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Impact of embedded AI mobile smart speech recognition on consumer attitudes towards AI and purchase intention across Generations X and Y

Received 29 March 2023
Revised 8 August 2023
28 October 2023
Accepted 31 October 2023

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Abstract

Purpose – This study aims to examine the influence of the derived attributes of embedded artificial intelligence-mobile smart speech recognition (AI-MSSR) technology, namely perceived usefulness, perceived ease of use (PEOU) and perceived enjoyment (PE) on consumer purchase intention (PI) through the chain relationships of attitudes to AI and consumer smart experience, with the moderating effect of consumer innovativeness and Generation (Gen) X and Gen Y in fashion retail.

Design/methodology/approach – The study employed a quantitative survey strategy, drawing a sample of 836 respondents from Sri Lanka and India representing Gen X and Gen Y. The data analysis was carried out using smart partial least squares structural equation modelling (PLS-SEM).

Findings – The findings show a positive relationship between the perceived attributes of MSSR and consumer PI via attitudes towards AI (AAI) and smart consumer experiences. In addition, consumer innovativeness and Generations X and Y have a moderating impact on the aforementioned relationship. The theoretical and managerial implications of the study are discussed with a note on the research limitations and further research directions.

Practical implications – To multiply the effects of embedded AI-MSSR and consumer PI in fashion retail marketing, managers can develop strategies that strengthen the links between awareness, knowledge of the derived attributes of embedded AI-MSSR and PI by encouraging innovative consumers, especially Gen Y consumers, to engage with embedded AI-MSSR.

Originality/value – This study advances the literature on embedded AI-MSSR and consumer PI in fashion retail marketing by providing an integrated view of the technology acceptance model (TAM), the diffusion of innovation (DOI) theory and the generational cohort perspective in predicting PI.

Keywords Perceived usefulness, Perceived ease of use, Perceived enjoyment, Consumer purchase intention, Voice assistant, Consumer innovativeness, Generational cohorts

Paper type Research paper

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The authors are grateful to the anonymous reviewers and the editorial team of the journal for their extremely useful suggestions to improve the quality of the article.

Declaration of conflicting interests: The authors declared no potential conflicts of interest with respect to the research, authorship and/or publication of this article.

European Journal of Management Studies
Emerald Publishing Limited
e-ISSN: 2635-2648
p-ISSN: 2183-4172
DOI 10.1108/EJMS-03-2023-0019

1. Introduction

People were able to connect with artificial intelligence (AI) for the first time in a useful and meaningful way (Arachchi and Samarasinghe, 2023d; Costa and Aparicio, 2023), when voice assistants (VAs) were added to mobile devices (McLean and Osei-Frimpong, 2019; Thaichon *et al.*, 2022). VAs for the home, like Amazon Echo and Google Home, have made it easier for people to connect with AI technology (Kim and Choudhury, 2021). This is because VAs for the home have more advanced natural language processing and machine learning capabilities. Human-computer interaction researchers have looked at how people connect with machines, including voice-based technologies and VAs. Embedded AI mobile device VAs provided individuals with the first opportunity to interact with AI in a useful and meaningful form (McLean and Osei-Frimpong, 2019; Hajishirzi and Costa, 2021; Costa and Aparicio, 2023).

Embedded AI-mobile-based smart speech recognition technology (hereafter MSSR) such as Alexa and Google Assistant has generated a new digital era in marketing. MSSR has altered consumer behaviour trends and purchasing patterns in recent years (Makarenko, 2023). Presently, the majority of fashion retail consumers are intending to adopt embedded AI–MSSR and embedded AI marketing tools such as Alexa, Google and Siri, which have substantially evolved to become common choices for mobile-based smart speech recognition in online shopping activities (Kautish *et al.*, 2023). Therefore, embedded AI-MSSR is currently another prominent research area in marketing studies (Thaichon *et al.*, 2022). AI-related applications are increasingly getting popular and help retail organizations enhance their competitiveness despite of economic downturn (Arachchi and Samarasinghe, 2023c). Automating the tracking of inventory, reducing labour expenses and changing the consumer experience are only three of the many benefits that these apps bring to the service industries of fashion retail, hospitality, banking, healthcare and education (Haenlein and Kaplan, 2021; Song and Kim, 2022). Many luxury fashion retailers such as Burberry, Louis Vuitton, Prada and Tommy Hilfiger also offer AI-based shopping assistants, reflecting the growing importance of embedded AI-MSSR technologies for fashion shopping (Kautish *et al.*, 2023).

As per Market.Us (2023), the Speech and Voice Recognition Market size accounted for USD 14 billion in 2022 and will expand to USD 83 billion by 2032, accelerating at a CAGR (Compound Annual Growth Rate) of 20%. Furthermore, Insider Intelligence (2022) reports that consumers are more likely to access VAs via smartphones. In each month of 2022, 42.7% of adults used a smartphone to connect with VAs whilst 32.2% frequently utilized a smart speaker. Almost all adult users of VAs access conversational AI technology via a smartphone (91.0% this year). Despite customer enthusiasm, mobile app VAs and more restricted voice interactive capabilities did not grow much in 2021 (Kinsella, 2022). However, despite the growth of this industry, scholarship has yet to deconstruct the multidimensionality of the MSSR purchasing experience (Tassiello *et al.*, 2021). In addition, to the best of the authors' knowledge, little prior research has investigated empirical research in the area and few past studies of consumer adoption of AI-enabled smart mobile voice recognition in fashion retail have been conducted. Empirical facts report that virtual VAs on mobile devices have the lowest customer satisfaction rating due to the lack of apparent comprehension, dependability and precision of virtual assistants (VAs) (PWC, 2022). A few empirical studies confirmed the use of VAs for fashion shopping (e.g. Morotti *et al.*, 2021; Kautish *et al.*, 2023), but these did not discuss the motivations for using VA technology for fashion shopping (Kautish *et al.*, 2023). Therefore, the goal of this study is to close this empirical gap by examining the effect of embedded AI smart speech recognition-specific features on the fashion retail shopping behaviour related to the customer's purchase intention (PI). The study has been conducted because there is no clear map showing the relationship between integrated MSSR and consumer PI in fashion retail.

Since a number of empirical behavioural models have been suggested in the information systems (IS) domain to explain/predict the adoption and usage of information technology and consumer PI, the purpose of the present study is to compare and contrast these models (Balakrishnan and Dwivedi, 2021). Some of these models, such as the technology acceptance model (TAM) (Davis, 1989), the diffusion of innovation (DOI) theory (Rogers, 1983) and the theory of planned behaviour (TPB) (Ajzen, 1991) have been utilized to study adoption and diffusion of technological innovation (Williams *et al.*, 2009). This study selects the TAM as the base model because it is one of the most robust frameworks with which to adopt new technology and it offers a platform for a better comprehension of users' acceptance of new technological devices (Acikgoz and Vega, 2021). Therefore, the TAM is the primary theory chosen for this study. Because embedded AI-MSSR devices have perceived ease of use (PEOU), perceived enjoyment (PE) and perceived usefulness, these are the significant predictors of the technology acceptance model, and they play a significant role in enhancing consumer intention and shedding light on consumer PIs (Rehman *et al.*, 2019) in the fashion retail industry. Meanwhile, only a few empirical studies have looked at the relationship between MSSR and consumer experience (Dellaert *et al.*, 2020; Tassiello *et al.*, 2021), but none have looked at the relationship between attitudes towards AI (AAI) and consumer experience in mobile-based AI-enabled smart speech recognition.

Similarly, the learning process of new product usage is related to the effect of consumer innovativeness on PIs and consumer experience (Thakur and Srivastava, 2015). Accordingly, a variance in outcomes has arisen with respect to the gaps in the existing literature, and the DOI theory presents academics with features associated with innovation that may have an influence on adoption behaviours (Rogers, 1983, 1995). Therefore, the secondary theory used in these studies has been the DOI theory, and this has been used in this study as well to investigate consumer innovativeness (Kautish *et al.*, 2023). However, consumer motivations to use MSSR and their effect on the PIs of fashion shoppers are as yet unexplored (Kautish *et al.*, 2023).

Future studies of the relationship between the age group and technology behaviour have been suggested by Han (2021), Liang *et al.* (2019) and Pal *et al.* (2018) due to a lack of empirical evidence in the area. The younger is more flexible with Smart Speech Recognition (SSR) usage compared to older generations, according to Pal *et al.* (2019). Customers have been segmented by researchers and marketing professionals using generational theory for decades. Technology greatly influences millennials' consumption patterns, and their reliance on technology and social networks hinders their ability to think independently (Canziani and MacSween, 2021). One study on emotions found a high association between younger technology users' perceived utility related to computer gadgets and their demand for social participation (Lu *et al.*, 2019). When it comes to technology, older consumers prefer a realistic experience (Kim *et al.*, 2020). According to PWC (2022), younger consumers acquire speech technology at a higher pace than older consumers, although they are statistically more likely to use their VAs less. Individuals between the ages of 25 and 49 use these devices most frequently and are statistically more likely to be called "heavy users." As a result, this conflicted discussion provides room for Gen X (Han, 2021; Liang *et al.*, 2019); and Gen Y (Pal *et al.*, 2019) studies. To the best of the authors' knowledge, limited research has investigated the relationship between the AI enabled MSSR adoption and consumer PI across Generations X and Y.

According to the above-mentioned conflicted discussion, current theoretical research on mobile-based smart speech recognition technology fails to merge technological adoption, smart user experience and generational cohorts into a unified framework. Therefore, Generations X and Y's impact is yet to be ascertained, and generational cohort theory is used in this study based on this insight.

The present study offers some fresh insights as it looks at embedded AI in mobile applications, though extant studies have looked at devices other than mobile devices. Further, our model has incorporated Generational (X and Y) distinctions as a crucial factor that differentiates innovative customers by borrowing from the generational cohort perspective. Hence, it adds a theoretical contribution to the research stream on TAM and DOI by integrating innovativeness that is derived from generational differences. Since there has been little theoretical and empirical discussion of the TAM, DOI and generational cohort theory together, this study will focus on filling the gaps in the current body of knowledge in the light of the following objectives.

Q1. To examine the relationship between the derived attributes of embedded AI-MSSR (perceived usefulness and ease of use and PE) and consumer attitudes towards AI.

Q2. To explain the chain effect of attitude towards AI (AAI) and consumer smart experience on consumer PI.

Q3. To elucidate the moderating impact of consumer innovativeness and Gen X and Y on the above-mentioned relationship.

The paper is structured as follows: First, we present a review of the key literature on the research context, theoretical perspectives and conceptual framework development. Second, we elaborate on the methodology. Third, we analyse and present the main findings. Finally, the last section presents the discussion and conclusions, as well as some directions for future research.

2. Literature review, hypothesis development and the conceptual model

Rapid advances in technology have prompted the development of a wide range of novel products that meet the needs of modern consumers. Every decade sees a sweeping change in the way technology is utilized by society at large. Human-computer interfaces have progressed from the desktop to the internet, touch screens, intelligent speech recognition and block chain technology (Hughes *et al.*, 2019; Lee *et al.*, 2020). Many academics and market practitioners have been drawn to the issue of technology adoption and they have proposed many models and frameworks based on consumer behavioural theories (Balakrishnan and Dwivedi, 2021; Hernandez-Ortega and Ferreira, 2021). However, it is critical that current theoretical models be updated to address the difficulties of changing customer behaviour and preferences as a result of technological improvements (Mishra *et al.*, 2022). Although SSRs are becoming more popular, data suggests that consumers' use of these features is limited to a few activities. Thus, although research has proven that usability has an influence on speech recognition adoption, little is known about how usability differs between speech recognition tasks and its relationship to user task adoption (Motta and Quaresma, 2021).

2.1 Technology adoption

The majority of research on technology adoption is grounded in the behavioural sciences and provides utilitarian-oriented frameworks. The TAM, for instance, to examine how perceived utility and ease-of-use influence attitudes towards technology and subsequent behavioural intentions to use the technology (Davis, 1989). Another popular model for explaining technology usage and adoption is the The Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh *et al.*, 2003; Williams *et al.*, 2015). The UTAUT2 updated version is also interconnected with motivation to comprehend people's motivations for adopting a new technology (Venkatesh *et al.*, 2012). Likewise, the TAM has been modified to a third version (TAM3) that incorporates components of experience, playfulness and enjoyment (Pillai *et al.*, 2020; Mishra *et al.*, 2022).

There is now a limited number of research studies focussing on the consumer adoption intent of VAs utilizing the TAM (Pal and Arpnikanondt, 2021). Existing research on technology adoption focusses on utilitarian and hedonistic motivations (Agarwal and

Karahanna, 2000; Lee *et al.*, 2020). Utilitarian motivations include technological elements such as usefulness and ease of use (e.g. TAM, Davis, 1989). The second category, on the other hand, is concerned with hedonic aims such as enjoyment (Mishra *et al.*, 2022). The perceived usefulness (PU) and PEOU constructs, which are regarded as the key facilitators of the TAM, are a sort of behavioural belief component that is frequently used to predict the adoption of any new technology, as is shown in smart speech recognition. Furthermore, in order to strengthen the TAM's explanatory power, researchers have included new components throughout time, depending on the context of the research (Pal and Arpnikanondt, 2021). The TAM has been frequently utilized in the fashion retail industry to assess customer acceptance of technology-related applications. The approach has been used to assess customers' perceptions of and adoption of mass-customization technologies (Liang *et al.*, 2019) and this research is based on the TAM as the primary theory.

2.2 Embedded AI smart speech recognition

Speech recognition technologies have become more prevalent and popular with worldwide customers with the emergence of globalization (Hernandez-Ortega and Ferreira, 2021). In 2019, 3.25 billion digital VAs were deployed in devices worldwide, including 110 million in the United States of America (Statista, 2020). Additionally, according to predictions, the number of speech recognition devices will triple by 2023, reaching around eight billion units. 82% of regular users use SVAs to search for information (news, weather, recipes and advice), 67% to listen to music or stream movies, 36% to contact customer service and 35% to buy things (e.g., groceries, home care, or clothes) (Hernandez-Ortega and Ferreira, 2021). Overall, these results suggest that SSRs have a bright future and emphasize the necessity of good partnerships between enterprises and fashion retail customers (Morotti *et al.*, 2021).

One of the most well-known AI applications is Apple's Siri, a VA. The iOS, iPadOS, macOS, watchOS, tvOS and audio versions of Apple's artificial intelligence-powered VA can all be used to their full potential. Siri is capable of calling, texting, answering questions and making suggestions all through voice searches and a natural language user interface (UI). Siri may learn the language and preferences of its users by delegating requests to other Internet services. As of now, Cortana may be accessed on the following platforms: Windows 10, Windows Mobile, the Invoke smart speaker, the Microsoft Band, Android, iOS, Windows Mixed Reality (MR), Amazon Alexa and Xbox One. Significant advancements have been made in Google's voice-activated, AI-enabled VA, Google Assistant. It is one of the most advanced VAs around, and it works with 10,000 different gadgets from 1,000 different manufacturers right now. Commonly referred to simply as "Alexa," Amazon's VA is powered by artificial intelligence. Initially used with Amazon's Echo and Echo Dot smart speakers, it is now also compatible with other devices and operating systems (Davies, 2022). There are no relevant empirical studies that use these four devices in the same research model, and therefore, this study is focussed on the four speech recognition mobile devices mentioned above.

2.3 Embedded AI smart speech recognition and perceived ease-of-use

Perceived ease-of-use shows how easily the customer feels that speech recognition can be utilized, whereas perceived usefulness represents how much the consumer believes that contact with the robot benefits him. Both aspects are likely to have a direct and beneficial influence on the acceptability of smart speech recognition and other automated service technologies (Fernandes and Oliveira, 2021). PEOU may be defined as the degree to which users believe the technology will minimize their effort, allowing them to use it more easily, whereas perceived usefulness can be defined as the degree to which users believe the technology will improve their performance (Balakrishnan *et al.*, 2022). Perceived usefulness is a key factor in smart product adoption, and it has the potential to minimize customer resistance to MSSR. Recent research on speech recognition has looked at perceived usefulness as a predictor of a customer's attitude, adoption, or contentment in order to understand why these sorts of assistants are used (Lucia-Palacios and Pérez-López, 2021).

A previous study found a link between PEOU and consumer attitudes towards technology. Kim *et al.* (2020) discovered that PEOU is a key determinant in smart retail technology adoption, whilst Lunney *et al.* (2016) and Buteau and Lee (2021) pointed out that PEOU positively affected customers' attitudes towards AI technology. The AI product's ease of use means that it is simple to use and communicate with. Customers engage with the product (e.g., Echo Look) by speaking whilst using the voice control capability. Liang *et al.* (2019), stated that consumers' satisfaction with digital assistants like Alexa would rise if they lived up to users' expectations. Consequently, if customers find it simple to use and engage with this product, they are more likely to acquire a favourable opinion of it. Furthermore, the multiple cues that VAs transmit can increase the accuracy of the data that they impart (e.g. detailed information about a product/service). They can alleviate uncertainty, resolve ambiguity and help consumers acquire the information they need. As a result, they may be perceived as being more useful and easy to use (Al Shamsi *et al.*, 2022; Flavián *et al.*, 2022). Therefore, we propose the following hypothesis,

H1. PEOU will have a significantly positive influence on consumers' attitudes towards AI.

2.4 Embedded AI smart speech recognition and perceived usefulness

Another significant aspect studied under the TAM is PU, which allows users to generate opinions about the technology based on its performance. The amount to which an individual feels that utilizing the system would improve his task is referred to as "perceived usefulness" (AL-Nawafleh *et al.*, 2019). Previous research has established PU as the major characteristic that contributes to a favourable attitude toward technology (Balakrishnan and Dwivedi, 2021). AI devices are naturally proficient in multitasking situations (Lemley *et al.*, 2017). These devices become increasingly optimized with each update, implying that performance will improve with time. There is, however, no information available to explain how people relate PU to AIVA. PEOU and perceived usefulness both influence attitudes toward information technology (IT) use, with the former having a direct impact on the latter (AL-Nawafleh *et al.*, 2019).

It has been discovered that PU in the TAM has a considerable influence on attitudes regarding adopting technology (Davis, 1989, p. 320; Buteau and Lee, 2021). Mobile smart speech recognition combined with AI is a camera that doesn't require the user to use their hands to take pictures or record videos ("selfies"). You can get expert advice on what to wear thanks to the product's style-check feature. Also, with the help of the in-built lighting and depth-sensing camera, you can take clear, high-definition videos and photos that can be uploaded to social media sites in a flash (Liang *et al.*, 2019). As a result of engaging in these behaviours, customers will have an easier time choosing the best outfit from the available trendy options and will have an easier time making decisions about what to wear. As a result, buyers are likely to be enthusiastic about the new fashion AI products (Liang *et al.*, 2019; Mohiuddin Babu *et al.*, 2022). Previous studies have found that PU drives attitudes toward using technology which ultimately impacts users' conscious behaviour to use or reject the technology (Buteau and Lee, 2021; Al Shamsi *et al.*, 2022). Based on the above discussion, this research proposes the following hypothesis.

H2. Perceived usefulness will have a significantly positive influence on consumers' attitudes toward AI.

2.5 Embedded AI smart speech recognition and perceived enjoyment

Many empirical studies have shown that PE influences people's desire to use new technologies. The term "enjoyment" has been defined as "the degree to which the action of utilizing a computer is seen to be delightful in and of itself" (Han, 2021, p. 54). Furthermore, consumers like conversing with their voice recognition systems, receiving hedonic value from their exchanges (Rzepka *et al.*, 2021). Although the novelty of the technology may account for users' satisfaction (McLean and Osei-Frimpong, 2019), they may also like the social component of interacting with a VA (Rzepka *et al.*, 2021). Consumers who believed they were interacting with genuine technology when using an e-commerce device (Ogonowski *et al.*, 2014) or a companion robot reported higher levels of happiness and delight (Han, 2021). According to certain research data, PE has a considerable beneficial influence on people's propensity to utilize voice recognition (Pal *et al.*, 2020; Yang and Lee, 2018), since users prefer VAs because they are more enjoyable (Rzepka *et al.*, 2021) and because they enjoy the interaction itself. There are limited empirical studies that show how PE is related to smart speech recognition in fashion retail, and the current study intends to address the above empirical gap as well.

The role of enjoyment has been studied in a variety of fields, including e-commerce and marketing, because consumers are willing to have fun when they believe they are interacting with AI technology (Han, 2021). Speech recognition influences consumer enjoyment whilst being used by consumers (Rzepka *et al.*, 2021). Models of technology adoption and usage (for example, the TAM) that incorporate user satisfaction are crucial in this setting because of the central role that enjoyment plays in driving people to adopt new technologies. Furthermore, users' PE during the interaction with speech recognition enhances its actual and future use (Al Shamsi *et al.*, 2022). This form of enjoyment is intended to enhance consumer trust (Pitardi and Marriott, 2021) and attitudes toward AI (Liang *et al.*, 2019). Thus, based on the above discussion and supporting empirical evidence, it is hypothesized that:

H3. PE will have a significantly positive influence on consumers' attitudes toward AI.

2.6 Attitude towards AI

Long-term, comprehensive evaluations of individuals, things, or situations are called attitudes (Baron and Byrne, 1987). "An individual's favourable or negative appraisal of executing the activity," as defined by Ajzen and Fishbein (1980, p. 6), is what we mean when we talk about someone's attitude. Previous studies have shown that tailoring behavioural modification treatments to certain consumer groups based on key characteristics is likely to encourage the manifestation of the target behaviours that can improve their efficacy (Tussyadiah and Miller, 2018). Since consumers' trust in intelligent agents appears to stem from their expectations of the outcomes of using (and interacting with) technologies (Tussyadiah and Wang, 2014), it is crucial that efforts to increase consumers' reliance on AI (i.e. consumers following AI recommendations) pay special attention to these expectations. Because of this factor, it is necessary to divide one's consumer base and profile consumers according to how they feel about artificial intelligence (Tussyadiah and Miller, 2018). In this research, "AI attitudes" refer to feelings towards four specific AI products: Amazon's Alexa, Google Assistant, Apple's Siri and Microsoft's Cortana. This specifically pertains to attitudes about the product performance of linked functions (Liang *et al.*, 2019). Few empirical studies have been conducted to investigate the relationship between speech recognition and attitudes toward AI (Balakrishnan and Dwivedi, 2021). Therefore, this research attempts to address this empirical gap and narrow it.

In relation to smart services (such as speech recognition), the findings will aid a better understanding of dealing with user behaviour by studying belief components and users' attitudes regarding conduct, as well as purchase intent (Gao and Huang, 2019). Therefore, speech recognition is enhancing AAI (Balakrishnan and Dwivedi, 2021) and providing a link with the consumer's new experience and unique purchasing intention (Chang and Chen, 2021). There has been no empirical study that looked into the role of AAI and smart consumer experience. Therefore, the following hypothesis has been proposed.

H4. Attitudes to AI will have a positive impact on smart consumer experience.

2.7 Consumer smart experience

Holbrook and Hirschman initially characterized customer experience in their seminal essay on customer experience (Holbrook and Hirschman, 1982), defining it as a renovated perspective of consumption that changes the rational approach used in economic literature (Schmitt, 1999). Following in this vein, marketing research emphasizes the concept's reactive aspect and defines it in terms of the customer's reactions to direct or indirect encounters with businesses, brands, or other actors (Hernandez-Ortega and Ferreira, 2021).

Early research on smart technologies focussed on technology acceptability and evaluating consumers' views such as ease of use and utility (McLean and Osei-Frimpong, 2019; Moriuchi, 2019). Nonetheless, as far as we are aware, only a few publications have investigated consumers' experiences with these devices. These works demonstrate that when consumers interact with smart technology (such as speech recognition, for example), they have unique experiences that shape their perceptions and subsequent behaviour (Kim and Baek, 2018). Some of these papers explicitly examine the impact of deploying smart technology in commerce (Hernandez-Ortega and Ferreira, 2021). However, consumers' smart experiences will become increasingly diluted by impersonal purchasing experiences (Priporas, 2020). Despite the fact that this viewpoint has gained traction, there has been little study on the relationship between consumers' smart experiences and voice recognition (Roy *et al.*, 2019). Furthermore, no previous research has examined the effect of smart technology in the shopping experience on customer behaviour (Chang and Chen, 2021).

Smart shops in the smart retailing business combine physical stores with technological advancements to give clients a fresh shopping experience and a one-of-a-kind purchase procedure (Chang and Chen, 2021; Roy *et al.*, 2019). Customers may enter smart stores to check out new technologies and fulfil their curiosity when smart technologies (such as speech recognition) that are new to them are used in smart shops. Thus, customers may have a more fun and satisfying shopping experience if stores are smart (Chang and Chen, 2021). Consequently, shoppers may just grab what they need and browse the stores without having to ask. Since a smart retail's purchasing procedure differs greatly from that of a typical store, it increases consumer purchase intent (Poncin *et al.*, 2017; Roy *et al.*, 2018; Chang and Chen, 2021). Thus, we formulate the following hypothesis.

H5. A consumer's smart experience will have a significant positive impact on that consumer's PI.

2.8 Consumer innovativeness

Some people are naturally more receptive to trying out new technology and developments, whilst others are normally more resistant to change (Arachchi and Samarasinghe, 2023b). Consumer studies have devoted substantial attention to consumer innovation (Anwar *et al.*, 2020). An individual's innovativeness has been characterized as the extent to which they are willing and receptive to test out a new information technology (Anwar *et al.*, 2020). The concept of consumer innovativeness is derived from the innovation diffusion theory (Rogers, 2003). This theory attempts to explain how, why and at what rate new ideas and technologies spread (Rogers, 2003). It has been extensively studied in the field of consumer behaviour because it represents an individual's inclination or desire to try new items or services.

Consumers with a high level of innovativeness are naturally inquisitive, like in creative inquiry and hence, are more likely to accept new products/services (Arachchi and Samarasinghe, 2023b).

As per Anwar *et al.* (2020), understanding the innovativeness of customers is becoming increasingly crucial for marketers, especially in the context of digital and mobile products and services, where innovation is ongoing. Some researchers discovered that consumer innovativeness related to AI-enabled checkouts is moderated by AI technology (Cui *et al.*, 2021), and consumer innovativeness is moderated by technology-based restaurant industries (Jeon *et al.*, 2020). To the best of the authors' knowledge, no prior study has investigated the moderating role of consumer innovativeness as it relates to smart speech recognition. We consider consumer innovativeness in attitudes toward AI and consumers' smart experience in this study.

2.9 Individual innovativeness

In this line, previous research has investigated the moderating effect of innovativeness in various circumstances. Anwar *et al.* (2020), for instance, found that innovativeness moderates the relationship between consumer involvement and their purchase and usage behaviour. Similarly, Li *et al.* (2015) investigated the positive moderating influence of innovativeness between the originality of a new product and customers' intentions to embrace the new product. In addition, Lee *et al.* (2020) found that personal inventiveness is directly and indirectly related to a greater propensity to promote the device to others, according to Artificial Intelligence Voice Assistant Speaker (AIVAS) technology users. However, in the absence of empirical research, it is interesting to enquire how consumer innovativeness influences attitudes toward AI and smart consumer experiences. Thus, based on the above discussion, the study proposes the following hypothesis.

H6. The relationship between AAI and consumer smart experience will be moderated by consumer innovativeness.

2.10 Effect of Gen X and Gen Y on the consumer smart experience–purchase intention relationship

Han (2021) suggested the study of AI technology's impact on different age groups, and Liang *et al.* (2019) also mentioned age group and VA adoption as future study opportunities. Therefore, this study is based on Gen X and Gen Y as per the above insights and due to the lack of empirical evidence in the area. Scholars of generational cohorts believe that Gen X covers people born between the 1960s and the 1980s, whereas Gen Y includes those born between 1981 and the 2000s (Williams and Page, 2011). However, generational time spans are not consistent and might vary amongst nations, and they can even overlap due to the widespread usage of the Internet.

Individuals within a generational group share similar ideas and opinions about how technology should be used (Alkire *et al.*, 2020). But, as per Ivanova *et al.* (2019), previous studies have indicated that Gen X and Gen Y have distinct backgrounds, abilities and expectations than previous generations. According to Marjane *et al.* (2019), generational cohort membership shares common values that influence Gen attitudes, favourites, buying patterns and behaviours. Similarly, Eger *et al.* (2021) contend that the experiences, basic values, attitudes, beliefs and preferences of generational cohorts impact their behaviours. In contrast to prior surveys, this study uses the generational cohort theory as a framework to investigate changes in the relationship between consumers' smart experiences and consumer purchasing behaviours. Indeed, past studies indicate that the Gen Y's and the elderly's usage and acceptance of technology vary because they have distinct needs and levels of personal innovativeness (Pal *et al.*, 2018). Consequently, more study is needed to determine if the present findings apply to the elderly as well (Pal *et al.*, 2018).

Today, five-year-olds who cannot yet type are amongst the most enthusiastic users of speech technology. It has been predicted that in a decade or two, a large portion of commerce will be carried out by a generation used to purchasing through speech recognition (Mayer and Harrison, 2019). Considerations about generational cohorts have an influence on retail stores and store management as well. The obvious consequence is that assortments must be regularly changed to reflect changing demands, purchasing patterns and habits. For different generations, purchasing has distinct meanings and forms (Chaney *et al.*, 2017). Speech recognition is now in a strong position in the retail sector, and it is enhancing consumer experiences and habits, including purchasing behaviour (Mayer and Harrison, 2019). As per Erickson (2020), 49% of Gen X and 53.1% of Gen Y used speech recognition for their day-to-day processes, and it is just another indication that speech recognition might be a helpful tool in the buying experience, such as when looking for items or reading product reviews (Kinsella, 2019). Based on the above discussion, this study proposes the following hypothesis.

H7. The relationship between consumer smart experience and consumer PI will be moderated by Gen X and Gen Y

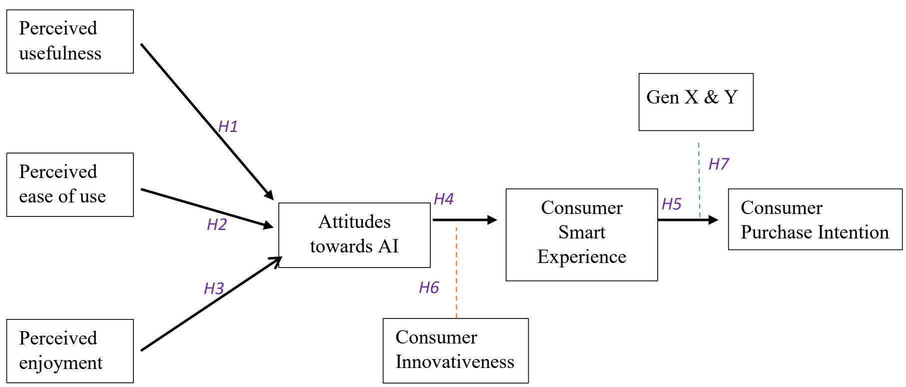
2.11 Conceptual model

Based on the theoretical background and the evidence obtained in extant empirical studies, the current study adopted the TAM, DOI and attitude to technology models. As per the TAM, perceived AI technology initiatives are impacting predicted behaviours. Further, customers' innovativeness impacts consumer PI. The conceptual framework illustrated (as shown in Figure 1) indicates the relationships tested within this study.

3. Methodology

3.1 Population, sampling and data collection

The researchers adopted a quantitative approach as the methodology of the study. The self-administered questionnaire method was used to collect the relevant data through a judgemental sampling technique (Schramm-Klein *et al.*, 2013; Moriuchi, 2019; Arachchi *et al.*, 2022) during the period February to May, 2022 via WhatsApp, Facebook, email (Sen Gupta and Wadera, 2020; Arachchi and Samarasinghe, 2022; Arachchi and Samarasinghe, 2023a) and telegram. The



Source(s): Figure by author (2023)

Figure 1.
Conceptual research framework of the study

population represents fashion retail consumers in India and Sri Lanka, who belong to Gen X and Y and who intend to use speech recognition assistants for fashion retail (Arachchi, 2022). Due to the unavailability of a representative sampling framework to draw the respondents, a judgemental sampling technique was employed (Gschwend, 2005) However, we maintained the representativeness of the respondents as much as possible with a reasonable coverage of various demographics of the two countries, as presented in Table 1. The anticipated completion time for this survey was 15–20 min. The screening questions were designed to weed out those who were unfamiliar with and had no experience with mobile speech user recognition. Therefore, at the beginning of the questionnaire, there was an option whereby it was possible to select whether a responder knows the MSSR or not. If the responder was not familiar with MSSR, he or she was unable to continue the survey (Balakrishnan *et al.*, 2022).

Asia has a vast population that is joining the Internet in increasing numbers (Vyas, 2022). Meanwhile, India and Sri Lanka have the highest IT export market percentage in South Asia, frequently between 0.26 and 2.05% (The Global Economy, 2020). Moreover, with ninety percent of new Internet users already opting to consume content in their native languages, an increasing number of Indians are relying on speech technologies to carry out online searches (Gutch, 2020). Furthermore, voice search queries in India are currently growing at 270% per year (Tewari, 2021) and 60% of smartphone users in India are communicating with VAs (Gutch, 2020). Therefore, this study has chosen the Indian and Sri Lankan fashion retail markets with which to examine the research problem.

As many as 1,000 respondents took part in the initial phase of this study, as per Krejcie and Morgan's estimation (Krejcie and Morgan, 1970), but only 836 respondents' data were assessed as useable: 338 for Gen X and 498 for Gen Y. The information of 32 respondents who did not complete the survey was removed. Respondents were asked to answer a few questions describing their experiences making purchases or carrying out informational queries using a mobile VA (Moriuchi, 2019) such as Alexa, Google Home, Cortana and/or Siri. This study is the first empirical examination of Alexa, Google Home, Cortana and Siri through the same sample, and the total response rate is 84%.

3.2 Measurement development

This study uses items derived from prior research to test the hypotheses. Perceived usefulness (PU) is measured based on Liang *et al.* (2019) and Pitardi and Marriott (2021), through seven scales. Furthermore, PEOU and PE are measured using five and four scales,

Variable	Item	*n*	Percentage
Country	India	635	76%
	Sri Lanka	201	24%
Civil Status	Married	382	46%
	Single	454	54%
Gender	1960–1980	338	40%
	1981–2000	498	60%
Education	Advanced level	62	7%
	Bachelor degree	392	47%
	Master degree	363	43%
	PhD	19	2%
Salary-$	0–300	34	4%
	301–500	230	28%
	501–800	196	23%
	801–1,000	376	45%

Source(s): Table by authors (2023)

Table 1. Demographic profile of respondents

respectively, based on Liang *et al.* (2019) and Pitardi and Marriott (2021). In addition, AAI and consumer PI are also measured by five measurement scales and three scales, respectively, based on Liang *et al.* (2019). Besides these, Hernandez-Ortega and Ferreira (2021) five scales and Kim *et al.* (2020)'s three scales are used to assess consumer innovativeness. Finally, this study uses Arachchi (2022)'s methods to measure Gen X and Y. At the end of the survey, all item statements used a seven-point Likert type scale ranging between "strongly disagree" and "strongly agree," with minor modifications drawn from the previous literature.

Descriptive statistics, tests of common method bias, tests of multivariate assumptions and tests of unidimensionality were performed using Statistical Package for the Social Sciences (SPSS), whilst the measurement and structural models were analysed using Smart PLS (4)-based structural equation modelling (SEM). The data did not fulfil the parametric assumptions. However, Smart PLS does not need the data to follow a normal distribution (Hair *et al.*, 2019; Ringle *et al.*, 2023). Therefore, SMART PLS for data analysis is justified because the data are non-normally distributed (Hair *et al.*, 2014); the aim of the research is to predict endogenous latent variables (Hair *et al.*, 2017); the focus of the study is to analyse certain target constructs' key sources of explanation (Ringle and Sarstedt, 2016); and research in the field of marketing, IS and retail management has begun to pay more attention to PLS-SEM (Menidjel *et al.*, 2019) for exploratory analysis of models in new contexts. Further, although Smart PLS-based SEM can be run using small sample sizes, such as those between 150 and 200 respondents, a large sample size helps to establish better results (Hair *et al.*, 2014). In line with this, the sample size of the present study fell beyond the recommended limit (Mubushar *et al.*, 2020). Further, our main intention was to test the conceptual framework from a predictive perspective. According to Hair *et al.* (2019), when the key intention of a study is to predict relationships, variance-based SEM techniques such as SMART PLS are more appropriate than covariance based SEM techniques. Therefore, this body of methodological literature warrants the employment of Smart PLS.

4. Data analysis

4.1 Demographic analysis

As shown in Table 1, in total, 836 completed surveys were obtained. 76% (n = 635) of responses were received from India and 24% (n = 201) from Sri Lanka, of a pooled sample. In terms of marital status, 54% of respondents (n = 454) were single. In addition, the sample was representative of 40% Gen X (n = 338) and 60% Gen Y (n = 498). 47% of respondents (n = 392) reported holding a bachelor's degree in terms of educational level. Furthermore, the majority of respondents (n = 376, or 45%) earned between $801 and $1,000 per month.

5. Measurement model assessment

5.1 Reliability, validity, AVE, factor loading and Fornell–Larcker criterion

Cronbach's alpha tests and factor analysis were used to assess the data's reliability and validity. According to Table 2, all constructs had a Cronbach's Alpha value of greater than 0.6 and a composite reliability value of greater than 0.6, indicating that the variables were reliable (Nunnally, 1978). All components, with the exception of PU5, had factor loadings larger than 0.5, according to the factor analysis results. Items with factor loading values less than 0.5 were eliminated (PU5), and the model was retested for validity, as recommended by Hair *et al.* (2011). Following that, using the standardized factor loadings, statistics for validity and reliability were generated (Appendix). Furthermore, all variables are related to an average variance extracted (AVE) value greater than 0.5 (Table 2). Therefore, the constructs were regarded as reliable indicators (Churchill, 1979). Furthermore, because all variables were

Factor	Code	Scale item
		MSSR . . . . . .
Perceived usefulness (PU)	PU1	Choose my outfit faster
(Liang *et al.*, 2019; Pitardi and Marriott, 2021)	PU2	Improve my performance in choosing the most trendy fashion outfit
	PU3	Increase my efficiency in choosing the most trendy fashion outfit
α = 0.794, CR = 0.794 and AVE = 0.563	PU4	Enhance my effectiveness in choosing the most trendy
	PU5	Make it easier for me to pick out what to wear
	PU6	Be useful for choosing the most trendy outfit
	PU7	Overall, I find my voice-based assistant useful when I am searching for information
Perceived ease of use (PEOU)	PEOU1	Learning to operate this device would be easy
(Liang *et al.*, 2019)	PEOU2	I think I would find it would be easy to get this device to do what I want it to do
α = 0.738, CR = 0.739 and AVE = 0.569	PEOU3	My interaction with this device would be clear and understandable
	PEOU4	This device would be flexible to interact with
	PEOU5	It would be easy to become skilful at using this device
Perceived enjoyment (PE)	PE1	I find using my MSSR enjoyable
(Pitardi and Marriott, 2021)	PE2	I find using my MSSR entertaining
α = 0.749, CR = 0.729 and	PE3	I have fun when using my MSSR
AVE = 0.641	PE4	I find using my MSSR pleasant
Attitudes toward AI (AAI)	AAI1	Worthless–valuable (Attitude 1)
(Liang *et al.*, 2019)	AAI2	Unfavourable–favourable (Attitude 2)
α = 0.609, CR = 0.655 and	AAI3	Disagreeable–agreeable (Attitude 3)
AVE = 0.531	AAI4	Harmful–beneficial (Attitude 4)
	AAI5	Dislike–like (Attitude 5)
Consumer smart experience (CSE)	CSE1	Experiences with my MSSR . . ..
(Hernandez-Ortega and Ferreira, 2021)	CSE2	are a success
α = 0.772, CR = 0.805 and	CSE3	are pleasant
AVE = 0.571	CSE4	make me feel involved
	CSE5	are appealing
Consumer innovativeness	CI1	I like to try MSSR
(Kim *et al.*, 2020)	CI2	I like purchasing novel products MSSR
α = 0.770, CR = 0.778 and AVE = 0.541	CI3	I enjoy trying unusual products
Consumer purchase intention (PI)	PI1	The likelihood that I would purchase trendy outfit via MSSR
(Liang *et al.*, 2019)	PI2	The probability that I would consider buying of my trendy outfit via MSSR
α = 0.747, CR = 0.739 and AVE = 0.593	PI3	My willingness to buy my trendy outfit via MSSR
Gen X and Y	G1	Gen X - 1965–1980 (43–57 years)
(Arachchi and Mendis, 2021)	G2	Gen Y - 1981–1996 (27–42 years)

Note(s): (1) PU: perceived usefulness; (2) PEOU: perceived ease of use; (3) PE: perceived enjoyment; (4) AAI: attitudes to AI; (5) CSE: consumer smart experience; (6) PI: consumer purchase intention and (7) CI: consumer innovativeness
Source(s): Table by authors (2023)

Table 2.
Reliability and validity

adopted from well-established measures in the literature, it was plausible to presume that they all had face and construct validity (Bougie and Sekaran, 2020).

In addition, the Fornell-Larcker criterion is a second and highly traditional method used to measure discriminant validity, and it compares the square root of the relevant AVE values with latent variable correlations (Sarstedt *et al.*, 2017). Following Henseler *et al* (2014), as a better, alternative and more modern approach to establish discriminant validity, we employed the heterotrait-monotrait ratio of correlations (HTMT), which output was generated based on the multitrait-multimethod matrix. These results provide an acceptable level of discriminant validity. The HTMT matrix is shown in Table 3 for all constructs, establishing discriminant validity since all HTMT values have a ratio less than 0.9 (Henseler *et al.*, 2014).

Furthermore, the Standardized Root Mean Square Residual (SRMR) values are less than 0.10 (0.099 for the saturated model and 0.083 for the estimated model) (Byrne and Hilbert, 2008). However, the Bentler-Bonett Normed Fit Index (NFI) value is shown as n/a. The study used Harman's single-factor test to determine if there was common technique bias because the data were acquired from each respondent using a survey questionnaire in which a single respondent responded to both independent and dependent variables (Podsakoff *et al.*, 2003). According to the findings, there was only a single-factor with a higher variance of 23.83%, which was below the 50% threshold. Thus, the common method bias did not appear to be a substantial concern because no single factor accounted for the bulk of the variation. Furthermore, it is essential to conduct a structural model assessment to test the hypotheses depicted in the conceptual model. This analysis is reported in the sections below.

6. Structural model assessment

6.1 Hypothesis testing

A structural equation model was utilized to determine the associations between the various components in this study. These assumptions were investigated using a structural model once the constructs' reliability and validity were established. Using the PLS technique and bootstrapping, the path coefficients and t-values were tested at a 5 and 1% level of significance.

As per Table 4, Hypotheses: H1, H2, H3, H4, H5 and H6 are accepted as the p-values are less than 0.05.

7. Analysis of Gen X and Gen Y as moderators

For the purpose of evaluating the generations (X and Y) as a categorical moderator as presented in Hypothesis 7, a binary categorical moderator analysis was performed. The purpose of this study is to examine the potential moderating effect of Gen X and Y on the path between consumer smart experience and consumer PI in fashion retail. There were two categories of generations. i.e. Gen X and Gen Y. Therefore, this is a case of a binary categorical moderator (Hoda *et al.*, 2023).

As mentioned by Hoda *et al.* (2023) and Ringle *et al.* (2023), the moderator must be numbered 0 and 1 to conduct moderation analysis in Smart PLS 4 when the moderator is a

	AAI	CSE	PE	PEOU	PI	PU
AAI						
CSE	0.758					
PE	0.142	0.128				
PEOU	0.471	0.527	0.092			
PI	0.580	0.595	0.073	0.357		
PU	0.503	0.576	0.158	0.922	0.338	0.671

Note(s): (1) PU: perceived usefulness; (2) PEOU: perceived ease of use; (3) PE: perceived enjoyment; (4) AAI: attitudes to AI; (5) CSE: consumer smart experience; (6) PI: consumer purchase intention and (7) CI: consumer innovativeness

Source(s): Table by authors (2023)

Table 3.
Heterotrait-monotrait ratio of correlations (HTMT)

Hypothesis	Relationship	Original sample (O)	Sample mean (M)	Standard Deviation (STDEV)	T statistics (|O/STDEV|)	*p* values	Decisions
H1	PU → AAI	0.419	0.415	0.071	5.896	0.00**	Supported
H2	PEOU → AAI	0.544	0.543	0.059	9.294	0.00**	Supported
H3	PE → AAI	0.068	0.079	0.029	2.318	0.02*	Supported
H4	AAI → CSE	0.758	0.760	0.023	32.701	0.00**	Supported
H5	CSE → PI	0.595	0.596	0.030	19.609	0.00**	Supported
H6	Mod CI – AAI → CSE	0.240	0.239	0.045	5.340	0.00**	Supported
H7	Mod Gen X & Y–CSE → PI	1.440	0.801	0.020	40.29	0.00**	*Strongly Supported*

Note(s): (1) PU: perceived usefulness; (2) PEOU: perceived ease of use; (3) PE: perceived enjoyment; (4) AAI: attitudes to AI; (5) CSE: consumer smart experience; (6) PI: consumer purchase intention and (7) CI: consumer innovativeness
$*p < 0.05$; $**p < 0.01$
Source(s): Table by authors (2023)

Table 4. Hypothesis testing

binary categorical one. Accordingly, the two generations were numbered as follows: 0 = Gen X and 1 = Gen Y. The process of moderation in Smart PLS 4 requires the moderating variable to be connected directly to the path between the predictor and the dependent variables (Hair *et al.*, 2019; Hoda *et al.*, 2023; Ringle *et al.*, 2023). Accordingly, a PLS algorithm was run to check the R^2 and detect if the moderator was influential. A bootstrapping procedure was also conducted with a subsample of 5,000 to test the significance of moderation.

According to Table 4, Hypothesis H7 was tested via PLS binary categorical moderator analysis, and it was accepted, as the *p*-value was less than 0.05 and the interaction effect had a path coefficient of 1.440. The significant and positive interaction term above 1 implies that Gen Y has a stronger effect on the path between consumer smart experience and PI than Gen X. This can be interpreted as the fact that Gen X and Gen Y both moderate the effect of consumer smart experience on PI, but highlights Gen Y as being more innovative in adopting embedded AI-MSSR applications in retail shopping than Gen X.

8. Discussion

In this study, we focussed on examining the relationship between mobile smart speech recognition and consumer PI in the fashion retail sector. Furthermore, we investigated the impact of innovative consumers, Gen X and Y, on the aforementioned relationship. This study utilizes the research theoretical lenses of the TAM, generational cohort theory and DOI theory.

First, our findings (as shown in Figure 2) are presented in terms of perceived usefulness, PEOU and PE in relation to AI attitudes. This finding supports previous research by Liang *et al.* (2019) and Lunney *et al.* (2016). A reasonable justification is that consumers value the promoted capabilities of the AI-enabled MSSR in fashion retail. With these functionalities and the user-friendly system, consumers' efficiency and happiness in selecting stylish clothing were greatly increased, resulting in a more favourable perception of AI. Furthermore, consumers are able to search for their fashionable clothes and get easy outfit recommendations (Cieslak, 2018) by using MSSR. Therefore, consumer perceptions and attitudes toward AI are positively influenced by MSSR (Alexa, Google Assistant, Siri and Cortana).

Secondly, in the fashion retail industry, this study discovered a positive relationship between AI attitude and consumers' smart experience. Limited empirical evidence is

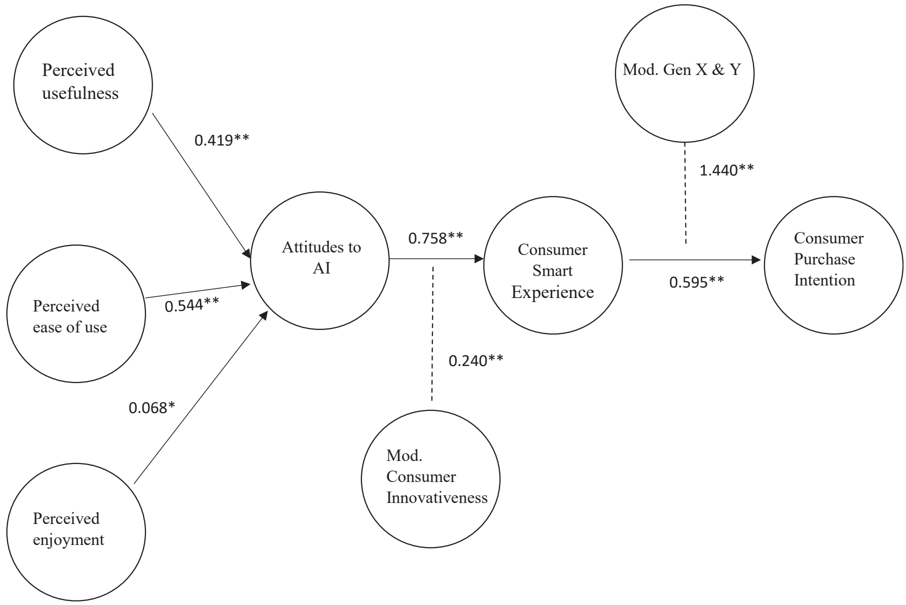


Figure 2.
Path estimate of PLS analysis

Note(s): $*p < 0.05$; $**p < 0.01$; Total sample ($N = 836$)
Source(s): Figure by author (2023)

available related to this relationship, and Persson *et al.* (2021)'s study corroborates our finding. According to Persson *et al.* (2021), a belief about AI was created and that changed consumer purchasing patterns. AI-powered devices are reshaping and improving consumer high-quality experiences. Moreover, it is intended to use AI technology in fashion retail (David *et al.*, 2022). Consumer AAI (AAI) and consumer smart experiences are novel research ideas, according to this study and consumer AAI assist consumers in selecting the correct trendy fashion outfits in a shorter time period. This advantageous, valuable and favourable attitude is associated with smart consumer experience.

According to the second objective of this study, a positive relationship was found between consumer smart experience and PI. This finding is novel in relation to MSSR smart experience and consumer PI in the fashion retail industry. Previous research on consumer experience and purchase intent related to VAs has been conducted (Chang and Chen, 2021; Poushneh, 2021; Hernandez-Ortega and Ferreira, 2021), but there is a conspicuous lack of evidence on mobile smart speech recognition. When consumers interact with an AI related smart device (such as a VA), they develop a distinct impression that influences their views, experiences, subsequent behaviour (Kim and Baek, 2018) and purchasing process (Chang and Chen, 2021). Furthermore, voice technology is integrated into physical store technology to provide consumers with a new and smart experience and the intention to purchase goods from a retail institution (Roy *et al.*, 2018; Chang and Chen, 2021).

Finally, the third goal of this study is to elucidate the moderating impact of consumer innovativeness and that of Generations X and Y on the association between MSSR and consumer PIs. Consumer innovativeness moderates the relationship between AI attitudes and consumer smart experience, and this is an insightful way to relate to MSSR. Consumer innovativeness is allowing consumers to search for the most trendy fashion outfits from fashion stores and then try them on. AI technology enables consumers to be creative by locating the most recent fashion outfits in their stores (Kim *et al.*, 2020). Therefore, fashion retail consumers intend to use MSSR and enhance an innovative consumer experience. This study also discovered that Gen X and Y had a moderating impact on consumer smart experience and PI. Because Gen Y has a stronger moderating impact (interaction coefficient above 1) than Gen X, this result is novel. This finding also represents a novel insight derived from this study, as there has been no prior empirical evidence in relation to this finding. As per PWC (2022), younger consumers acquire speech technology at a higher pace than older consumers. Furthermore, as per Insider Intelligence (2022), the most likely to utilize voice assistance are younger millennials (Gen Y) rather than Gen X. This year, it is anticipated that roughly two-thirds of 25- to 34-year-olds will use VAs monthly. This percentage falls below 50% amongst Generation X (ages 42 to 57). This moderating impact changes the consumer's PI during shopping activity in fashion retail. Since they are more innovative, Gen Y is more familiar with digital devices, and there is an intention created to use mobile applications for shopping activities (Khoa *et al.*, 2021) and decision making processes related to purchasing.

9. Implications and conclusion

9.1 Theoretical implications

These discoveries contribute significantly to the field of theory. First, mobile smart speech recognition has increased tremendously over time, which has made consumers' smart experiences more pleasant and easy in the fashion retail industry with AI enabled emerging tech applications (Priporas, 2020). However, there is still a need to investigate the impact of MSSR in the fashion retail industry. Consequently, this research has made a significant contribution towards filling this gap in the domain of experiential marketing. Recent MSSR technology is a new kind of machine-human interaction that has led to a novel way of acquiring comfortable purchase facilities in the fashion retail industry.

Secondly, this study examined perceived usefulness, PEOU and PE in relation to MSSR. This study also looked at how the three variables AI attitude, consumers' smart experience and PI are related to each other. The impact of MSSR on consumer perceptions and PIs has yet to be investigated, as previous MSSR literature has only examined? Third, consumer innovativeness, Gen X and Y are important for the research direction. The study draws from the generational cohort perspective and highlights the influence of generational attitudes in adopting innovative technologies. From a theoretical perspective, this highlights the role of generation-specific values, attitudes and beliefs that are congruent with technology innovation adoption in addition to the traditional innovativeness dimensions of consumer behaviour as moderators. Therefore, this result has overcome the past research limitations of the studies of Han (2021), Liang *et al.* (2019) and Pal *et al.* (2018). In this study, the effect of different Gen groups on consumer PIs was investigated. According to the findings, Gen Y prefers to use MSSR more than Gen X. In addition, innovativeness means that consumers are searching for novel experiences by using MSSR. These findings provide additional theoretical backing and application potential for MSSR in fashion retail. In this study, the critical aspects of an MSSR device useful for the fashion retail business are identified, compensating for the lack of literature on the application of technologies such as artificial intelligence (AI) embedded in MSSR in this field. Fourthly, this study is based on Alexa from Amazon, Siri from Apple, Google Assistant from Google and Cortana from Microsoft. There was a previous lack of empirical studies using the above four brands, and the current research fills this empirical gap.

Finally, theoretically, this study contributed to the TAM by expanding the paradigm to include the evaluation of a new fashion technology by consumers. Furthermore, attitudes to AI were integrated into the TAM framework, and our test results demonstrated a positive influence on PI. Further, the TAM is underpinned by generational cohort theory and DOI theory, and this integration is a novel theoretical contribution for marketing theoretical aspects and is better in predicting PI in an AI-based experiential economy. The incorporation of these elements informed a subsequent study on the application of embedded AI-MSSR to fashion retail. In addition, the TAM was applied to two samples drawn from two different nations, which adds to the comprehensiveness of the TAM literature.

9.2 Managerial implications

This study has several managerial implications for marketing practitioners, focussing mainly on MSSR in the fashion retail industry. Firstly, we established that consumers' evaluations of perceived usefulness, PEOU and PE have a substantial impact on their AAI. The platforms of this new fashion technology product might be continuously upgraded by fashion retailers to maintain a user-friendly attitude and experience. Amazon's Alexa, Apple's Siri, Google Assistant and Microsoft's Cortana, are AI-powered MSSR that have become a vital part of brands' and merchants' consumer engagement strategies in the digital age, since now consumers are able to choose their most trending fashion outfits in a few seconds and interact with it without looking at any devices in fashion retail. As a result, fashion consumers' beliefs and AAI are influential in projecting their adoption of these innovative and emerging applications. These applications can provide them with a beneficial, agreeable, favourable and valuable fashion attire-related experience.

Secondly, our research discovered that MSSRs improve the smart experience in the fashion retail sector. MSSR apps are pleasant and appealing because they help fashion retail consumers succeed in choosing the attire that will suit them best. Therefore, MSSR usability will improve in the future. Nevertheless, the techniques that have not been explored to their full potential include product discovery, personalized suggestions and customer service. As the number of smart speaker owners continues to rise, so too will the proportion of MSSR searches and voice-activated purchases. As a result, fashion retailers must implement the MSSR platform in their stores to improve customer experiences and activate purchasing decision making processes.

Thirdly, our study found that innovative consumers are searching for digitalization in fashion retail. MSSR has since provided consumers with technology-based experiences and triggered PIs. Thus, more consumers are using mobile phones to search for trendy fashion outfits. It is clear that the installation of MSSR allows fashion consumers to quickly search for trendy fashion outfits. Therefore, fashion retailers can implement advertising strategies that target forward-thinking consumers. Additionally, they should advertise relevant promotions and discounts amongst those who have purchased earlier through MSSR.

Finally, this study discovered a link between MSSR and generations X and Y. Gen Y has a stronger impact on the relationship of interest in this research model. Therefore, fashion retailers can easily implement the MSSR concept amongst their Gen Y purchasers, because Generation Y has grown up with the Internet and is looking for technology to purchase products, and the implementation of MSSR benefits consumers who buy fashion outfits from stores, Furthermore, relevant retailers can implement advertising that is primarily targeted at Gen Y consumers rather than those from Gen X.

9.3 Limitations and future research

The current study has some limitations that provide directions for future studies. To begin with, this sample primarily comprises Sri Lankan and Indian Gen X and Y consumers. Since this sample size is not adequate for generalizing the results, researchers can expand this sample size in the future to investigate how Gen Y and Z behaviour affects MSSR by undertaking a comprehensive multi-group analysis. Additionally, future researchers will be able to examine how native language and/or multilingualism (Gutch, 2020), localization (Moriuchi, 2019), consumers' personality traits (Anwar *et al.*, 2020) and high and low consumer innovativeness (Li *et al.*, 2021) impact MSSR by drawing multiple samples that have different geo-demographic attributes from the population in a region. Furthermore, this study is based only on Amazon's Alexa, Apple's Siri, Google Assistant and Microsoft's Cortana. However, there is a possibility to undertake studies that take into account other multi-brand and multi-country analyses.

9.4 Conclusion

To summarise, the study emphasized the impact of the primary components of the TAM on customers' AAI and behavioural intentions in fashion retail as a chain relationship. In addition, the moderating effect of consumer innovativeness and Generations X and Y enhanced the significance and depth of the paper's findings. In fashion retail, MSSRs are supporting customers and regulating their purchasing behaviour, which makes their lives more comfortable by including more technological components. Using DOI theory and generational cohort theory, the study investigated the potential impacts on the constructs of the TAM. In the present study, a substantial contribution has been made to readers, academics and marketing professionals. By addressing the significant literature gap and establishing the impactful role played by consumer innovativeness together with Gen Y as a dominant consumer segment that adopts MSSR in a fashion retail context. A summary of the key conclusions and their implications are also presented in Table 5.

Conclusions	Theoretical and managerial implications
Findings emphasized the impact of the primary components of the TAM model on the customers' attitudes towards AI and behavioural intentions in fashion retail as a chain relationship in an MSSR mediated environment	- TAM model can be enriched by integrating it with generation cohort theory and DOI theory for better predicting purchase intention in AI based experiential economy
The moderating effects of consumer innovativeness and Gen X and Gen Y are influential in strengthening attitudinal and behavioural outcomes in modern tech-based fashion retail consumption decisions	- Generation specific values, attitudes and beliefs that are congruent with technology innovation adoption in addition to traditional innovativeness dimensions of consumer behaviour as moderators - Fashion retailers must implement the MSSR platform in their stores to improve the customer experience and activate purchasing decision making process using suitable advertising strategies.for their Gen Y target markets
Attitudes towards AI is a significant predictor of consumers' smart experience in fashion retail environment	- The new platforms of technology such as AIs-powered MSSR can play a vital part of brands' and merchants' retail marketing strategies in developing tech-based consumer experiences

Source(s): Table by authors (2023)

Table 5. Conclusions, theoretical and managerial implications

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Appendix

Code	Outer loadings	Mean	SD
PU1	0.718	4.92	0.98
PU2	0.814	5.02	0.93
PU3	0.682	5.02	1.35
PU4	0.653	5.11	1.25
PU5	0.404	5.01	1.04
PU6	0.530	5.11	1.31
PU7	0.663	5.15	1.23
PEOU1	0.686	4.96	1.01
PEOU2	0.839	4.98	0.93
PEOU3	0.730	5.00	1.34
PEOU4	0.675	5.03	1.27
PEOU5	0.547	4.91	1.12
PE1	0.638	4.95	1.23
PE2	0.753	5.03	0.92
PE3	0.713	5.02	1.34
PE4	0.847	5.09	1.23
AAI1	0.515	4.93	1.15
AAI2	0.536	4.98	1.18
AAI3	0.791	4.75	1.15
AAI4	0.862	5.15	1.34
AAI5	0.811	4.80	1.10
CSE1	0.808	4.83	1.17
CSE2	0.855	5.36	1.27
CSE3	0.800	4.95	1.10
CSE4	0.838	5.13	1.15
CSE5	0.580	4.75	1.19
CI1	0.896	5.50	0.98
CI2	0.856	4.97	0.86
CI3	0.728	5.17	0.98
PI1	0.813	4.51	1.36
PI2	0.845	5.01	1.17
PI3	0.777	4.67	1.22
G1	1.000	1.61	0.49
G2	1.000	1.39	0.48

Source(s): Table by authors (2023)

Table A1. Cumulative factor loadings

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