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Why do consumers adopt smart voice assistants for shopping purposes? A perspective from complexity theory

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ABSTRACT

The widespread appeal of Smart Voice Assistants (SVAs) stems from their ability to enhance the everyday lives of consumers in a practical, enjoyable, and meaningful manner. Despite their popularity, the factors that shape consumer adoption of SVAs remain largely unexplored. To address this research gap, we utilized complexity theory to construct an integrated model that sheds light on the determinants of consumer decision-making in regard to SVA adoption. Furthermore, we applied fuzzy-set Qualitative Comparative Analysis (fsQCA) to examine the proposed model and uncover the causal recipes associated with SVA adoption. Our necessary condition analysis highlights that perceived ease of use, perceived usefulness, perceived humanness, and perceived social presence are necessary predictors for consumers' intentions to adopt SVA. This study constitutes a significant addition to the existing literature by providing a comprehensive and nuanced understanding of the drivers of SVA adoption. Moreover, it offers crucial implications for online service provider managers to improve the adoption of SVAs among their customers.

1. Introduction

Smart voice assistants (SVAs) are AI-based tools, such as Alexa, Google Home, and Siri, that enable customers to interact with technology through voice commands and questions (Mishra et al., 2021). SVAs are a recent entrant in the dynamic field of customer-technology interaction (Hernandez-Ortega et al., 2021). The sales of SVAs witnessed a record surge in 2019, reaching 146.9 million units due to COVID-19′s impact on the supply chain and retail distribution (Kim & Choudhury, 2021). As COVID-19 has urged individuals to avoid physical contact, SVA use is anticipated to surge, promoting SVAs as a preferred means of interaction (Mishra et al., 2021). The adoption of Virtual Assistants (VAs) is expected to alter the customer experience by transforming how people communicate with brands and retailers (Lucia-Palacios & Pérez-López, 2021). The growth in VA ownership is a clear indication of this transformative potential, with over 30% of US households owning a VA by 2020 (Acikgoz & Vega, 2022). In Japan, where only 3.7 million households owned a VA in 2018, the number is anticipated to surge by approximately 500% to over 22 million by 2024 (Jain et al., 2022; Klaus & Zaichkowsky, 2022).

Smart speakers and voice assistants have transformed the customer decision-making process, particularly with respect to voice-enabled searches and purchasing patterns (McLean & Osei-Frimpong, 2019; Poushneh, 2021a). Customers have seamlessly integrated SVAs into their daily routine, primarily for shopping, multitasking, and voice search (Al Shamsi et al., 2022). The increasing pervasiveness of the internet, with approximately 54% of the global population having access, and the greater adoption of voice assistants on mobile devices (58%) compared to smart speakers (22.9%), is creating a potentially vast market for new technologies (PWC, 2019). Consequently, marketers need a comprehensive understanding of how customers are using SVAs to effectively tailor their products and services to this expanding group of SVA users (Ammari et al., 2019).

Prior research on the adoption of Smart Voice Assistants (SVAs) has predominantly relied on established technology adoption theories and models, including the "Technology Acceptance Model" (TAM), "Unified Theory of Acceptance and Use of Technology" (UTAUT), and "Theory of Planned Behavior" (TPB) (Davis, 1989; Acikgoz & Vega, 2022; Venkatesh et al., 2003; Vimalkumar et al., 2021; Ajzen, 2011). However, SVAs represent a unique market segment compared to other technologies such as virtual reality or augmented reality and are often utilized in private or discreet settings to deliver instant gratification to users (Lee

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et al., 2020). As a result, researchers interested in comprehending the adoption of SVAs should broaden their focus beyond conventional adoption models.

Previous research on the adoption of SVAs has primarily focused on linear, symmetrical modeling and net effects, which may not fully capture the complexity of consumers' behaviors (Kopplin & Rösch, 2021; Olya & Nia, 2021). This approach is limited because it assumes that the association between two constructs is symmetrical, which may not be the case in all instances, and it fails to capture the complex processes underlying consumer behavior (Gligor & Bozkurt, 2020). To address this gap, we employ complexity theory as a framework to explore the interactions of variables affecting consumers' intentions to adopt SVA, incorporating demographic, functional, and social constructs. The theory of complexity is particularly well-suited for the examination of intricate relationships between outcome conditions and causal antecedents in complex and diverse settings, such as retailing, where the interrelated nature of stakeholders and the dynamic nature of processes significantly affect customer behavior (Farmaki et al., 2022). To analyze the data, we utilized fuzzy-set Qualitative Comparative Analysis (fsQCA) to identify causal recipes, which refer to the combined effects of predictors, and Necessary Condition Analysis (NCA) to ascertain the variables that are essential for determining consumers' intention to adopt SVAs. Our study offers new insights into the complex factors driving SVA adoption, extending beyond the limitations of conventional adoption models.

The subsequent section will offer a comprehensive elucidation of the theoretical underpinnings and the formulation of research propositions. Section 3 concentrates on outlining the study methodology and the procedures employed to conduct this research. In section four, we will present our data analysis and the principal findings derived from it. Subsequently, we will examine the study and its implications in section five, while section six will be dedicated to discussing the primary limitations and outlining potential avenues for future research.

2. Research background and propositions

2.1. Smart voice assistant adoption

The technology of SVA refers to "Internet-connected software which responds to voice commands to provide content and services, interacting with users via digitally-generated voice responses" (Centre for Data Ethics & Innovation, 2019). An SVA can be described either as a smartphone app (i.e., Apple's Siri or Google's Assistant) or as dedicated hardware which now exists as the primary delivery mechanism for SVAs (e.g., Amazon Echo, Google Home, Apple HomePod) (Balakrishnan et al., 2021; Ling et al., 2021). Technologies like speech recognition, natural language processing, semantic web, machine learning, and AI, all come together to deliver SVAs (Balakrishnan et al., 2021; Ling et al., 2021). The ability of SVAs to remember the context of previous queries and apply it to subsequent ones has greatly improved thanks to recent design changes (Canziani & MacSween, 2021). However, widespread adoption of SVAs is hampered by several persistent technical limitations. An SVA has many shortcomings, such as its inability to distinguish between different voices, its poor understanding of diction, and its inability to guarantee users' privacy and security (Sohn & Kwon, 2020).

As technology continues to permeate all aspects of society, the use of AI-enabled smart devices by customers is constantly on the rise (Canziani & MacSween, 2021). SVAs have gained popularity and widespread usage as a feature of both smart speakers and smartphone applications, among other devices (Moriuchi, 2019), providing a simple channel for customers to communicate with businesses (Mishra et al., 2021; Yuan et al., 2022). The convenience of SVAs is that customers can give voice commands without being distracted from what they are currently doing, such as replying to emails, getting traffic updates while driving, shopping online, and booking a taxi (Fernandes & Oliveira, 2021; Poushneh, 2021b). Additionally, SVAs powered by AI can tailor their communications with customers on a cognitive and emotional level, allowing for the possibility of marketer-customer interaction through voice-based channels (Kowalczuk, 2018).

Lee et al. (2020) adopted the uses and gratification model to investigate the underlying determinants that drive customers to adopt SVAs, while Lucia-Palacios and Pérez-López (2021) scrutinized the literature on technology acceptance to understand how an SVA affects shoppers' enthusiasm for online purchases.

Despite the burgeoning interest in SVAs and their anticipated expansion, there remains a dearth of comprehension regarding the determinants of their adoption. Table 1 summarizes examples of existing empirical research conducted in this field. As can be noted from Table 1, previous research relies heavily on insights gleaned from established acceptance models such as TAM and UTAUT. As a result, previous studies focused on these factors using symmetrical modeling and the net effect of drivers on behavior in the retail industry, customers' complex behavior affects their intention to adopt an SVA but did not take into account the complexity of consumer behavior. Thus, our study bridges this research gap by employing complexity theory and fsQCA to uncover how, in the retail industry, customers' complex behavior affects their intention to adopt an SVA.

2.2. Functional and social variables

Wirtz et al. (2018) introduced the Service Robot Acceptance Model (sRAM) for explaining the adoption of SVAs, which comprises three dimensions: "functional", "social-emotional", and "relational". According to the sRAM, a user's perception of the helpfulness of their interactions with an SVA is closely linked to their evaluation of its "usefulness" and "ease-of-use". Improvements in "ease-of-use" and "usefulness" are expected to directly benefit automated service technologies like SVAs. The functional dimension is particularly relevant for SVAs as it enables quick and easy adoption and provides guidance and reassurance throughout the entire service encounter (Chong et al., 2021; Wirtz et al., 2018). In their study, Shao and Kwon (2021) discovered that utilitarian benefits, namely "usefulness and convenience", have a positive impact on an individual's adoption of in-home voice assistants.

The adoption of new technologies is influenced by an individual's "subjective social norms", which are formed based on their assumptions about the expectations of their significant others in a given situation (Sawang et al., 2014). If an individual perceives that their actions will be supported by their social referents, they are more likely to adopt a new technology, indicating a positive correlation between social norms and technology adoption (Yang & Jolly, 2009). The increasing popularity and trendiness of SVAs may lead to their use as a means of enhancing one's social status and perceived importance within their peer groups (Kaushik et al., 2015, p. 281).

Social variables such as "perceived humanness", "social interaction", and "social presence" play an important role in the adoption and acceptance of service virtual agents (SVAs). Anthropomorphic features, such as physical appearance and behavior, are key in creating a sense of humanity in SVAs, thereby enhancing customers' sense of empathy and relatedness to the non-human agents (Wirtz et al., 2018). However, some scholars argue that anthropomorphizing technology could lead to unrealistic expectations of their capabilities (Duffy, 2006). Additionally, the Uncanny Valley theory posits that as a robot becomes more human-like, the sense of familiarity increases, but it could also create feelings of discomfort or even fear, leading to a disruption in human-SVA interaction (Fernandes & Oliveira, 2021; Lucia-Palacios & Pérez-López, 2021). Therefore, while anthropomorphic features can enhance social variables, caution must be exercised to avoid crossing the line into an uncanny and frightening territory, which could negatively impact SVA adoption and acceptance.

The concept of "perceived social interactivity" pertains to the extent to which an individual perceives that an SVA exhibits socially acceptable behaviors and emotions (Wirtz et al., 2018). Anthropomorphic qualities

Table 1
Overview of empirical research on factors driving customer's acceptance of intelligent devices.

Author (s)	Method	Research focus	Key findings
Alepis and Patsakis (2017)	Cross-sectional	Analyzed five VAs: Google Assistant, S. Voice, Cortana, Alexa, and Siri	The IPAs can be exploited from applications or nearby devices leading to malicious attacks and privacy risks
Nasirian et al. (2017)	Cross-sectional	Offline survey of 104 students from a University in the US	Interaction quality, trust, and personal innovativeness are significant motivators for using Vas
Kowalczuk (2018)	Mixed methods approach	Voice-activated smart speakers	Based in TAM, 60.4% of behavioral intention variance is explained and is influenced by (a) perceived usefulness; (b) perceived enjoyment and (c) risk (surveillance anxiety and privacy risk). Ease-of-use has only an indirect effect.
Belanche, Casaló, and Flavián (2019)	Cross-sectional	Robo-advisors in FinTechs	Based in TAM, 68.4% of usage intention variance is explained and is influenced by (a) subjective norms and (b) attitude towards the technology, which in turn is influenced by perceived usefulness and ease-of-use.
Castelo et al. (2019)	Experimental	4 Online Lab Studies with over 1400 participants and two online field studies with over 56,000 participants	Increasing VA devices' algorithms' perceived affective human-likeness is effective at increasing the use of such algorithms for subjective tasks
Gursoy, Chi, Lu, and Nunkoo (2019), Lin et al. (2019)	Cross-sectional	Artificially intelligent robotic devices	Based in the Artificially Intelligent Device Use Acceptance (AIDUA) theory, 75% to 78% of acceptance variance is explained and is influenced by (a) social influence, (b) hedonic motivation, (c) anthropomorphism, (d) performance, (e) effort expectancy and (f) emotions
Guzman (2019)	Cross-sectional	Responses of 28 participants of different races and ethnicities (Latino, self-identified white, Black, Asian, Middle-Eastern) from field sites	Voice-based, mobile virtual assistants such as Siri, Google have complex designs. Some users perceive the conversational agent's voice as representing the phone, while other users perceive the conversational agent's voice as the assistant in the phone.
McLean and OseiFrimpong (2019)	Cross-sectional	Survey of 724 in-home VA users	The utilitarian benefits, symbolic benefits, and social benefits provided by VAs are significant. Hedonic benefits only motivate the use of income VAs in smaller households.
Moriuchi (2019)	Cross-sectional	368 respondents surveyed from Amazon's Mechanical Turk (mTurk)	User's subjective norms in using the internet impact perceived usefulness and perceived ease of use of VA.
Fernandes and Oliveira (2020)	Cross-sectional	Survey of 238 young consumers	Customer-robot rapport building - Extends the service robot acceptance model by Wirtz (2018) to show that Customers increasingly organize their everyday activities with the support of technology.
Vimalkumar et al. (2021)	Cross-sectional	252 Indian respondents using virtual-based digital assistants	Perceived privacy risk has a strong negative and significant influence on perceived trust. To increase trust, one has to address the risk perception towards technology.
Jain et al. (2022)	Mixed methods approach	1937 respondents were selected using a mixed multistage sampling method	A key study finding is that brand credibility significantly moderates the relationship between VA features and the overall perceived value of VAs – higher brand credibility reduces users' perception of privacy risks.

such as voice, conversation, and the performance of human-like roles can provide users with the impression that they are interacting with real people rather than artificial agents (Gansser & Reich, 2021). Users may be more likely to embrace new technologies if they perceive them to possess "social attractiveness" and engage with them in a socially desirable manner (Fernandes & Oliveira, 2021).

In order for an SVA to be regarded as socially present, it must evoke in its users a sense of proximity to another social being (Cao and Wang, 2022). The extent to which users perceive the SVA as "present" during use can impact their evaluation and acceptance of the SVA (Wirtz et al., 2018). Due to an SVA's ability to communicate through language, customers are more inclined to "treat the artificial agent as they do other humans and respond to them socially" (Fernandes & Oliveira, 2021, p. 187). McLean and Osei-Frimpong (2019) suggest that social presence engagement is critical to the success of technological products. Therefore, our study examines the influence of functional variables (i.e., "perceived ease of use", "perceived usefulness", and "subjective social norms") and social variables (i.e., "perceived humanness", "perceived service interactivity", and "perceived social presence") on customers' intentions to adopt an SVA. Fig. 1 depicts the conceptual research model.

2.3. Complexity theory

The concept of utilizing multi-element patterns to forecast the behavior of systems with complex features is central to complexity theory, which has its roots in chaos theory (Guanrong, 2021). According to this theory, complex phenomena are the consequence of different permutations of attributes that converge to the same outcome (Urry, 2005). As a result, a linear analysis of a complex phenomenon would not suffice to identify its causes. While linear analysis may prove useful in some circumstances, it can also fail to account for essential details of the X→Y relationships. Conversely, nonlinear analyses facilitate the identification of various combinations of attributes that explore the complex phenomenon of interest. These analyses may reveal that X has a positive, negative, or no relationship to Y within the same context (Woodside, 2017). Therefore, complexity theory's approach can unveil how combinations of causal attributes can result in the same outcome, a concept referred to as equifinality (Woodside, 2015, p. 43). It is crucial to recognize that, while linear analysis may have its applications, complexity theory's perspective is indispensable for comprehending complex systems.

Equifinality is a central principle in both complexity theory and configuration theory (Pappas et al., 2017), which suggests that there

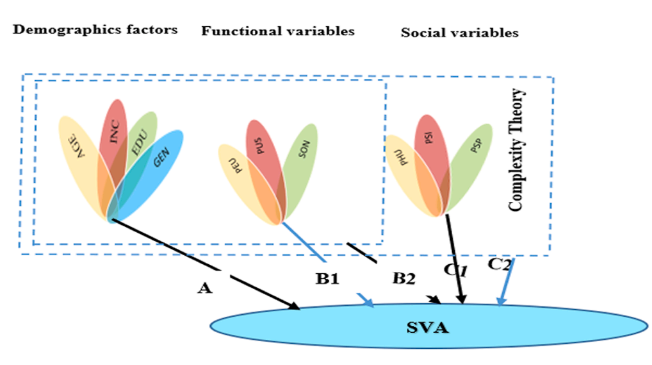

Fig. 1. The conceptual research model.

may be multiple configurations of initial conditions that lead to the same final state. Configuration theory also rests on the principle of causal asymmetry, indicating that the variables responsible for the presence of an outcome may differ from those responsible for its absence or negation (Ragin, 2009). Moreover, a given factor may be necessary and sufficient for a given outcome (Pappas & Woodside, 2021), but its absence or negation may not necessarily produce the opposite result.

The relationship between factors may also be complex, whereby the presence of one factor (X) may result in the presence of another factor (Y), which demonstrates sufficiency. However, factor Y may still exist even in the absence of factor X, suggesting that the presence of X is necessary but not sufficient for Y to occur. It is also possible that factor X is necessary but not sufficient on its own when other factors are present. In some cases, a third factor (Z2) may be necessary for the occurrence of outcome Y, given the presence or absence of factor X. As a result, multiple permutations may lead to the expected result, referred to as "configurations" in fsQCA. Configurations are sets of factors that have synergistic effects and may lead to desired outcomes.

The present study makes a valuable contribution to the literature by investigating the variables that can influence the adoption of SVA and presents a novel model that identifies the factors impacting customers' decisions to adopt or reject SVA.

4. Research propositions

Recipes, according to Ordanini et al. (2014, p.134), are "more important than ingredients" when it comes to quality control analysis. It is possible that a number of factors are at play when it comes to a consumer's decision to use an SVA, but it is more important to understand the various predictor combinations than to find all possible predictors. Prior studies on consumer IT adoption behavior have indicated the potential existence and importance of complex relationships among variables, which cannot be fully explained through isolated or indirect relationships (Pappas et al., 2020). However, this idea has not been empirically tested. Therefore, identifying and understanding the joint effects of multiple predictors can be more beneficial for managers than solely focusing on isolated predictors, even if they lack certain capabilities or resources.

The adoption of SVA is a complex and multifaceted phenomenon that requires a more nuanced approach than simple correlations between isolated factors. Equifinality, a fundamental principle of both configuration theory and complexity theory, posits that there are multiple possible explanations for any given outcome (Pappas et al., 2020). These explanations may involve one or more conditions that are necessary by themselves or in combination to account for the result (Pappas et al., 2020; Woodside, 2015). To understand why customers choose to adopt an SVA, it is important to consider both their intentions and underlying motivations, which are two independent but interrelated factors that can be combined in various ways.

Pappas et al. (2020) discovered that customers' intentions to adopt an SVA can be influenced by both functional and social variables. Moreover, social variables are linked to functional variables, and both are used as predictors of consumer behavior (Fernandes & Oliveira, 2021). Despite the fact that functional variables may not affect their behaviors, customers' intentions to adopt an SVA may still increase (Vimalkumar et al., 2021). However, social variables, such as "perceived social presence", are directly linked to customers' behavior when it comes to adopting an SVA (Balakrishnan & Dwivedi, 2021). Therefore, understanding the interplay between functional and social variables is essential for comprehending customers' adoption of SVAs. Thus, we suggest the following.

Proposition 1. *"No single optimal configuration of demographic variables, functional variables, and social variables leads to a high intention to adopt an SVA, but there exist multiple, equally effective configurations of causal factors."*

The configuration theory proposes the principle of causal asymmetry, which posits that the presence or absence of a causal recipe for an outcome depends on how this construct interacts with other constructs (Pappas & Woodside, 2021; Woodside, 2015). While customers' perceptions of how easy a product or service is to use can influence their decisions (Lee et al., 2022), this factor alone may not fully explain the high adoption of SVA (Pappas & Woodside, 2021). Additionally, functional variables can have varying effects on customers' behavior depending on their perception of usefulness. For example, some customers may value simplicity of use more than practicality, leading to a higher propensity for adoption (Pappas & Woodside, 2021). However, if the service's usefulness is low, these same customers may express strong adoption intentions when other factors, such as "perceived social interactivity", come into play (Aluko et al., 2022; Pappas, 2021). Therefore, we propose the following.

Proposition 2. *"Demographic variables, functional variables, and social variables, may be present or absent as single causal conditions for a customer's high intention to adopt an SVA, depending on how they combine with other causal conditions."*

3. Research methods

The present study aims to explore the factors that drive consumers' adoption of smart voice assistants for shopping purposes using a perspective from complexity theory. To achieve this goal, we followed a mixed methods approach to avoid inconsistent results that might arise when using only quantitative or qualitative methods (Creswell and Plano Clark, 2007). We collected data from a sample of 380 consumers who have used smart voice assistants for shopping. Participants completed a questionnaire that includes measures of complexity theory constructs (e.g., "perceived ease of use", "perceived usefulness", "subjective social norms", "perceived humanness", "perceived social interactivity", and "perceived social presence"). The quantitative data were analyzed using confirmatory factor analysis (CFA) to examine the validity of the measures and the relationship between the constructs.

To establish the reliability of our measures, Cronbach's alpha coefficient was employed to evaluate the internal consistency of the items that assess different constructs (Al-Fraihat et al., 2020). This coefficient gauges the degree of correlation between items on a scale, with a value of 0.70 or greater generally deemed acceptable. The discriminant validity of our measures was evaluated by utilizing the Heterotrait-Monotrait (HTMT) ratio of correlations. This ratio gauges the degree to which a construct is more highly correlated with its own items relative to the items of other constructs. HTMT ratios below 0.85 indicate discriminant validity between constructs (Hair et al., 2020).

In order to evaluate the convergent validity of our measures, an assessment of the average variance extracted (AVE) will be conducted. The AVE serves as a quantification of the proportion of variance accounted for by the items measuring a given construct. Acceptable values of AVE are typically considered to be greater than 0.5, as indicated by Al-Fraihat and colleagues (2020). Additionally, a post-hoc analysis will be conducted to investigate the indirect effects of complexity theory constructs on adoption intention, with particular attention given to the mediating roles of "perceived usefulness" and "perceived ease of use".

To investigate strategies for achieving high levels of smart voice assistant (SVA) adoption behavior among retailers, an explanatory sequential design was utilized in this study. Specifically, the study employed fuzzy-set Qualitative Comparative Analysis (fsQCA) to examine how combinations of functional variables, social variables, and demographics influence SVA adoption behavior (Ragin, 2008; Pappas & Woodside, 2021). The study was conducted in two phases, beginning with an online survey of consumers. In a subsequent phase, some of the participants were engaged in a follow-up examination, aimed at interpreting and expanding upon the explanatory power of the fsQCA findings. Overall, this research adds to the current understanding of the determinants that influence the adoption of SVA (Scan, Visit, and Act) behavior within the retail context, thereby offering valuable insights to retailers who aim to improve their performance in this domain.

3.1. Quantitative phase

In this study, a positivist research philosophy was adopted to construct and evaluate the study model. Data collection was carried out through an online survey in December 2022. Unlike prior research that has primarily focused on the US and UK, where smart voice assistants (SVA) are already prevalent in retail settings, this investigation targeted a novel market for these services, specifically in Jordan. This country represents an emerging market for retail investment in the Middle East region and was ranked eighth globally in the 2019 Global Retail Development Index (GRDI), trailing behind China, India, Malaysia, Ghana, Indonesia, Senegal, and Saudi Arabia with annual consumer spending amounting to approximately $15 billion USD (Al Watan, 2019). In light of prevailing market conditions, the incorporation of cutting-edge technological advancements such as Artificial Intelligence (AI) is imperative for enhancing the retail landscape, particularly in regards to the execution of financial services (Mogaji and Nguyen, 2022).

Quantitative sample

To gather data on the usage of smart voice assistants (SVA) for shopping purposes among Jordanian consumers, an online survey was designed and administered, with age and gender being used as criteria for quota sampling to ensure a representative sample. Participants were also provided with additional information on SVAs through a YouTube video link. After removing incomplete responses, the study collected 380 usable responses, which was deemed sufficient based on statistical power analysis using G* Power (Arend & Schäfer, 2019). This sample size was necessary to achieve a statistical power of 0.95 and an effect size of 0.16. Of the 380 participants, 194 were female (51%) and 186 were male (49%). The largest age group represented was 30–39 years (32%), and the highest academic qualification held by participants was a bachelor's degree (29%). In terms of income, 24% of participants reported earning between $25,000-$39,999 (USD). Finally, 27% of participants reported using SVAs for shopping purposes between 3 and 6 times in the previous year. These findings provide insights into the characteristics of the Jordanian consumer base and their usage patterns of SVAs for shopping purposes as summarized in Table 2.

3.2. Measures

Validated instruments from previous studies were utilized in this study to ensure the validity and reliability of the measures. In order to operationalize the construct of intention to adopt a smart voice assistant (SVA), the study utilized a set of four items adapted from Malodia et al. (2022), including the statement "I intend to use a SVA for online shopping in the future." Similarly, "perceived ease of use" was assessed using a set of four items adapted from Weinmann et al. (2016), such as "Using my SVA for online shopping is very easy." "perceived usefulness" was operationalized using a set of four items adapted from Balakrishnan et al. (2021), including the statement "Using an SVA would improve my shopping performance." Lastly, "subjective social norms" were assessed using a set of three items adapted from Fernandes and Oliveira (2021), such as "People who influence my behavior think I should use an SVA for shopping." The use of these validated measures ensured the robustness of the study's findings.

To measure "perceived humanness", "perceived social interactivity", and "perceived social presence", this study used three items adapted from Fernandes and Oliveira (2021) for each construct. Examples of the items used include "Sometimes the SVAs seem to have real feelings" for "perceived humanness", "I find the SVA pleasant to interact with" for "perceived social interactivity", and "When interacting with the SVA, I felt like talking to a real person" for "perceived social presence".

To ensure the accuracy and comprehensibility of the survey for the Jordanian participants, the questionnaire underwent a rigorous translation process. Initially, the questionnaire was translated into Arabic by a team of professional linguists from the United Kingdom. Then, the translated questionnaire was back-translated into English to check for accuracy. After that, professional translators reviewed the back-translated questionnaire to ensure its precision. Moreover, to refine the survey and ensure its clarity, a pilot test was conducted with 30 customers. This process ensured that the survey was clear, easy to understand, and culturally appropriate for the Jordanian context.

The constructs examined in this study were assessed through the use of a 5-point Likert scale, a widely recognized and dependable tool for evaluating attitudes and beliefs. The measures employed in this study were derived from previous studies and underwent meticulous selection and modification to ensure their relevance and applicability to the context of SVA adoption in the Jordanian retail market. The use of rigorously tested and validated measures bolsters the study's internal consistency and strengthens the reliability and validity of its findings, thereby facilitating its potential to make a valuable contribution to the ongoing scholarly discussion on this subject.

3.3. Common method variance

To address the potential concern of common method variance (CMV), various measures were implemented both before and after the data collection process. Anonymity was assured by administering the survey anonymously to encourage honest and candid responses. Furthermore, the order of the measurement items was randomized and the constructs were masked to minimize the possibility of response biases, as recommended by Podsakoff et al. (2003). Additionally, we utilized the common latent factor (CLF) technique proposed by Eichhorn (2014) to account for any shared variance in the observed factors.

Two models, one with and one without CLF, were compared to assess the effectiveness of the CLF approach in addressing CMV. The standardized regression weights and model fit indices were examined for both models. The results indicated that the standardized regression weights for the two models were highly comparable, with differences of less than 0.2 (Gaskin, 2021). Moreover, the model fit indices for the model with CLF ($\chi2/df = 1.7059$) and the model without CLF ($\chi2/df =$

Table 2
Characteristics and usage patterns of Smart Voice Assistants for shopping purposes among Jordanian consumers.

Characteristics	Percentage
Gender	
- Female	51%
- Male	49%
Age group	
- 18–29 years	28%
- 30–39 years	32%
- 40–49 years	20%
- 50 years and above	20%
Academic qualification	
- High school diploma	17%
- Bachelor's degree	29%
- Master's degree	23%
- PhD or above	12%
Income	
- Less than $25,000	32%
- $25,000-$39,999	24%
- $40,000-$59,000	17%
- $60,000 and above	27%
Usage of SVAs for shopping	
- 0–2 times in the past year	47%
- 3–6 times in the past year	27%
- More than 6 times in the past year	26%

1.9830) were similar. Based on these findings, no substantial CMV issue was detected in our data.

To summarize, various precautions were implemented to reduce the potential impact of CMV, such as anonymity, randomization of item order, and masking of construct names. In addition, the CLF approach was utilized to further minimize the possibility of shared method variance. The analysis indicated that these measures were effective, and there was no evidence of significant CMV in the study's data.

3.4. Necessary conditions analysis

Necessary conditions analysis is a research methodology employed to identify the essential elements required for a specific outcome or phenomenon to occur. This approach involves the identification of potential necessary conditions and the evaluation of their sufficiency in causing the occurrence of the outcome. One of the primary benefits of this method is that it provides researchers with valuable insights into the underlying factors that contribute to particular events and outcomes. By identifying the necessary conditions, researchers can gain a deeper understanding of the causal relationships between different factors and the occurrence of the outcome, which can inform the development of interventions or policies aimed at promoting or preventing the outcome in question.

There are several methods that researchers can use to evaluate the sufficiency of necessary conditions, including Qualitative Comparative Analysis (QCA) and statistical models. QCA involves the comparison of cases with similar outcomes to identify the necessary and sufficient conditions contributing to the outcome. This method is flexible and can be used with both small and large datasets. Statistical models, such as regression analysis or causal inference models, can also be used to identify necessary conditions by analyzing the relationship between various variables and the occurrence of the outcome.

In this study, necessary conditions analysis was utilized to identify the essential elements required for consumers to adopt smart voice assistants (SVA) for shopping purposes. By identifying the necessary conditions, a deeper understanding of the underlying factors that contribute to consumer adoption of this technology is gained. To begin, the outcome or phenomenon of interest was defined as consumer adoption of smart voice assistants for shopping purposes. Potential necessary conditions, such as age, gender, education, income, “perceived ease of use”, “perceived usefulness”, “subjective social norms”, “perceived humanness”, “perceived social interactivity”, and “perceived social presence”, were identified. The sufficiency of each condition was evaluated by assessing whether it was both necessary and sufficient for consumer adoption of the SVA.

In summary, necessary conditions analysis was employed in this study to identify the essential elements required for consumers to adopt smart voice assistants for shopping purposes. This research methodology involved defining the outcome of interest, identifying potential necessary conditions, and evaluating the sufficiency of each condition. To identify necessary conditions, the study utilized Qualitative Comparative Analysis (QCA), which allowed for the comparison of cases with similar outcomes and the identification of the key factors influencing consumer adoption of SVAs. Overall, necessary conditions analysis was a valuable approach that provided researchers with valuable insights into the causal relationships between different factors and the occurrence of the outcome, thereby informing the development of interventions or policies to promote or prevent consumer adoption of the technology.

3.5. Data calibration

This study employed the software package fsQCA 3.0 (Ragin and Fiss, 2008) to conduct the calibration process utilizing the direct method. This method is preferable when the researchers possess a sound understanding of the subject matter and the variables under investigation (Ragin, 2009). The Likert scale was employed using a five-point system to measure the variables, and the calibration cut-off values were derived from consensus among the researchers. Each variable was calibrated independently, and the calibrated data were subsequently utilized for the requisite analyses.

The calibration process is an integral step in configuration analysis, as it transforms qualitative data into fuzzy sets that can be analyzed using logical principles. The choice of the calibration method is contingent on the researcher's familiarity with the subject matter and the specific research question. Calibration guarantees that the data are structured into a format that can be analyzed utilizing the fsQCA software and allows for the identification of necessary and sufficient conditions contributing to the outcome of interest.

3.6. Qualitative phase

The present study utilized fuzzy set Qualitative Comparative Analysis (fsQCA), a method for conducting qualitative comparative analysis that offers several benefits, including the ability to handle small to medium-sized samples, incorporate fuzzy logic, provide a qualitative approach to analysis, and allow for the identification of multiple causal pathways (Ragin, 2009; Pappas & Woodside, 2021). This flexible and nuanced approach can aid researchers in identifying patterns and relationships that may be overlooked by traditional methods. The combination of fuzzy sets and logic principles with qualitative comparative analysis has led to the development of fsQCA (Woodside, 2017).

In fsQCA, both necessary and sufficient conditions may be present or absent for a solution and may not contribute to the solution at all. A necessity analysis was conducted initially in this study to identify whether any conditions were necessary for the presence or negation of intention to adopt SVA. From a set-theoretic perspective, necessity is defined as a condition being a superset of the result (Ragin, 2009). A condition is considered necessary if its consistency is greater than 0.9 (Woodside, 2017). Consistency refers to the level of agreement among sample cases that share a common configuration of causes and exhibit the same key result (Ragin, 2009).

Qualitative sample

Following the first stage of the investigation, a second stage was conducted where 22 consumers from the initial sample were invited for a qualitative follow-up interview based on their fsQCA configuration. The purpose of the interviews was to gain a more profound understanding of each configuration and uncover statements that could provide insights into the factors that lead to a higher intention to adopt SVA (Woodside, 2014). Ultimately, 18 face-to-face interviews were conducted between January 10 and February 10, 2023, with an average interview duration of 40 min. These interviews were conducted with representatives from all the identified configurations. A summary of the study sample is presented in Table 3.

Qualitative method

In line with Woodside's (2014) recommendations, a qualitative follow-up study was conducted to gain a deeper understanding of the causal recipes for the adoption of SVA that were explored using fsQCA in the previous quantitative phase. This technique enables researchers to generalize beyond specific examples and to explore individual cases in greater depth (Ragin, 2008). Qualitative research has been widely acknowledged as beneficial for studying consumers' values, attitudes, and meanings in depth (Ali et al., 2023).

Interviews were conducted with consumers from each of the causal recipes explored in the quantitative phase, using questions developed based on the quantitative examination items and literature review (e.g., Beugre, 2012; Bockarjova and Steg, 2014). In addition, questions were asked to understand how the consumers perceived the effect of respective variables on their adoption behavior (Kallmuenzer et al., 2019). All interviews were tape-recorded and transcribed, and the interview content was structured based on the explored causal recipes from the quantitative phase. Two authors independently translated relevant Arabic quotations into English to ensure accuracy and meaningfulness of the translations, and a professional language editor was consulted to further ensure translation accuracy.

The information gathered in the follow-up study helped identify the five categories explored in the quantitative study, in addition to interpreting the results.

4. Analysis and results

4.1. Measurement model results

To ensure the reliability and validity of our constructs, a confirmatory factor analysis was employed. Reliability was evaluated using the Cronbach alpha and Composite reliability measures, with all indicator values exceeding the recommended threshold of 0.7, indicating high reliability (Hair et al., 2020). Additionally, convergent validity was deemed acceptable, with the average variance extracted (AVE) for all study constructs exceeding 0.5 (Table 4). This analysis confirms the robustness of our measurement model and the reliability of the data collected.

Discriminant validity was established with item loadings demonstrating the greatest association with their designated variables and the AVE's square root on the diagonal being larger than its corresponding correlations with other constructs (Table 5).

Furthermore, we applied the "Heterotrait–Monotrait" (HTMT) ratio of correlation criteria (Henseler et al., 2015). Our analysis indicated that the discriminant validity of HTMT was achieved, as all HTMT values were below the 0.85 thresholds. Additionally, we assessed several fit indices of our proposed model, which demonstrated high and acceptable fit indices. Specifically, the x2/df ratio was 2.6109, TLI was 0.92, CFI was 0.93, and RMSEA was 0.07.

4.2. Necessary conditions analysis results

Table 6 presents the necessary conditions analysis results, which identified the antecedents that are necessary for a consumer to adopt an SVA. Without these conditions, the desired outcome of adoption will not be achieved. The study findings indicate that "perceived ease of use", "perceived usefulness", "perceived humanness", and "perceived social presence" are all essential predictors of a consumer's intention to adopt an SVA.

Table 3
Overview of qualitative sample.

Respondents	Interview date	Age	Gender	Education	Interview duration
RESP1	10.01.2023	39	Female	Master's	45 mins
RESP2	11.01.2023	33	Female	Bachelor's	48 mins
RESP3	12.01.2023	40	Male	Diploma	36 mins
RESP4	13.01.2023	42	Male	Bachelor's	34 mins
RESP5	13.01.2023	36	Female	Master's	51 mins
RESP6	14.01.2023	38	Male	Bachelor's	48 mins
RESP7	15.01.2023	29	Male	Bachelor's	58 mins
RESP8	17.01.2023	32	Female	Master's	53 mins
RESP9	18.01.2023	25	Male	Master's	43 mins
RESP10	19.01.2023	31	Female	Bachelor's	45 mins
RESP11	20.01.2023	20	Female	Other	39 mins
RESP12	22.01.2023	25	Male	Bachelor's	43 mins
RESP13	02.02.2023	43	Female	Master's	44 mins
RESP14	03.02.2023	48	Female	Bachelor's	49 mins
RESP15	04.02.2023	54	Male	Bachelor's	50 mins
RESP16	05.02.2023	38	Male	Master's	39 mins
RESP17	06.02.2023	29	Female	PhD	41 mins
RESP18	10.06.2023	31	Male	Master's	48 mins

4. 3 fsQCA results

The findings of the fsQCA configuration analysis are displayed in Table 6, where the existence of a condition is represented by a filled black circle (●), while its non-existence is represented by a crossed-out circle (⊗), as per Park et al. (2020). The size of the circle indicates whether the condition is a central or peripheral factor, while a blank space on the answer sheet signifies "do not care". The table also reports the consistency and coverage values for the entire solution and for each individual solution. All values exceed the threshold of 0.75, indicating good model fit (Ragin, 2009). The consistency value denotes the level of approximation of a relationship, while the coverage value establishes the empirical relevance of a consistent subset. The "overall solution coverage" is presented in Table 6, which can be compared to the R-squared value to assess the predictive power of the configurations for high intention to adopt an SVA (Woodside, 2017). The findings suggest that the five solutions account for a substantial portion of the outcome (0.892). Furthermore, fsQCA also computes raw and unique coverage, where raw coverage represents the proportion of the outcome explained by a particular solution alone, and unique coverage indicates the proportion explained exclusively by that solution. As shown in Table 7, the proposed solutions explain 29% to 57% of the cases where the outcome is related to the consumer's intention to adopt an SVA.

Table 6 displays the outcomes of the configuration analysis, presenting the influence of demographic, functional, and social variables on customers' intentions to adopt SVA across five solutions. The presence or absence of each variable is indicated by black circles (●) and crossed-out circles (⊗), respectively. Depending on their interactions with other variables, demographic, functional, and social variables appear as either central or ancillary conditions in the solutions. Solutions 1–3 offer combinations among the variables under consideration when functional variables are high and of high importance to customers. In contrast, solutions 4 and 5 provide a variety of explanations for why customers have a strong adoption intent, even when functional variables are minimal. Solution 1 suggests that a combination of "age", "gender", "perceived ease of use", "perceived usefulness", "perceived subjective norms", and "perceived social presence" can indicate a high intention to adopt SVA, regardless of "perceived humanness" and "education", while "perceived social interactivity" and "income" are absent. Solution 2 reveals that a combination of "age", "gender", "perceived ease of use", and "perceived social presence" can indicate a high intention to adopt SVA, regardless of "perceived usefulness", "income", and "education", while "perceived social interactivity" is absent. Solution 3 demonstrates that a combination of age, "perceived ease of use", "perceived usefulness", "subjective social norms", and "perceived humanness" can indicate a high intention to adopt SVA, regardless of "perceived social presence", while "perceived social interactivity", "education", and "income "are absent. Solution 4 suggests that a combination of "age", "gender", "perceived ease of use", "perceived humanness", "perceived social interactivity", and "perceived social presence" can indicate a high intention to adopt SVA, regardless of "perceived usefulness" and "subjective social norms", while "education" and "income" are absent. Finally, solution 5 indicates that a combination of "perceived ease of use", "perceived usefulness", "perceived humanness", "perceived social interactivity", and "perceived social presence" can indicate a high intention to adopt SVA, regardless of "subjective social norms", while "age", "gender", "education", and "income" are absent.

4.4. Robustness checks

In prior research, it has been recommended to use various calibration methods to assess the robustness of fsQCA findings since calibration can have an impact on the results. This approach can help to identify alternative interpretations that arise from discrepancies in the results (Scarpi et al., 2021). To ensure the robustness of our study findings, we followed the method suggested by Fiss (2011) and Scarpi et al. (2018)

Table 4
Measurement statistics of construct scales.

Construct/Indicators	FL	Mean	Standard deviation	Cronbach's α	CR	AVE	T-values	Skewness	Kurtosis
Smart Voice assistants adoption (SVA)				0.920	0.947	0.582			
SVA1	0.930	2.893	1.278				21.290	-1.18	1.47
SVA2	0.961	3.034	1.126				23.107	-1.30	1.09
SVA3	0.928	2.912	1.308				10.236	-1.32	1.21
Perceived ease of use (PEU)				0.917	0.939	0.617			
PEU1	0.921	2.397	1.780				19.309	-1.40	1.27
PEU2	0.948	3.019	1.216				21.278	-1.28	1.14
PEU3	0.903	2.963	1.472				29.120	-1.04	1.08
PEU4	0.926	3.104	1.201				11.267	-1.15	1.46
Perceived usefulness (PUS)				0.910	0.941	0.609			
PUS1	0.936	3.183	1.049				18.203	-1.23	1.27
PUS2	0.919	3.206	1.216				23.203	-0.94	1.08
PUS3	0.908	2.549	1.289				11.290	-1.06	1.39
PUS4	0.925	3.257	1.420				25.128	-1.31	1.06
Subjective social norms (SON)				0.908	0.921	0.593			
SON1	0.989	3.019	1.038				12.340	-1.08	1.09
SON2	0.954	3.021	1.314				17.209	-1.23	1.01
SON3	0.921	2.348	1.166				27.308	-1.18	1.21
Perceived humanness (PHU)				0.893	0.910	0.636			
PHU1	0.932	3.206	1.109				17.340	-1.09	1.21
PHU2	0.885	3.154	1.218				19.126	-1.12	1.08
PHU3	0.874	2.720	1.430				22.035	-1.27	1.26
Perceived social interactivity (PSI)				0.928	0.961	0.594			
PSI1	0.981	2.790	1.092				22.190	-1.08	1.31
PSI2	0.937	3.019	1.127				18.302	-1.21	1.39
PSI3	0.926	3.124	1.419				19.770	-1.63	1.05
Perceived social presence (PSP)				0.909	0.928	0.641			
PSP1	0.910	2.892	1.034				16.320	-1.14	1.10
PSP2	0.883	2.930	1.418				25.173	-1.30	1.37
PSP3	0.926	3.318	1.328				13.784	-1.45	1.29

Notes: FL: Factor loading; **: **FL** is significant at the 0.001 level; **AVE** = Average variance extracted; **CR** = Composite reliability.

Table 5
Discriminant validity of the correlations between constructs.

Construct	Correlations and square roots of AVE						
SVA	SVA	PEU	PUS	SON	PHU	PSI	PSP
PEU	0.763a						
PUS	0.419b	0.785					
SON	0.384	0.417	0.78				
PHU	0.397	0.389	0.316	0.77			
PSI	0.49	0.481	0.477	0.538	0.797		
PSP	0.438	0.373	0.389	0.266	0.447	0.771	
	0.31	0.509	0.43	0.308	0.39	0.419	0.801

Note: a Composite reliability values are along the diagonal, b Correlations.

Table 6
Necessary conditions analysis results.

Antecedent condition	Outcome condition	
	Consistency	Coverage
Age	0.804	0.841
Gender	0.817	0.71
Education	0.715	0.526
Income	0.794	0.884
perceived ease of use	**0.993**	**0.881**
perceived usefulness	**0.997**	**0.897**
subjective social norms	0.801	0.71
perceived humanness	**0.98**	**0.88**
perceived social interactivity	0.769	0.594
perceived social presence	**0.985**	**0.891**

Note: to meet the necessary conditions, consistency should be higher than 0.90 (bolded).

and conducted two additional analyses. First, we altered the threshold values for inclusion/exclusion in the set by using the extreme points of the scales as thresholds. Specifically, we set 2 as the threshold for being fully out of the set and 4 as the threshold for being fully in. The findings of this re-analysis were consistent with those presented in Table 6. Second, we conducted separate analyses by changing the cut-off point from the original 3 to 2.5 and 3.5. Again, the results were consistent with those reported in Table 6. Finally, we conducted another analysis using a stronger consistency criterion of 0.8 instead of 0.75. This analysis also produced the same five configurations with a consistency goal of 0.8 as presented in Table 6. Overall, the results of our different re-analyses suggest that our findings are stable and robust.

Table 7
fsQCA results: configurations for achieving a high level of SVA adoption.

Configuration	Solution				
	1	2	3	4	5
Functional variables					
perceived ease of use	●	●	●	●	●
perceived usefulness	●	⊗	●	⊗	●
subjective social norms	●	•	●	⊗	⊗
Social variables					
perceived humanness	⊗	•	●	●	●
perceived social interactivity				●	●
perceived social presence	●	●	⊗	●	●
Demographics variables					
Age	●	●	●	●	
Gender	●	●		●	
Income		⊗			
Education	⊗	⊗			
Consistency	0.939	0.947	0.920	0.876	0.948
Raw coverage	0.341	0.329	0.257	0.570	0.296
Unique coverage	0.026	0.016	0.031	0.004	0.042
Overall solution consistency	**0.894**				
Overall solution coverage	**0.892**				

4.5. *Qualitative interviews results*

The results of the study based on interviews with 18 respondents indicate that SVA adoption behavior is influenced by "perceived ease of use", "perceived usefulness", and "subjective social norms". Quotes from the interviewees suggest that these factors play a significant role in the decision to adopt smart voice assistants for shopping purposes. For example, some respondents felt confident in using SVAs for shopping without assistance and found them useful for improving their shopping performance. Others found learning to operate SVAs for shopping purposes to be easy and felt that using them helped them complete their shopping more quickly. Additionally, some respondents reported that their friends and relatives encouraged them to use SVAs for shopping. The study also found that "perceived humanness", "perceived social interactivity", and "perceived social presence" are important factors in fostering SVA adoption behavior. Respondents reported feeling that SVAs had real feelings and were able to understand them well, making them more comfortable to use for shopping. Some even felt like they were interacting with a real person, making the process much easier. For example:

"I think I can use the smart voice assistants for shopping purposes without any help, well I have used it for buying a t-shirt without some help from anyone couple of weeks ago" (**RESP6**). "I find the smart voice assistants can help me with many things, yes its useful for improving my shopping performance" (**RESP11**). "I feel learning to operate the smart voice assistants for shopping purposes is easy" (**RESP14**).

"I think that Using the smart voice assistants for shopping purposes enables me to accomplish my shopping quickly" (**RESP10**). "My friends and relatives think I should use the smart voice assistants for shopping purposes" **(RESP16).**

In addition to functional variables, we also investigated the impact of social variables on SVA adoption behavior. Our study participants indicated that "perceived humanness", "perceived social interactivity", and "perceived social presence" are important factors in promoting SVA adoption. They mentioned that they can sometimes imagine SVA as a living creature and that it seems to have real feelings (RESP2). Some participants expressed feeling understood by the SVA, which made them more comfortable using it for shopping (RESP5). A few participants even reported feeling as though they were interacting with a real person, which made the process of using the SVA easier (RESP9, RESP13). For example:

"I can imagine the smart voice assistants to be a living creature, sometimes the smart voice assistants seem to have real feelings" (**RESP2**). "Well, I feel the smart voice assistants understands me very well, which makes me feel more comfortable to use it for the shopping purpose" (**RESP5**).

"To be honest with you, I often think the smart voice assistants is a real person" (**RESP9**). "When interacting with the smart voice assistants, I felt like talking to a real person process much easier" **(RESP13).**

5. Discussion of results

The present study employs a complexity theory perspective to investigate the factors that influence consumers' adoption of smart voice assistants (SVA) for shopping purposes. The study findings indicate that in the online shopping context, demographic characteristics (e.g., age, gender, income, education), functional variables (e.g., "perceived ease of use", "perceived usefulness", "subjective social norms"), and social variables (e.g., "perceived humanness", "perceived social interactivity", "perceived social presence") interact to form causal recipes for driving consumers' intentions to adopt an SVA. Specifically, an integrated model was developed based on complexity theory and data collected from 380 Jordanian consumers were analysed using fsQCA. The analysis revealed five solutions that can lead to a high level of intention to adopt an SVA.

The study's findings underscore the significance of functional variables in the domain of SVAs, as identified by prior research (Balakrishnan & Dwivedi, 2021; Cao et al., 2022; Fernandes & Oliveira, 2021). Additionally, our examination uncovers intriguing results, indicating that functional variables, including "perceived ease of use", "perceived usefulness", and "subjective social norms", outweigh social variables, such as "perceived humanness" and "perceived social interactivity". This pattern is discernible across all solutions (1–5), with at least one functional variable appearing in each. This finding indicates that customers prioritize the ease of use and perceived benefits of SVAs over social variables when deciding to adopt them, aligning with Balakrishnan and Dwivedi's (2021) findings.

The present study findings suggest that social variables have a significant impact on customers' intentions to adopt Smart Voice Assistants (SVA) for online shopping purposes, albeit in a complex manner. Specifically, when one of the three social variables ("perceived humanness", "perceived social interactivity", and "perceived social presence") serves as a primary variable in driving the adoption of an SVA, the other variables are absent or less important (as observed in solutions 1, 4, and 5). This implies that while social variables play a crucial role, one variable may outweigh the others in influencing adoption behavior.

Our analysis further reveals that "perceived humanness", "perceived social interactivity", and "perceived social presence" are critical to the adoption of an SVA for online shopping (as demonstrated in solution 5). This suggests that customers with low functional variables may still adopt an SVA if they perceive it as highly human-like and socially interactive. Additionally, demographic factors, including age and gender, were found to be significant predictors of SVA adoption, consistent with previous studies that highlight the influence of demographic variables on IT adoption.

Overall, our findings support the two initial propositions of the study, namely that there are several equally effective combinations of causal factors that can result in a strong intention to adopt an SVA, and that demographic variables, functional variables, and social variables can act as individual causal factors for a customer's intention to adopt an SVA, but their presence or absence may depend on how they interact with other causal factors.

6. Implications

6.1. Theoretical implications

The present research adds substantial value to the existing body of literature on the integration of service virtual assistants (SVAs) in online shopping settings by uncovering the determinants that shape consumers' adoption intentions towards such technology. While previous research has examined the influence of various functional and social variables on the behavior of consumers, these investigations have tended to focus on the core influences of individual predictors on one or more dependent factors, rather than exploring the interconnected causal structures among these factors (Fernandes & Oliveira, 2021; Pappas & Woodside, 2021; Woodside, 2017). In contrast, this study employs a configurational perspective on SVA adoption, drawing on insights from complexity theory to shed light on the interplay among demographic, functional, and social variables as they influence consumer decisions to adopt SVAs.

This research addresses gaps in the existing literature on SVA adoption for online shopping by providing an explanation for the contradictory findings reported in previous research. While functional variables have been found to directly influence the adoption of SVAs and the perceived benefits of using them (Pappas & Woodside, 2021), social factors (Fernandes & Oliveira, 2021; Ho et al., 2017; Yang & Jolly, 2009) and perceived benefits (Belanche et al., 2019) may also play a role. Moreover, prior research has produced conflicting findings on the impact of functional variables on consumer behavior in the online shopping context (Shaw & Kesharwani, 2019). This study addresses these discrepancies by demonstrating how different combinations of demographic, functional, and social variables can influence a person's propensity to adopt an SVA.

In addition to its substantive contributions, this study also advances the methodology of SVA adoption research. Specifically, it is among the first to employ configural frequency analysis at the individual level to explore the complex causal patterns of predictors and outcomes in this area (Woodside, 2017). By utilizing this approach, this study is able to confirm the presence of outlier cases, asymmetric associations among predictors and outcomes, and other complex causal patterns that would be missed by more traditional methods of data analysis.

Overall, this study offers a comprehensive and nuanced exploration of the factors that influence consumer decisions to adopt SVAs for online shopping. By taking a configurational perspective and employing complexity theory, this study advances our understanding of the interplay among demographic, functional, and social variables in shaping consumer behavior in this context. The results of this research have important implications for marketers and retailers seeking to promote the adoption of SVAs, as well as for scholars interested in the theoretical underpinnings of consumer behavior in the digital age.

6.2. Practical implications

The present study offers meaningful implications for managers of online service providers. One of the crucial factors for the long-term success of a technology is its adoption by users. However, despite the widely acknowledged benefits of automated forms of interaction in service delivery, such tools may only receive modest preferences from consumers. Thus, the study results can provide managers with valuable insights into the drivers of customer adoption of SVAs during interactions with service providers, which is essential for a successful rollout. Particularly, the findings demonstrate that, for experienced customers, the primary motivation for using an SVA is its functionality. Therefore, managers may prioritize the pragmatic benefits of an SVA, such as the ability to learn customers' preferences and become an essential part of their daily routines..

Moreover, the study reveals that SVAs are perceived differently by different customers, and this variability may be utilized for segmentation purposes based on customers' interaction preferences and levels of expertise. Natural dialogues with an SVA can enhance social interactivity and result in social presence perceptions among customers who prefer the personal touch of human interactions. However, conversational agents that appear too human may discourage customers, especially less experienced ones, from using the technology. Therefore, attracting millennial customers may require a different strategy than investing in an SVA with human-like traits.

Finally, the study findings suggest that males, highly educated individuals, the elderly, and consumers with high income are more willing to adopt an SVA. However, inconsistencies in adopting SVAs exist among different segments of consumers, which necessitates targeted interventions. Encouraging customer adoption of SVAs in Jordan should focus on motivating younger females with lower educational levels and those with low income to engage in adoption. Educational messages that are well-designed, personalized, and illustrated with descriptive diagrams may be an effective means of reaching out to this segment of consumers.

7. Limitations and future works

There are several limitations to our study that suggest interesting directions for future research. Firstly, our study used a single cross-sectional method to assess the proposed conceptual framework. Future research could use experimental approaches to better understand the effects of the study variables on SVA adoption. Secondly, our study focused on the influence of functional and social variables on SVA adoption, but future research could include additional variables, such as trust in technology and the internet, to provide a more comprehensive understanding. Thirdly, our study explored the determinants of SVA adoption in the specific context of Jordan. Future research could test the proposed model in different cultural contexts to assess its generalizability. Finally, our study utilized quantitative methods to collect data. Future studies could employ mixed methods to provide a more thorough understanding of the main determinants of SVA adoption.

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Declaration of Competing Interest

The authors declare no competing interests.

Data availability

The data that has been used is confidential.

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