & Lang, G. (2019). Would you like to play? A comparison of a gamified survey with a traditional online survey method. *International Journal of Information Management*, 49, 242–252. <https://doi.org/10.1016/j.ijinfomgt.2019.06.001>
- Turkyilmaz, C. A., Erdem, S., & Uslu, A. (2015). The Effects of Personality Traits and Website Quality on Online Impulse Buying. *Procedia - Social and Behavioral Sciences*, 175, 98–105. <https://doi.org/10.1016/j.sbspro.2015.01.1179>
- Tyrväinen, O., Karjaluoto, H., & Saarijärvi, H. (2020). Personalization and hedonic motivation in creating customer experiences and loyalty in omnichannel retail. *Journal of Retailing and Consumer Services*, 57, 102233. <https://doi.org/10.1016/j.jretconser.2020.102233>
- Ufer, D., Lin, W., & Ortega, D. L. (2019). Personality traits and preferences for specialty coffee: Results from a coffee shop field experiment. *Food Research International*, 125, 108504. <https://doi.org/10.1016/j.foodres.2019.108504>
- Venkatesh, V., Sykes, T. A., & Venkatraman, S. (2014). Understanding e-Government portal use in rural India: role of demographic and personality characteristics. *Information Systems Journal*, 24(3), 249–269. Retrieved from <http://10.0.4.87/isj.12008>
- Verhoef, P. C. (2003). Understanding the Effect of Customer Relationship Management Efforts on Customer Retention and Customer Share Development. *Journal of Marketing*, 67(4), 30–45. <https://doi.org/10.1509/jmkg.67.4.30.18685>
- Verhoef, P. C., Lemon, K. N., Parasuraman, A., Roggeveen, A., Tsiros, M., & Schlesinger, L. A. (2009). Customer Experience Creation: Determinants, Dynamics and Management Strategies. *Journal of Retailing*, 85(1), 31–41. <https://doi.org/10.1016/j.jretai.2008.11.001>
- Visinescu, L. L., Sidorova, A., Jones, M. C., & Prybutok, V. R. (2015). The influence of website dimensionality on customer experiences, perceptions and behavioral intentions: An exploration of 2D vs. 3D web design. *Information and Management*, 52(1), 1–17. <https://doi.org/10.1016/j.im.2014.10.005>
- von Briel, F. (2018). The future of omnichannel retail: A four-stage Delphi study. *Technological Forecasting and Social Change*, 132, 217–229. <https://doi.org/10.1016/j.techfore.2018.02.004>
- Wagner, G., Schramm-Klein, H., & Steinmann, S. (2020). Online retailing across e-channels and e-channel touchpoints: Empirical studies of consumer behavior in the multichannel e-commerce environment. *Journal of Business Research*, 107, 256–270. <https://doi.org/10.1016/j.jbusres.2018.10.048>

- Wang, Y., & Herrando, C. (2019). Does privacy assurance on social commerce sites matter to millennials? *International Journal of Information Management*, 44, 164–177. <https://doi.org/https://doi.org/10.1016/j.ijinfomgt.2018.10.016>
- Webber, S., Payne, S., & Taylor, A. (2012). Personality and Trust Fosters Service Quality. *Journal of Business & Psychology*, 27(2), 193–203. Retrieved from <http://10.0.3.239/s10869-011-9235-4>
- Whang, C. (2018). Voice Shopping: The Effect of the Consumer-Voice Assistant Parasocial Relationship on the Consumer's Perception and Decision Making. *ProQuest Dissertations and Theses*, 174. Retrieved from <https://search.proquest.com/docview/2130559314?accountid=168248%0Ahttp://www.yidu.edu.cn/educhina/educhina.do?artifact=&svalue=Voice+Shopping%3A+The+Effect+of+the+Consumer-Voice+Assistant+Parasocial+Relationship+on+the+Consumer%27s+Perception+and+Decision>
- While, V. S. D., Home, G., Shopping, W. V., Tennant, B. E., Is, W., Most, I., & Ahead, L. (2018). Voice Shopping Is Revolutionizing E-Commerce. *Twice*, 33(18), 9. Retrieved from <https://www.twice.com/blog/voice-shopping-revolutionizing-e-commerce>
- Williams, L., Buoye, A., Keiningham, T. L., & Aksoy, L. (2020). The practitioners' path to customer loyalty: Memorable experiences or frictionless experiences? *Journal of Retailing and Consumer Services*, 57, 102215. <https://doi.org/10.1016/j.jretconser.2020.102215>
- Witell, L., Kowalkowski, C., Perks, H., Raddats, C., Schwabe, M., Benedettini, O., & Burton, J. (2020). Characterizing customer experience management in business markets. *Journal of Business Research*, 116, 420–430. <https://doi.org/https://doi.org/10.1016/j.jbusres.2019.08.050>
- Woodside, A. G. (2014). Embrace perform model: Complexity theory, contrarian case analysis, and multiple realities. *Journal of Business Research*, 67(12), 2495–2503. <https://doi.org/10.1016/j.jbusres.2014.07.006>
- Wottrich, V. M., van Reijmersdal, E. A., & Smit, E. G. (2018). The privacy trade-off for mobile app downloads: The roles of app value, intrusiveness, and privacy concerns. *Decision Support Systems*, 106, 44–52. <https://doi.org/10.1016/j.dss.2017.12.003>
- Wu, I.-L. (2013). The antecedents of customer satisfaction and its link to complaint intentions in online shopping: An integration of justice, technology, and trust. *International Journal of Information Management*, 33(1), 166–176. <https://doi.org/https://doi.org/10.1016/j.ijinfomgt.2012.09.001>
- Wu, W. Y., & Ke, C. C. (2015). An online shopping behavior model integrating personality traits, perceived risk, and technology acceptance. *Social Behavior and Personality*, 43(1), 85–98. <https://doi.org/10.2224/sbp.2015.43.1.85>
- Xie, X.-Z., & Tsai, N.-C. (2020). The effects of negative information-related incidents on social media discontinuance intention: Evidence from SEM and fsQCA. *Telematics and Informatics*, 101503. <https://doi.org/https://doi.org/10.1016/j.tele.2020.101503>
- Yang, S., & Lee, Y. J. (2017). The Dimensions of M-Interactivity and Their Impacts in the Mobile Commerce Context. *International Journal of Electronic Commerce*, 21(4), 548–571. <https://doi.org/10.1080/10864415.2016.1355645>
- Yoon, H. S., & Oceaña, L. G. (2015). Influencing factors of trust in consumer-to-consumer electronic commerce with gender and age. *International Journal of Information Management*, 35(3), 352–363. <https://doi.org/https://doi.org/10.1016/j.ijinfomgt.2015.02.003>
- Yuan, L. (Ivy), & Dennis, A. R. (2019). Acting Like Humans? Anthropomorphism and Consumer's Willingness to Pay in Electronic Commerce. *Journal of Management Information Systems*, 36(2), 450–477. <https://doi.org/10.1080/07421222.2019.1598691>

- Yueh, H.-P., Lu, M.-H., & Lin, W. (2016). Employees' acceptance of mobile technology in a workplace: An empirical study using SEM and fsQCA. *Journal of Business Research*, 69(6), 2318–2324. <https://doi.org/https://doi.org/10.1016/j.jbusres.2015.12.048>
- Yun, H., Lee, G., & Kim, D. J. (2019). A chronological review of empirical research on personal information privacy concerns: An analysis of contexts and research constructs. *Information and Management*, 56(4), 570–601. <https://doi.org/10.1016/j.im.2018.10.001>
- Zhu, H., Ou, C. X. J., van den Heuvel, W. J. A. M., & Liu, H. (2017). Privacy calculus and its utility for personalization services in e-commerce: An analysis of consumer decision-making. *Information and Management*, 54(4), 427–437. <https://doi.org/10.1016/j.im.2016.10.001>
- Zhu, Y. Q., & Kanjanamekanant, K. (2020). No trespassing: exploring privacy boundaries in personalized advertisement and its effects on ad attitude and purchase intentions on social media. *Information and Management*, 103314. <https://doi.org/10.1016/j.im.2020.103314>