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Understanding the attitude and intention to use smartphone chatbots for shopping

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ABSTRACT

Using the technology acceptance model and diffusion of innovations theory, this study evaluated the intention of consumers to use chatbots on smartphones for shopping. Chatbot is a relatively new technology and is expected to dominate mobile commerce and shopping applications in future. Hence, this study aimed to determine the association of perceived usefulness, perceived ease of use, perceived enjoyment, price consciousness, perceived risk, trust, and personal innovativeness with attitude and intention to use chatbots for shopping. Respondents were asked to fill a questionnaire after using a Facebook e-commerce chatbot that was specifically created for this study. In total, 350 responses were analyzed using partial least squares structural equation modeling. Results indicated that attitude toward chatbots was considerably influenced by the variables perceived usefulness, perceived ease of use, perceived enjoyment, price consciousness, perceived risk, and personal innovativeness. However, intention to use was directly influenced only by trust, personal innovativeness, and attitude. Mediation analysis indicated that full mediation occurs through the attitude variable for most direct relationships. Moderation analysis by using age, gender, and prior experience with mobile shopping applications indicated considerable differences between the groups in terms of the strength of certain relationships and the mean responses between the variables.

1. Introduction

Mobile commerce was considered the technology that revolutionized e-commerce. However, with smartphone evolution, the traditional web-based mobile commerce was replaced by mobile shopping applications. Furthermore, with the advancement of mobile shopping applications, the big question is "Which technology will replace mobile shopping applications?" Mobile chatbot is one of the technologies that could revolutionize mobile commerce once again. American Marketing Association and various other sources claim that chatbots are the future of marketing, and as they can be integrated with messaging applications such as Facebook, WhatsApp, and Skype, they can replace mobile applications for shopping [1]. Consumers can interact with a chatbot through a chat interface by using written or verbal statements. Chatbot is considered the hottest development trend of 2018; since the last quarter of 2015, the use of messaging apps has surpassed that of social networking sites in terms of monthly active users [2]. While using a mobile, an estimated 90% of the time is spent on email and messaging platforms [3]. Millennials are especially keen on using chatbots, as this technology suits their habits and routines [4].

Chatbots have been around for many years but are making a comeback due to the rise of artificial intelligence and internet of things. ELIZA, a computer program created by Joseph Weizenbaum in 1966, is generally recognized as the first chatbot. Earlier, chatbots were considered an intriguing but a mostly useless technology. Today, chatbots are poised to revolutionize our communication method and are expanding into all possible fields requiring human interaction, from simple weather chatbots for daily forecast (the most notable example being Facebook's Poncho chatbot) to news chatbots for updates on current events, or for finding a ride (such as the Uber chatbot, which was created as an alternative to the app). Furthermore, chatbots are used in most of the standard e-commerce fields (e.g., delivering flowers, ordering pizzas, or booking flights) as well as in information procurement on various topics (mortgage, health care, food recipes, and so on) [4].

The literature on mobile chatbot is scarce in the fields of marketing and behavioral sciences as it is a relatively new technology. Eeuwen [5] was the first to evaluate user attitude toward chatbot technology from a mobile shopping perspective. He categorized chatbots as "conversational commerce" (c-Commerce), which was coined by Messina [6], and

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defined it as "utilizing chat, messaging, or other natural language interfaces (i.e., voice) to interact with people, brands, or services." Of the five variables considered by Eeuwen [5], perceived usefulness, compatibility, and internet privacy concern were considerably associated with and perceived ease of use and attitude toward mobile advertising were insignificantly associated with consumer attitudes toward chatbot use for mobile shopping. Eeuwen's study directed future researchers to focus on other variables such as enjoyment, risk, and trust. Chatbots have various advantages such as availability, cost-effectiveness, customer interaction, automation, and personal assistance. However, it has the disadvantage of reduced flexibility in comparison with products across different e-commerce vendors. Mobile shopping applications have reduced flexibility, and chatbots decrease the flexibility further. This factor may play a major role in influencing attitudes and usage intentions of users in developing countries, which are highly priced sensitive markets. Hence, price consciousness of consumers is an exciting study area.

This study aimed to identify factors that influence attitude and intention to use chatbots for mobile shopping. The chatbot considered in this study is a conversational smartphone interface (through Facebook messenger) that can interact with users and assist in reading reviews, browsing for and researching of products, comparing products, accessing saved coupons, buying products, keeping a track of orders, and receiving rewards and loyalty points. A literature review of research articles that used grand theories such as diffusion of innovations (DOI), theory of planned behavior (TPB), and technology acceptance model (TAM) was performed to identify factors that affect intention to use various technologies such as mobile commerce, mobile applications, mobile payments, and gaming. Thereafter, a generic model was created. The significance of user demographics is prevalently studied for technology adoption, and this has been widely researched in the fields of e-commerce, mobile commerce, and mobile applications. The prognostic power of these models must be well understood, and with readily available demographic variables, demographic-based models can be quickly formulated and used to provide solutions for emerging problems in businesses [7–9]. Chatbots for mobile shopping is a relatively new technology promising revolution in marketing [1]. Hence, demographic variables must be studied at the initial stage of the study to efficiently design and tailor services for consumers with increased personalization. Furthermore, this study aims at identifying differences among genders, age groups, and users with different levels of experience with mobile applications in terms of chatbot adoption. In line with the objectives of the study and gaps identified in the literature, the following research questions were proposed:

Research Question 1: What factors significantly influence attitude and intention of chatbot users to use mobile messenger e-commerce?

Research Question 2: Do gender, age group, and prior experience in using mobile shopping applications significantly moderate adoption of chatbots?

The remainder of the paper is organized as follows. Section 2 deals with the hypotheses and model development in line with the research questions. The methodology, data collection, and analysis to validate the research model are presented in Section 3. Results are presented in Section 4 followed by discussion and conclusion in Sections 5 and 6, respectively.

2. Theoretical model and hypothesis development

2.1. Technology acceptance model

TAM, which was first proposed by Davis [10], is the most influential of research models explaining information technology adoption and is considered useful for studying acceptance in various contexts related to information technology [11]. The central message of this model is that technology users make rational decisions regarding using a technology [11]. Perceived usefulness and perceived ease of use are the factors that must be taken into account to make these rational decisions, which are considered determinants to user attitude and behavior [10].

Venkatesh and Davis [12] were two of the most influential scholars to expand the model, making a new standardized model of technology acceptance, namely TAM2, through introduction of new factors and exclusion of attitude. The unified theory of acceptance and use of technology (UTAUT) is another standardized model developed through comparison and unification of existing models of information systems [13]. Furthermore, this model excludes attitude and introduces four key factors for determining usage intention and behavior. These factors are effort expectancy, performance expectancy, social influence, and facilitating conditions, which are connected to the moderating constructs of age, gender, use voluntariness, and experience [13].

Although both these models continue to be extended and improved with new research, which further legitimate these models, TAM is more influential and popular than UTAUT [11]. Moreover, in contrast to UTAUT, TAM includes attitude as a major determinant of user acceptance, which has proven to have a significant effect on mobile application acceptance earlier [14–16]. Hence, it was used as the core model in this research. TAM has several benefits when determining factors for technology acceptance. First, it possesses consistent tools of measurement, empirical soundness, and conciseness [14,17]. Second, it explains a major part of variance in usage intentions [14,18,19]. Third, as it has been applied in many studies, it offers a wide range of questions related to each factor, adding reliability to the relevance of the questions asked in the questionnaire. Although TAM is useful in terms of explaining the behavioral intention of using a technology, extended variables related to the specific technology must be addressed to clearly understand the its acceptance [10].

2.2. Diffusion of innovations

An innovation can be defined as something that is perceived as new by an individual or a social system. Conversely, diffusion is explained as "the process by which an innovation is communicated through certain channels over time among the members of a social system" [20]. This theory shows the innovation–decision stages from invention to the wide use of a new technology, as well as differences among the categories of adopters [21]. According to Rogers [20], people go through five stages before they accept an innovation: knowledge, persuasion, decision, implementation, and confirmation. Additionally, five characteristics of technology influence acceptance: relative advantage, compatibility, complexity, trialability, and observability [20]. Finally, five adopter categories are available: innovators, early adopters, early majority, late majority, and laggards [20]. In summary, the DOI model describes how users create beliefs regarding innovation characteristics based on which an innovation is adopted or rejected by the user [22–24], and this provides an excellent platform for researchers to study the adoption of new technologies such as chatbots.

2.3. Perceived usefulness

Venkatesh and Davis believe that "perceived ease-of-use play an important role and get more attention, while the perceived usefulness is believed as equally important as ease-of-use and lean toward service-dependent" [25]. Perceived usefulness of an information system is defined as "the extent to which individuals believe that using the new technology will enhance their task performance" [26].

As initially argued by Davis and subsequently supported by research, usefulness is central to the acceptance of information technology. This theory was extrapolated and applied to mobile shopping. Research confirmed that usefulness has a substantially positive influence on behavioral intention to mobile shopping [27]. If consumers believe that they can gain from this shopping channel, they are likely to adopt it. Gains in mobile shopping might include saving time, comparing pricing, obtaining promotional information, or receiving customized offers [28].

Preliminary studies have empirically proven that in the technological field, perceived usefulness is an essential factor that stimulates the use of a specific form of technology [29–38]. Thus, studying the effect of perceived usefulness on attitude and the intention to use chatbots for mobile shopping is appropriate. Simply put, individuals who find chatbots useful will adopt the technology. As the chatbot technology can save time and offer flexibility and convenience, its usefulness must be understood. The following hypotheses were therefore proposed:

H1a: Perceived usefulness has a significant positive influence on attitude toward chatbots.

H1b: Perceived usefulness has a positive influence on the intention to use chatbots.

2.4. Perceived ease of use

The perceived ease of use of an information system is defined as "the degree to which an individual believes that using a particular technology will be free of mental effort" [10]. Moreover, Davis suggests that ease of use is an indicator for technology acceptance. Consumers are more likely to adopt mobile shopping using chatbots if the technical infrastructure for it already exists. Infrastructure includes internet-enabled phone plans, user-friendly interfaces, and messenger apps that are compatible with various phones. Making it easy for consumers to shop on their mobile devices can prevent any barrier-to-entry that may be caused by technological confusion [28]. In other words, consumers will willing accept a technology they can easily understand and use. Shoppers are likely to use the technology if they can merely add a contact to their traditional messaging apps, such as WhatsApp, Facebook, or Skype, easily and navigate interfaces without hassle.

Many researchers [10,39,40] have indicated that users of technologies have predefined assumptions regarding how easy or difficult it will be to use a technology. Thus, researchers must study the perceived ease of use from users to understand their expectations. Studies have shown that the ease of use largely affects users' perceptions toward technological devices and must be seriously considered [29,30,32–38]. Natarajan, Balasubramanian and Kasilingam [18] observed that perceived ease of use affects the intention to use mobile shopping applications. As chatbots are closely associated with the technology in terms of functionality, perceived ease of use is a core variable in our study.

H2a: Perceived ease of use has a significant positive influence on attitude toward chatbots.

H2b: Perceived ease of use has a significant positive influence on the intention to use chatbots.

2.5. Perceived enjoyment

For many years, perceived enjoyment was believed to influence the behavior of individuals [41]. Kim [42] discovered that smartphone users are more likely to accept a technology and use it comprehensively than others if they experience pleasure or delight in using the technology. The TAM was extended across various technologies as it possesses one core variable, namely perceived enjoyment. According to Ha, Yoon and Choi [43], perceived enjoyment is one of the most essential variables to determine the adoption of mobile games by users. This necessitates the urge to determine whether this perceived enjoyment is also a factor that influences chatbot users because it affects internet usage and web-based commerce.

Teo [44] observed that in terms of using the internet for activities such as browsing, messaging, and downloading, the idea of "perceived enjoyment" plays an important part in the intention to use the internet among consumers in Singapore. Other studies in the field of technology adoption have revealed the positive influence of perceived enjoyment on user attitudes and behavior [32,34,38,45]. Enjoyment strongly affects one's engagement in mobile shopping [27]. One study found that "consumers' shopping intentions via mobile technology are positively influenced by attitude toward mobile commerce, subjective norm, and perceived enjoyment" [46]. The more an individual enjoys the shopping experience through chatbots, the more likely he/she will continue using this channel. In this study, the following hypotheses were proposed:

H3a: Perceived enjoyment has a significant positive influence on attitude toward chatbots.

H3b: Perceived enjoyment has a significant positive influence on the intention to use chatbots.

2.6. Price consciousness

Prices of products and services have always been a significant influencer of consumer attitudes and intentions [47–50]. According to Goldsmith and Newell [51], price sensitivity indicates the reactions of consumers to varying price levels. Price consciousness can influence a customer's decision when choosing or buying a product or service if that customer has high levels of price consciousness [52]. Price is a critical factor when purchasing products online [53]. The notion of price is essential in the purchase of products using a new technology. Unlike traditional e-commerce or even mobile commerce, chatbots for shopping do provide enough flexibility to compare or verify prices between various platforms for the same product. According to many studies on the importance of price, price is a deciding factor for using an online service by a customer. It is a bothersome issue [54] and relates to the intention of behavior [55]. Hence, studying this construct in our model is crucial and in line with the objectives of the study. The following hypotheses were proposed:

H4a: Price consciousness has a significant negative influence on attitude toward chatbots.

H4b: Price consciousness has a significant negative influence on the intention to use chatbots.

2.7. Perceived risk

The concept of perceived risk and its different constructs affect acceptance and adoption of new technologies [29,34,35,37,56–60]. The concept of perceived risk is a group of several risk components, and one of the most common ways to break down the concept of perceived risk was introduced by Jacoby and Kaplan [61], where they listed five different components: financial, performance, psychological, social, and physical risk. As physical risk is not applicable to the context of information technology adoption, it is usually excluded from perceived risk, whereas privacy risk is introduced as it affects customers online [62,63]. Psychological and social risks have been grouped together as social risk as they address similar areas of risk. Adding privacy risk is a natural step while analyzing risks online as technological evolution has introduced security concerns regarding identity thefts online and misuse of financial information [62]. Moreover, privacy risk is a barrier in the adoption of mobile banking as consumers are not in full control of their information, for example, credit card numbers [64]. Recently, concerns have arisen regarding privacy risks in terms of phishing, where criminals manage to obtain user information and carry out financial transactions [63]. Financial risk can be a consequence of privacy risk when mobile bank users are subjected to monetary losses due to phishing or hacking [63]. Moreover, financial risk can occur because of fraudulent behavior by the recipient as the transaction occurs online, where the consequence is monetary loss in this case as well [62]. Performance risk can be described as the risk due to failure of a product or service, which leads to a loss in performance, and predicts overall perceived risk best [65]. Social risk refers to the perception of others while a consumer adopts and uses products or services. Depending on how that usage is perceived by others, one's self-esteem could be affected positively or negatively [62].

As chatbot users could be exposed to all of the aforementioned risk dimensions, and as the variable of perceived risk has been widely used as one of the extensions of the TAM, this research includes it as one of the variables in our model. If customer expectations are not met with chatbots from a risk perspective, their relationship with that retailer will be affected. Hence, the following hypotheses were formulated in the area of perceived risk:

H5a: Perceived risk has a significant negative influence on attitude toward chatbots.

H5b: Perceived risk has a significant negative influence on the intention to use chatbots.

2.8. Trust

From a web retailer's perspective, trust can be defined as "the subjective probability by which the consumers expect that a Web retailer will perform a given transaction by their confident expectation" [57]. Because of the nature of internet shopping, consumers always face some level of risk in the shopping process. In fact, actions by other parties can be favorable (as in the case of a well-known web vendor) or harmful (as in the case of hackers). Once consumers face uncertain situations, trust can solve the risk conundrum [66]. When risk is absent, trust is not needed. Risk brings uncertainty into the buying process, and trust can be a successful strategy in dealing with uncertain future [57].

The importance of trust and its crucial role in online transactions and buying behavior in creating expected positive results has been studied by many researchers [67–71]. Trust may be a fundamental element that shapes a customer's belief system, ensuring that online vendors would not behave opportunistically [72].

Trust in incorporated into the TAM in several ways. The results of earlier studies place trust as a determinant of perceived ease of use [67], perceived usefulness [67,73], attitude [74,75], and behavioral intention [67,74,76]. According to the findings of Dahlberg, Segesten, Nyström, Suserud and Fagerberg [73], the model of trust-enhanced technology acceptance explains technology adoption of customers [73]. Trust affects intention both directly and indirectly. Its indirect effect is through the formation of a positive attitude toward shopping online [67]. Chatbots are new technologies in the market, and trust is a crucial factor in explaining users' attitudes and intentions to use.

H6a: Trust has a significant positive influence on attitude toward chatbots.

H6b: Trust has a significant positive influence on the intention to use chatbots.

2.9. Personal innovativeness

Rogers and Shoemaker [77] define innovativeness as "the degree to which an individual is relatively earlier in adopting new ideas than other members of his social system." Personal innovativeness regarding a new technology has been studied in different technology contexts and countries. AbuShanab, Pearson and Setterstrom [78] studied internet banking in Jordan, while Xu and Gupta [79] studied the acceptance of location-based services in Singapore, both including the aspect of personal innovativeness in their research.

Prior research in the field of consumer behavior has always given increased attention to the innovativeness of individuals [23,80,81]. It is considered a key variable in the online environment [82]; in the context of omnichannel retail, it significantly affects the purchase intention of consumers [81]. Moreover, it is one of the most significant variables in driving technology acceptance and adoption [31,32,34,56,58,83–86]. Herrero Crespo and Rodríguez del Bosque [87] and Rogers [20] argue that highly innovative individuals take a high level of risk while adopting new technologies. All in all, personal innovativeness is an interesting and a crucial variable to explore and may have an effect on attitude and intention to use new technologies like chatbots; hence, the following hypotheses were proposed:

H7a: Personal innovativeness has a significant positive influence on attitude toward chatbots.

H7b: Personal innovativeness has a significant positive influence on the intention to use chatbots.

2.10. Attitude and intention to use

Human beings have an evaluation scheme for the consequences of performing a particular behavior, which is called attitude [88]. Briefly, on the basis of TPB [89,90], which is the extended version of the theory of reasoned action (TRA) [91], behavior is a direct function of elements like behavioral intention, which is formed by the person's attitude. Attitude is the users' negative or positive feeling regarding chatbots use on a mobile phone for shopping. From TRA and TAM, individuals' belief regarding the consequences of their behavior significantly affects their attitude toward behaving in that manner. Both models posit that attitude significantly influence individual intentions toward behavior. This relationship has been studied and found to be significant in various technologies such as e-banking [92], smart homes [93], virtual worlds [94], academic social networking sites [95], and mobile payment services [96]. Thus, the relationship between attitude and intention to use was included in the research model [97].

H8: Attitude toward chatbots has a significant positive influence on the intention to use.

Fig. 1 shows the research model for the study.

2.11. Gender

Gender is defined as the "biological differences between sexes," and this definition is widely used in today's society [98]. Researchers in all disciplines of management always report significant differences between genders in terms of attitudes and intentions [99]. Gender-based differences have been observed in the different facets of consumer behavior among which are attitudes toward shopping behavior and purchasing behavior [100,101]. It is generally considered the one most common and a primary variable used by marketers for segmentation. Venkatesh and Morris [102] proved that women's perception of usefulness of a technology influences adoption weakly compared with men. Moreover, various recent studies have revealed considerable differences between the genders in numerous forms of technology, such as mobile commerce, mobile payment, and mobile shopping applications [19,37,59,83,103,104]. When studying risk- and trust-related topics in online shopping, gender is used as a determinant [57]. Chatbot is a new technology in the market, and hence, the adoption of the technology itself may vary across gender. To develop strategies catering to each gender, which have high success rates, it is necessary to understand differences between women and men regarding adoption of the mobile messenger chatbot. Hence, the following hypotheses were proposed in the context of chatbots for

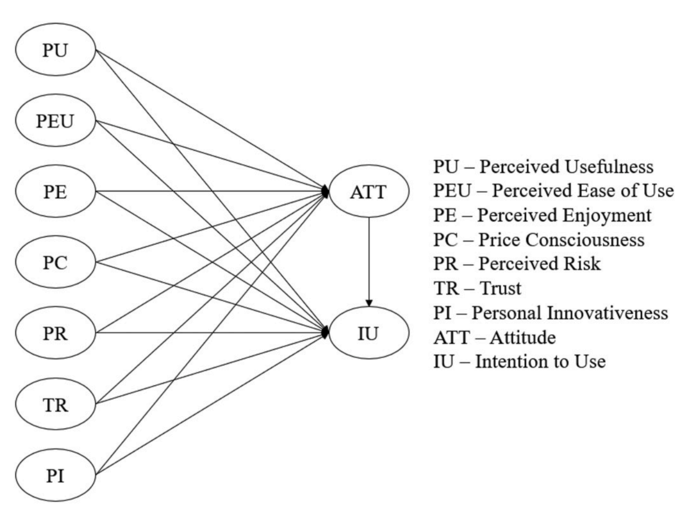

Fig. 1. Research model.

mobile shopping:

H9: There is a significant difference between genders in "a: perceived usefulness, b: perceived ease of use, c: perceived enjoyment, d: price consciousness, e: perceived risk, f: trust, g: personal innovativeness, h: attitude, and i: intention to use" of chatbots for mobile shopping.

H10: Gender moderates the relationships in H1 to H8.

2.12. Age

Younger users, who are de facto more familiar with newly introduced technologies and more eager to accept innovative tools, would have fewer issues with acclimatization than older users and would consider chatbots for mobile shopping as useful. This notion is empirically backed by a study regarding mobile and internet usage within this age group and shows that an affinity exists for adopting an online, continually evolving platform, such as chatbots for mobile shopping with little to no amount of perceived effort from their part [105]. Conversely, older adult users would perceive the need for more efforts to familiarize themselves with chatbot technologies for mobile shopping in general and are more likely to find its use as not being commensurate to the effort than the younger adult group. Moreover, compared with youngsters, the older group is likely to be affected by external influences more explicitly [106] and would be less willing to accept change without considerable investment on behalf of the developers and representatives of the chatbot [107].

However, older adults tend to trust the endorsement made by their online contacts and other early adopters within the context of their personal and online social circle, remaining mostly unaffected by third parties for a new technology or product. By contrast, younger adults, who are more familiar and therefore more comfortable in their online surroundings than the older ones, would be more likely to believe the promises of a marketing campaign or third-party developer or marketer, owing to their subjective perception of the effectiveness of mobile payment in general [105].

A study by Plaza, MartíN, Martin and Medrano [108] on the effects of mobile phone use on older adults in the United States, Japan, and Europe revealed that the most efficient way to allow this age group to adopt new technologies is through the implementation of design choices and approaches that are tailored according to their needs and are customizable to some degree to suit their lifestyle [108]. Further research carried out in the Netherlands cemented the notion that age played a significant role when determining online trends among users. Specifically, older mobile and online users deviated considerably from the norm established by younger adults by focusing mostly on shopping and other online ventures and information research in general [109]. Numerous researchers have, in fact, proven that a clearly defined "digital divide" exists among users based almost entirely on age, with entire platforms or technologies explicitly adapted for use by older adults to facilitate their adoption. Information, enterprise, and commerce follow a similar pattern, gravitating toward the demographic that possesses a steadier, more disposable income [110–115].

H11: A significant difference exists between age groups in terms of "a: perceived usefulness, b: perceived ease of use, c: perceived enjoyment, d: price consciousness, e: perceived risk, f: trust, g: personal innovativeness, h: attitude, and i: intention to use" of chatbots for mobile shopping.

H12: Age moderates the relationships in H1 to H8.

2.13. Experience in using mobile shopping applications

Fishbein and Ajzen [91] posit that a consumer's current behavior toward an item is largely influenced by that individual's positive dealings in the past with the same item. Prior experience in using a form/tool of technology moderates variables and relationships in various technology fields including mobile and internet messaging [116,117]. TAM2 had, in fact, included the moderating effect of experience in the original TAM model and found moderating effects [12]. In addition to moderation, this variable directly influences attitudes and intentions of the users [42,118]. Some studies have revealed that an individual's acquaintance and perceived benefit of use increase with increase in experience with the internet [119–121], ultimately leading to the intention of use [122]. Moreover, the reviewed literature showed that regarding the moderating influence of experience, new users who possess less levels of experience would need a higher ease of use than users with more experience. Thus, users with less experience are likely to be driven both intrinsically and extrinsically. Studies by Gefen, Karahanna and Straub [123] and Moon and Kim [124] conclude that users with limited experience are likely to be highly attentive to variables associated with the user interface itself and hence pay less attention to the purpose of their visit.

Moreover, Miyazaki and Fernandez [125] support the notion that experience with internet use can diminish perceived risk in the context of online shopping, as well as security and privacy concerns, and this concept can also be extended to chatbots and mobile shopping applications. Chatbots for mobile shopping is a new technology that most of the digital population has not used yet or is even unaware of. However, this technology is expected to storm the mobile applications market [1]. As both these technologies serve the same purpose and users of mobile applications would mainly adopt the chatbot technology, it is logical to determine whether the previous experience of users in using mobile shopping applications moderates the relationships.

H13: A significant difference exists between experience in using mobile shopping applications in "a: perceived usefulness, b: perceived ease of use, c: perceived enjoyment, d: price consciousness, e: perceived risk, f: trust, g: personal innovativeness, h: attitude, and i: intention to use" of chatbots for mobile shopping.

H14: Experience in using mobile shopping applications moderates the relationships in H1 to H8.

2.14. Methodology, data collection, and analysis

For this study, a custom Facebook e-commerce chatbot was developed for performing most e-commerce functions such as searching for information, recommend products, process orders and transactions, track shipping locations, and track orders. With an expected value of 150 billion USD by 2022 and 93% of internet traffic coming from mobile devices [126], Indian e-commerce market is mobile driven and is perfect for testing the research model. Verified e-commerce users, whose demographic details matched with the digital population of India, were selected for the study [127] to ensure that the selected sample represents the population. The participants were asked to use the chatbot to search for a product of their choice and complete an order placement with the cash on delivery option. The study participants were asked to use the chatbot for at least 5 min to ensure that they understood the technology properly. After using the chatbot, the participants were asked to fill a questionnaire with 46 questions followed by their demographic details. Van den Broeck, Zarouali and Poels [128] used a similar method that involved deploying a real-time chatbot followed by data collection from the users to understand chatbot advertising effectiveness.

The items of the questionnire were adapted from the literature. The items of the perceived risk construct were adopted from Featherman and Pavlou [62], perceived usefulness and perceived ease of use from Davis [10], perceived enjoyment from Davis, Bagozzi and Warshaw [129], personal innovativeness from Goldsmith and Hofacker [130], trust from Chong, Chan and Ooi [131] and Tsu Wei, Marthandan, Yee Loong Chong, Ooi and Arumugam [33], price consciousness from Dickinger and Kleijnen [132], Lichtenstein, Ridgway and Netemeyer [133], and Swaminathan and Bawa [134], attitude form Taylor and Todd [135], and intention to use from Kim, Mirusmonov and Lee [11]. A seven-point Likert scale was used to measure the constructs. In total, 399 responses were obtained of which 34 had missing data and were hence rejected. Furthermore, 15 responses were eliminated due to non-engagement while filling the survey. Finally, 350 responses were analyzed. The youth of India aged ≤35 years were categorized as the younger age group, as reported by the Ministry of Statistics and Programme Implementation, Government of India [136]. Hence, on the basis of the report, participants were categorized as young (≤35 years) and old (>35 years). For experience in using mobile shopping applications, people with experience of <3 years were categorized as "Low Experience" group and those with experience >3 years were categorized as "High Experience" group. Demographic details of the respondents are given in Table 1.

The partial least squares structural equation modeling (PLS-SEM) tool was used for testing the hypotheses. PLS-SEM was mainly used for the analysis because it is flexible regarding data requirements, model complexity, and relationship specifications [137]. Another major advantage of using this technique is the ability to compare two or more groups by specifying a permutation-based analysis of variance approach, which helps in maintaining the familywise error rates without relying on distributional assumptions and at the same time exhibiting an adequate level of statistical power [138]. SPSS 23.0 and Smart-PLS 3.0 were used as statistical software tools for different analysis. An independent sample *t*-test using SPSS was conducted to compare group responses for the variables. Smart-PLS 3.0 was used to analyze the structural model and to conduct the multi-group moderation analysis to compare the strengths of the relationships between the groups. The percentile bootstrap procedure using the PLS algorithm was performed on 5000 samples. For analyzing the structural model, a minimum confidence level of 95% for both independent sample *t*-test and moderation analysis and a minimum significance of 0.1 or a confidence level of 90% were considered.

3. Results

3.1. Reliability and validity

The measurement model was assessed using two validity tests, namely discriminant validity and convergent validity. Convergent validity generally refers to the condition that verifies whether the indicators of a multi-item construct are indeed measuring the same construct [60,139]. To accept measurement items, the factor loadings of the individual items belonging to a construct must be greater than the threshold value of 0.50 and reported as significant [140], and the average factor loading for the particular construct must be > 0.70 [141]. The items PI4, PS3, and PEU1 were removed from the analysis as they showed loadings <0.50 or cross loadings.

Table 2 shows that for all the variables, the Cronbach's alpha value is > 0.70, which proves that the measurement is reliable [142]. Moreover, composite reliability was greater than the desirable value of 0.60 in all the cases [143]. The average variance extracted, reported in Table 3, was >0.50 for all the factors, thereby fulfilling the conditions of Fornell and Larcker [144]. Therefore, the conditions for reliability and

Table 1
Respondent demographics.

	No.	Percentage
Gender		
Male	242	69.14
Female	108	30.86
Experience of Mobile Shopping		
High (>36 months)	169	48.29
Low (≤36 months)	181	51.71
Awareness of Chatbot Technology		
Aware	194	55.43
Unaware	156	44.57
Age		
Younger (≤35 years)	176	50.29
Older (>35 years)	174	49.71
Frequency of Mobile Shopping		
High (Daily to Weekly)	186	53.14
Low (Monthly to Occasionally)	164	46.86

convergent validity were met by the measurement model. Discriminant validity of the constructs was assessed using cross-loadings, Fornell and Larcker [144] criterion, and heterotrait monotrait ratios (HTMT). Tables 3 and 4 display indication for the model's discriminant validity. As shown by the correlation matrix, all pairs have a correlation <0.70 [145]. Similarly, all the inter-item correlations reported below the diagonal are not more than the square roots of the average variance extracted ($\sqrt{AVE}$) for the corresponding factors [144]. Furthermore, Table 4 shows that all the HTMT ratios were <0.85, indicating excellent discriminant validity [146]. SRMR was found to be 0.057, which was lesser than the threshold of 0.08, indicating an excellent model fit [147]. Additionally, tests for skewness, kurtosis, common method bias, multicollinearity, and invariances between groups (prior to moderation analysis) were conducted, and the model passed all tests with exceptional statistical significance and standard thresholds [140,148].

3.2. Partial least squares structural equation modeling

The statistical significance of the relationships in the model was tested by using bootstrapping procedure with 5000 subsamples and no sign changes with a confidence interval method of bias-corrected and accelerated bootstrap and two-tailed test with a significance of 0.05 in Smart PLS 3.0. On analyzing the structural model (Table 5), Hypothesis H3a relating to perceived enjoyment to attitude was found to have a significance of 0.001 and was the strongest relationship in the model. Hypotheses H6b, H7b, and H8 relating to trust, personal innovativeness, and attitude, respectively, with intention to use chatbots for mobile shopping also had a significance of 0.001. Hypotheses H1a, H2a, H4a, H5a, and H7a relating to perceived usefulness, perceived ease of use, price consciousness, perceived risk, and personal innovativeness with attitude toward chatbots had a significance of 0.05. All the significant relationships in the model were positive except for the effect of perceived risk on attitude. All remaining hypotheses, namely H1b, H2b, H3b, H4b, H5b, and H6a, were rejected although the effect of trust on attitude was close to the significance of 0.05. The main reason for rejecting these hypotheses could be because attitude may mediate them. Hence, the total effects and indirect effects in the model must be studied to conclude.

The total effects in Table 6 for the rejected hypotheses involving indirect relations indicate that the strengths of the regression coefficients change. Hypothesis H3b relating to the effect of perceived enjoyment on the intention to use was significant at a confidence level of 99%. Hypotheses H4b and H5b, although insignificant, were still close to a significance of 0.05.

Analysis of the indirect effects presented in Table 7 indicate mediation through attitude. Considering a significance of 10%, attitude mediates all constructs that relate to attitude. The strongest mediation is in the indirect relationship between perceived enjoyment and intention to use at a level of 99% confidence. This is followed by the indirect relationships between perceived ease of use and perceived usefulness with the intention to use at 0.05 significance. Finally, all the remaining relationships leading to intention to use from price consciousness, personal innovativeness, perceived risk, and trust were also mediated by attitude weakly at a significance of 0.10. Overall, the model had an explained variance (R^2) of 62.1% for the attitude variable and 70.8% for the intention to use variable.

3.3. Independent sample t-test

3.3.1. Gender

The results of the independent sample *t*-test to compare the mean responses of the variables between respondents based on gender are given in Table 8. Hypotheses H9e and H9g were supported by a high significance of 5%. A significant difference in the mean responses was observed between genders for the variables perceived risk and personal

Table 2
Reliability and convergent validity.

Factors		Individual Factor Loading	Average Loading (AL)	Cronbach's Alpha (CA)	Composite Reliability (CR)	Average Variance Extracted (AVE)
Attitude (ATT)	AT1	0.931	0.943	0.938	0.938	0.960
	AT2	0.947				
	AT3	0.952				
Intention to Use (IU)	IU1	0.906	0.864	0.888	0.923	0.753
	IU2	0.914				
	IU3	0.913				
	IU4	0.722				
Price Consciousness (PC)	PC1	0.747	0.704	0.809	0.856	0.501
	PC2	0.780				
	PC3	0.717				
	PC4	0.566				
	PC5	0.649				
	PC6	0.763				
Perceived Enjoyment (PE)	PE1	0.926	0.924	0.915	0.946	0.854
	PE2	0.942				
	PE3	0.905				
Perceived Ease of Use (PEU)	PEU1	0.706	0.793	0.853	0.895	0.633
	PEU2	0.722				
	PEU3	0.830				
	PEU4	0.878				
	PEU5	0.827				
Personal Innovativeness (PI)	PI1	0.566	0.759	0.818	0.875	0.588
	PI2	0.831				
	PI3	0.840				
	PI4	0.829				
	PI5	0.731				
Perceived Risk (PR)	PR1	0.723	0.809	0.868	0.905	0.657
	PR2	0.840				
	PR3	0.849				
	PR4	0.777				
	PR5	0.856				
Perceived Usefulness (PU)	PU1	0.824	0.868	0.918	0.939	0.754
	PU2	0.859				
	PU3	0.903				
	PU4	0.889				
	PU5	0.864				
Trust (TR)	TR1	0.884	0.872	0.947	0.957	0.762
	TR2	0.899				
	TR3	0.877				
	TR4	0.911				
	TR5	0.905				
	TR6	0.778				
	TR7	0.849				

Table 3
Discriminant validity.

	ATT	IU	PC	PE	PEU	PI	PR	PU	TR
ATT	**0.943**								
IU	0.761	**0.868**							
PC	0.237	0.246	**0.708**						
PE	0.706	0.640	0.169	**0.924**					
PEU	0.517	0.462	0.130	0.543	**0.796**				
PI	0.531	0.604	0.249	0.480	0.539	**0.767**			
PR	−0.478	−0.504	−0.054	−0.434	−0.310	−0.286	**0.811**		
PU	0.653	0.609	0.137	0.725	0.487	0.439	−0.454	**0.868**	
TR	0.614	0.705	0.192	0.562	0.369	0.461	−0.608	0.590	**0.873**

Elements on the diagonal in bold indicate ($\sqrt{AVE}$).

innovativeness. Chatbots for shopping were considered less risky by male respondents than by female respondents. Moreover, men were more innovative than women. Innovators tend to take risks, and this may also be the case in the context of chatbots. All remaining hypotheses were rejected.

3.3.2. Age

The results of the independent sample *t*-test comparing the mean responses of the variables between the age groups of the respondents are given in Table 9. Hypotheses H11a and H11c were supported by a low significance of 10%. The variables perceived usefulness and perceived enjoyment were significantly different between age groups in the mean responses. The young respondents believe that chatbots are useful and increase the level of enjoyment in shopping using a mobile phone. Hypotheses H11g, H11h, and H11i were strongly supported by a significance of 0.05. The personal innovativeness, attitude, and the intention to use chatbots for mobile shopping were significantly high for the younger population. Hence, the results prove that age will always be a crucial variable for segment users. Hypotheses H11d and H11f were close to being accepted by a significance of 10%. All remaining

Table 4
HTMT ratios.

	ATT	IU	PC	PE	PEU	PI	PR	PU	TR
ATT									
IU	0.835								
PC	0.256	0.269							
PE	0.761	0.703	0.187						
PEU	0.576	0.525	0.156	0.607					
PI	0.608	0.703	0.297	0.559	0.643				
PR	0.527	0.562	0.081	0.481	0.349	0.334			
PU	0.702	0.669	0.149	0.790	0.549	0.505	0.503		
TR	0.649	0.763	0.220	0.603	0.404	0.526	0.673	0.630	

Table 5
PLS-SEM path coefficients.

Hypothesis		Regression Coefficient	T Statistics	p Values	Result
H1a	PU → ATT	0.167*	2.546	0.011	Supported
H1b	PU → IU	0.032	0.529	0.597	Not Supported
H2a	**PEU → ATT**	**0.106***	**2.005**	**0.045**	**Supported**
H2b	PEU → IU	−0.026	0.703	0.482	Not Supported
H3a	**PE → ATT**	**0.305*****	**4.347**	**0.000**	**Supported**
H3b	PE → IU	0.063	1.004	0.315	Not Supported
H4a	**PC → ATT**	**0.082***	**2.132**	**0.033**	**Supported**
H4b	PC → IU	0.032	0.931	0.352	Not Supported
H5a	**PR → ATT**	**−0.101***	**2.207**	**0.027**	**Supported**
H5b	PR → IU	−0.044	1.11	0.267	Not Supported
H6a	TR → ATT	0.141	1.835	0.067	Not Supported
H6b	**TR → IU**	**0.291*****	**4.018**	**0.000**	**Supported**
H7a	**PI → ATT**	**0.138***	**2.311**	**0.021**	**Supported**
H7b	**PI → IU**	**0.211*****	**4.274**	**0.000**	**Supported**
H8	**ATT → IU**	**0.388*****	**3.984**	**0.000**	**Supported**

***p < 0.001, **p < 0.01, *p < 0.05.

Table 6
PLS-SEM total effects path coefficients.

Hypothesis		Regression Coefficient	T Statistics	p Values	Result
H1b	PU → IU	0.098	1.542	0.123	Not Supported
H2b	PEU → IU	0.014	0.196	0.845	Not Supported
H3b	**PE → IU**	**0.183****	**2.933**	**0.003**	**Supported**
H4b	PC → IU	0.064	1.723	0.085	Not Supported
H5b	PR → IU	−0.084	1.878	0.060	Not Supported

***p < 0.001, **p < 0.01, *p < 0.05.

hypotheses were rejected.

3.3.3. Experience in using mobile shopping applications

Independent sample *t*-test are given in Table 10 to compare the mean responses of the variables between the respondents with different experience levels in using mobile shopping applications. Hypotheses H13b and H13i were supported by a low significance of 10%. The variables perceived ease of use and intention to use were significantly different in the mean responses between the respondents with different experience levels in using mobile shopping applications. Respondents with a high experience of >3 years in using mobile shopping applications found chatbots for mobile shopping easy to use and showed a significantly high intention to use the technology than did respondents with less experience. Hypothesis H13e was strongly supported by a significance of 0.05. The perceived risk in using chatbots for mobile shopping was significantly high for the respondents with low experience in using mobile shopping applications. Hence, the results prove that experience level in using mobile shopping applications are useful for segmenting users, and strategies must be implemented accordingly. Hypothesis H13g was accepted by a significance of 10%. All remaining hypotheses were rejected.

Table 7
PLS-SEM indirect effects path coefficients.

Indirect Path	Regression Coefficient	T Statistics	p Values	Result
PC → ATT → IU	0.03*	1.811	0.070	Supported
PE → ATT → IU	0.122***	2.762	0.006	Supported
PEU → ATT → IU	0.04**	1.957	0.050	Supported
PI → ATT → IU	0.053*	1.833	0.067	Supported
PR → ATT → IU	−0.039*	1.699	0.089	Supported
PU → ATT → IU	0.063**	1.960	0.049	Supported
TR → ATT → IU	0.056*	1.884	0.060	Supported

***p < 0.01, **p < 0.05, *p < 0.1.

3.4. Multigroup moderation analysis

3.4.1. Gender

Table 11 shows the results of moderation analysis using gender as the grouping variable. The effect of price consciousness on attitude (H10-4a) was moderated by using gender at a significance of 5% and was significant only for female respondents. The effects of personal innovativeness (H10-7a) and perceived risk (H10-5a) on attitude toward chatbots were moderated by using gender at a significance of 10%. Both these relationships hold true only for the male respondents and are statistically insignificant for the female population. Moreover, the effects of price consciousness (H10-4b) and personal innovativeness (H10-7b) on the intention to use chatbots for shopping applications were moderated by using gender at a significance of 10%. The relationship between trust and intention to use is stronger among men than among women. However, although gender moderates the relationship between price consciousness and intention to use, it was insignificant for both cases. All remaining hypotheses were rejected.

3.4.2. Age

Table 12 shows the results of moderation analysis using age as the grouping variable. From the results, moderation effect is evident. The effects of perceived risk (H12-5b) and trust (H12-6b) on the intention to use were moderated by using age at a significance of 5%. The relationship between perceived risk and intention to use was only significant for the younger age group, whereas the relationship between trust and intention to use was significant for the older age group. The effect of perceived usefulness on attitude toward chatbots (H12-1a) was

Table 8
Comparison of Mean Responses of Constructs between Gender (Independent Sample *t*-test Results).

H. No.	Construct	Gender (Mean Response)					Result
		Male	Female	Mean Difference	t-value	p Value	
H9a	Perceived Usefulness	4.219	4.190	0.029	0.263	0.793	Not Supported
H9b	Perceived Ease-of-use	4.703	4.649	0.053	0.585	0.559	Not Supported
H9c	Perceived Enjoyment	5.065	5.037	0.028	0.205	0.837	Not Supported
H9d	Price Consciousness	3.223	3.114	0.110	1.430	0.154	Not Supported
H9e	**Perceived Risk**	**1.425**	**1.666**	**0.242****	**2.508**	**0.013**	**Supported**
H9f	Trust	3.995	3.912	0.082	0.629	0.530	Not Supported
H9g	**Personal Innovativeness**	**3.332**	**3.179**	**0.153****	**2.277**	**0.023**	**Supported**
H9h	Attitude	4.991	4.855	0.137	1.077	0.282	Not Supported
H9i	Intention to Use	5.580	5.407	0.173	1.216	0.225	Not Supported

Note: *p < 0.10; **p < 0.05; ***p < 0.01.

Table 9
Comparison of Mean Responses of Constructs between Age Groups (Independent Sample *t*-test Results).

H. No.	Construct	Age (Mean Response)					Result
		Younger	Elder	Mean Difference	t-value	p Value	
H11a	**Perceived Usefulness**	**4.298**	**4.121**	**0.177***	**1.718**	**0.087**	**Supported**
H11b	Perceived Ease-of-use	4.709	4.662	0.047	0.557	0.578	Not Supported
H11c	**Perceived Enjoyment**	**5.174**	**4.938**	**0.236***	**1.890**	**0.060**	**Supported**
H11d	Price Consciousness	3.244	3.134	0.110	1.554	0.121	Not Supported
H11e	Perceived Risk	1.497	1.502	0.005	0.055	0.960	Not Supported
H11f	Trust	4.064	3.873	0.191	1.585	0.114	Not Supported
H11g	**Personal Innovativeness**	**3.352**	**3.216**	**0.136****	**2.187**	**0.029**	**Supported**
H11h	**Attitude**	**5.067**	**4.830**	**0.237****	**2.031**	**0.043**	**Supported**
H11i	**Intention to Use**	**5.668**	**5.383**	**0.285****	**2.180**	**0.030**	**Supported**

Note: *p < 0.10; **p < 0.05; ***p < 0.01.

Table 10
Comparison of Mean Responses of Constructs between Experience in Using Mobile Shopping Applications (Independent Sample *t*-test Results).

H. No.	Construct	Experience (Mean Response)					Result
		Low	High	Mean Difference	t-value	p Value	
H13a	Perceived Usefulness	4.158	4.266	0.108	1.049	0.295	Not Supported
H13b	**Perceived Ease-of-use**	**4.615**	**4.762**	**0.147***	**1.750**	**0.081**	**Supported**
H13c	Perceived Enjoyment	5.055	5.058	0.004	0.032	0.978	Not Supported
H13d	Price Consciousness	3.171	3.209	0.038	0.538	0.591	Not Supported
H13e	**Perceived Risk**	**1.586**	**1.406**	**0.180****	**2.018**	**0.044**	**Supported**
H13f	Trust	3.883	4.061	0.178	1.469	0.143	Not Supported
H13g	Personal Innovativeness	3.237	3.336	0.099	1.588	0.113	Not Supported
H13h	Attitude	4.870	5.034	0.164	1.402	0.162	Not Supported
H13i	**Intention to Use**	**5.422**	**5.639**	**0.217***	**1.656**	**0.099**	**Supported**

Note: *p < 0.10; **p < 0.05; ***p < 0.01.

moderated by age group at a significance of 10%. This relationship was significant only for the older age group. All remaining hypotheses were rejected.

3.4.3. *Experience in using mobile shopping applications*

Table 13 shows the results of moderation analysis based on experience in using mobile shopping applications. The effects of perceived ease of use (H14-2a), perceived enjoyment (H14-3a), perceived risk (H14-5a), and trust (H14-6a) on attitude were significantly moderated by users' experiences in using mobile shopping applications. The effect of perceived enjoyment on attitude toward chatbots was significantly strong for respondents with increased experience in using mobile shopping applications. The relationship between perceived risk and attitude was significant only for users with considerable experience. The effect of perceived ease of use, trust, and price sensitivity on attitude toward chatbots was significantly strong for respondents with low experience in using mobile shopping applications. Moreover, all three relationships were true only for users with low experience and was insignificant for the other group.

4. Discussion

As introduced in our theoretical framework, the TAM model [129] concludes that consumers are likely to accept technology based on factors of enjoyment, usefulness, and ease of use. Consumers are willing to adopt a technology that is new and exciting, deemed as an enjoyable experience. Retailers adopt a different approach while adopting a technology. Online retailers invest in technology to gain a competitive advantage, appeal to their consumer base, and ultimately thrive economically. Whether the consumer will like or benefit from the new technology is not the primary aim. Instead, retailers must maintain healthy margins and increase topline numbers. This influences technology adoption in two ways. First, it creates hesitation in taking risks and, second, it gives large, well established companies a high control. The second fact is evident with companies such as Apple, Google, and Amazon, who are known for their large R&D budgets and their

Table 11
Multigroup analysis with gender as a moderator.

H. No.	Hypothesis	Gender			Result
		Path Coefficient		Path Coefficient Difference	
		Male	Female		
H10-1a	PU → ATT	0.170**	0.108	0.062	Not Supported
H10-1b	PU → IU	0.010	0.046	0.036	Not Supported
H10-2a	PEU → ATT	0.065	0.203*	0.138	Not Supported
H10-2b	PEU → IU	−0.026	−0.041	0.015	Not Supported
H10-3a	PE → ATT	0.335***	0.315**	0.02	Not Supported
H10-3b	PE → IU	0.015	0.183	0.169	Not Supported
H10-4a	**PC → ATT**	**0.012**	**0.182****	**0.169****	**Supported**
H10-4b	**PC → IU**	**0.004**	**0.119**	**0.115***	**Supported**
H10-5a	**PR → ATT**	**−0.144****	**−0.007**	**0.137***	**Supported**
H10-5b	PR → IU	−0.021	−0.044	0.023	Not Supported
H10-6a	TR → ATT	0.098	0.301*	0.203	Not Supported
H10-6b	TR → IU	0.356***	0.227*	0.128	Not Supported
H10-7a	**PI → ATT**	**0.189*****	**−0.002**	**0.191***	**Supported**
H10-7b	**PI → IU**	**0.150*****	**0.325*****	**0.175***	**Supported**
H10-8a	ATT → IU	0.475***	0.199	0.276	Not Supported

Note: *$p < 0.10$; **$p < 0.05$; ***$p < 0.01$.

Table 12
Multigroup analysis with age as a moderator.

H. No.	Hypothesis	Age			Result
		Path Coefficient		Path Coefficient Difference	
		Younger	Elder		
H12-1a	**PU → ATT**	**0.080**	**0.271*****	**0.192***	**Supported**
H12-1b	PU → IU	0.052	0.038	0.013	Not Supported
H12-2a	PEU → ATT	0.101	0.089	0.012	Not Supported
H12-2b	PEU → IU	−0.019	−0.030	0.011	Not Supported
H12-3a	PE → ATT	0.265**	0.325***	0.060	Not Supported
H12-3b	PE → IU	0.039	0.097	0.059	Not Supported
H12-4a	PC → ATT	0.040	0.112**	0.072	Not Supported
H12-4b	PC → IU	0.026	0.053	0.027	Not Supported
H12-5a	PR → ATT	−0.106	−0.088	0.017	Not Supported
H12-5b	**PR → IU**	**−0.163*****	**0.037**	**0.201****	**Supported**
H12-6a	TR → ATT	0.223	0.084	0.139	Not Supported
H12-6b	**TR → IU**	**0.112**	**0.405*****	**0.293****	**Supported**
H12-7a	PI → ATT	0.156*	0.115	0.041	Not Supported
H12-7b	PI → IU	0.244***	0.183***	0.061	Not Supported
H12-8a	ATT → IU	0.449***	0.310***	0.139	Not Supported

Note: *$p < 0.10$; **$p < 0.05$; ***$p < 0.01$.

willingness and ability to invest in innovative technologies.

From the results of the analysis, it is evident that the factors price consciousness, perceived enjoyment, perceived ease of use, personal innovativeness, perceived risk, and perceived usefulness influence the intention to use chatbots indirectly through forming attitudes. Trust does not influence their attitudes but is one of the core variables influencing the intention to use chatbots for mobile shopping.

The majority of the respondents in the survey thought that all questions relative to usefulness were essential, although it did not strongly influence attitude and intention to use chatbots for shopping when compared with the enjoyment variable. Kim, Chan and Gupta [149] explained that the consumer's knowledgeable valuation of the quality or supremacy of a technology defines its usefulness. Thus, if a consumer does not consider chatbots for mobile shopping better or superior to traditional means of mobile shopping, he/she may not consider it useful [149]. Chatbots for mobile shopping must have more perceived usefulness than their substitutes to create an intention to adopt. Improving the attitude of consumers toward perceived usefulness can enhance adoption and approval rating of chatbots by consumers [149]. Furthermore, respondents want a technology to be useful according to the effectiveness usability criteria by Seffah and Metzker [150], concerning the extent to which it helps the respondents to achieve and complete their goals or task with the mobile system [150].

Ease of use is an essential factor that affects the adoption intent of consumers in the TAM model. In the survey, it was crucial for respondents to know that the chatbot technology is easy to use. Understanding the prejudice of the consumers is vital because technicality can negative affect adoption intentions. A unified and cohesive experience must be created for consumers, and they must be enabled to access all requisite aspects such as offers, discounts, and coupons directly within the chatbot. Streamlining the checkout process and making it easy for the consumers to use the technology would certainly influence adoption rates. This can be achieved through keeping the number of taps to a minimum, making the information easy to read, and minimizing input from the user. A strenuous and slow process can often be an obstacle for the customer. Therefore, consumers must find the transaction faster and more convenient than the mobile shopping application. A significant number of consumers would, for example, use chatbots to shop on their mobiles if they did not have to input their information such as credit card numbers and shipping location with every purchase. Therefore, storing relevant information for the consumer is recommended while considering the importance of privacy and safety of personal information.

Attitude toward using chatbots for shopping was the most significantly influenced by perceived enjoyment. Perceived enjoyment is an intrinsic motivation. If individuals enjoy shopping on their mobile device using chatbots and ultimately reap the rewards from it, they will continue using that technology. If the interface is attractive, customers would be happy and would be interested in using the technology in future. Different aspects of technology interface design include its layout, color, background pictures, and text size. Moreover, chatbot developers can provide customers options to customize the interface to match their requirements or personality. This includes the capability of changing the background color, background picture, and text size. This enhances users' experience, and they would continue using chatbots for mobile shopping in future.

Analysis of essential dimensions of the level of innovativeness of customers shows that self-perception of the customers is an essential aspect as well. If customers consider themselves unconventional, they will tend to use new technologies that are introduced in the marketplace. This self-perception of customers may encourage them to leave old or routine technologies like web-based mobile commerce or mobile shopping applications. Such people generally tend to be unique, and so, they do not hesitate to let go of popular technologies to explore new

Table 13
Multigroup analysis with experience in using mobile shopping applications as a moderator.

H. No.	Hypothesis	Experience			Result
		Path Coefficient		Path Coefficient Difference	
		Low	High		
H14-1a	PU → ATT	0.137*	0.181*	0.043	Not Supported
H14-1b	PU → IU	−0.018	0.089	0.107	Not Supported
H14-2a	**PEU → ATT**	**0.172*****	**0.010**	**0.163***	**Supported**
H14-2b	PEU → IU	0.007	−0.063	0.069	Not Supported
H14-3a	**PE → ATT**	**0.199****	**0.454*****	**0.255***	**Supported**
H14-3b	PE → IU	0.057	0.065	0.008	Not Supported
H14-4a	PC → ATT	0.108**	0.062	0.046	Not Supported
H14-4b	PC → IU	−0.003	0.066	0.07	Not Supported
H14-5a	**PR → ATT**	**−0.012**	**−0.191*****	**0.178****	**Supported**
H14-5b	**PR → IU**	**−0.059**	**−0.009**	**0.05****	**Supported**
H14-6a	**TR → ATT**	**0.240****	**0.011**	**0.230***	**Supported**
H14-6b	TR → IU	0.274***	0.301***	0.027	Not Supported
H14-7a	PI → ATT	0.139*	0.129*	0.009	Not Supported
H14-7b	PI → IU	0.237***	0.209***	0.028	Not Supported
H14-8a	**ATT → IU**	**0.395*****	**0.383*****	**0.012**	**Supported**

Note: *p < 0.10; **p < 0.05; ***p < 0.01.

technologies such as chatbots, which are not popular among the mass. Furthermore, findings related to the level of innovativeness of customers show that if the level of innovation among customers is high, then they tend to experiment new things. As chatbots for mobile shopping is a new technology in the market, a significant majority are yet to try it for the first time. Generally, when retailers promote their technologies, they highlight benefits associated with the user. It would create a situation where customers would abandon traditional methods of shopping or start using the new chatbot technology for mobile shopping in addition to traditional mobile commerce technologies. Such people continue browsing information about new products, services, and technologies. If any technology matches their interests and requirements, they will tend to use it. Findings of this research are consistent with that of the study by Siu and Chang [151]. They highlighted that if a person is curious, then he/she would attempt new things in life. Likewise, if a person intends to experiment new things, he/she is innovative.

Moreover, findings of this research corroborate the work of Lin, Marshall and Dawson [152] who suggested that customers purchase products and use technologies to promote their self-image. This study found that customers want to use chatbots for mobile shopping as they perceive themselves to be risk takers and innovative. Likewise, findings of this research were aligned to the work of Siu and Chang [151] who suggested that if a person tends to try new technologies, then his level of innovativeness is high.

Furthermore, this study shows that perceived risk is negatively associated with attitude toward chatbots for shopping. Although this relationship is not significant, the risk is still a crucial variable. Hence, marketers must reduce the risk involved in using chatbots to the greatest extent. A perception of a high level of security in transactions would lead to a high intention to purchase from that e-commerce business [153], and this can be expected in the case of chatbots for mobile shopping also. Moreover, developers can focus on improving information privacy as it can also help in reducing risks and ultimately lead to adoption [57].

Trust is one of the most crucial variables, which directly influences the intention to use chatbots for mobile shopping. Trust and risk generally go hand in hand. When trust toward a technology increases, the perceived risks associated with it significantly reduces. However, the importance of perceived ease of use and perceived usefulness is highlighted in this work; people rely on trust and perceived risk when using chatbots for online shopping. Moreover, trust plays a major role in the process of decision-making for customers who want to purchase some items online [149]. Furthermore, many studies on online consumer behavior have indicated that perceived risk negatively influences concepts such as attitude toward internet shopping [97,154,155]. This research proves that the relationship is also true in the case of chatbots for online shopping.

Previously developed theories posit that an attitude is an educated inclination to evaluate an object to be favorable or unfavorable. A positive attitude is recognized by a favorable evaluation of an object [156]. The overall means of the items within the factors display an overall positive attitude toward the chatbot technology for mobile shopping. It can be then presumed that the respondents have positive views about the technology based on their positive attitudes [91].

This study aimed to identify significant differences in the strengths of the relationships between gender, age groups, and prior experience in using mobile shopping applications. Moreover, it explored differences in the mean responses for the variables between gender, age groups, and experience in using mobile applications for shopping. The mean comparison using independent sample *t*-test revealed that the younger population is more innovative and perceives chatbot technology for mobile shopping to be more useful and enjoyable than the older one. Furthermore, they have a significantly favorable attitude and the intention to use the technology when compared with the elderly population. This again supports findings of the previous literature on the age effects [157–161].

Regarding gender, men were significantly more innovative and consider new chatbot technology significantly less risky than women did, consistent with earlier studies on technology adoption [57]. As chatbot technology is going to replace mobile applications for shopping, the influence of prior experience in using mobile application must be understood. Results showed that people with more than 3 years of experience in using mobile applications perceived chatbots to be easy to use and less risky. Moreover, they seemed to have a significantly high intention to use chatbots for mobile shopping. This proves that mobile applications have been in the market long enough, and people are looking for newer technologies for their shopping activities. Younger people with significant experience in using mobile shopping applications can be used as a sample to pilot study the chatbot technology before launching it in the market by companies as this population primarily has a favorable attitude and intention to use the technology. Moreover, they will act as innovators and positively influence the population to use chatbots through word of mouth.

Moderation analysis revealed few exciting findings. The variables perceived usefulness, perceived risk, and personal innovativeness influence attitude toward chatbot technologies for mobile shopping only among men. Similarly, perceived ease of use, price consciousness, and trust on attitude toward chatbots significantly influenced only men. Attitude significantly influenced the intention to use chatbots for shopping only among male consumers. Hence, marketers could tailor variables to cater the chatbots to the targeted gender. When using chatbot technologies for mobile shopping, attitude and intention to use of the older population can be influenced by concentrating on the variable perceived usefulness and trust, whereas these relationships remain insignificant for the younger population. The influence of the perceived risk on the intention to use is significant only among younger users, and hence, implementing risk-reducing actions is necessary to attract these target consumers. The price consciousness of older users significantly influences attitude toward chatbots, whereas the relationship between attitude and personal innovativeness remains significant only for the younger age group. Furthermore, prior experience in using mobile shopping applications moderates the relationships. The effect of perceived risk on attitude was significant only for people with significant experience in using mobile shopping applications. The effect of perceived ease of use and trust on attitude was significant only for people with little experience in using mobile shopping applications.

Comparing the mean responses of common variables in the studies by Natarajan, Balasubramanian and Kasilingam [19] and Natarajan, Balasubramanian and Kasilingam [18] with the those in this study revealed that the perceived ease of use, usefulness, and enjoyment are low with chatbot technologies compared with mobile shopping applications. However, the intention to use chatbots for shopping is higher than to use mobile shopping applications. Hence, consumers are ready to adopt new technologies for mobile shopping. Mobile applications are undoubtedly the best mode of purchasing products and services on mobile in the current market. However, the high difference in the intentions toward the technologies suggests a market shift soon, and chatbots may replace mobile applications for shopping.

The implications of this research to the management is that managers and marketers must pay special attention to perceived usefulness, ease of use, enjoyment, risk, and trust variables and should ensure that these factors are met with respect to the demographic profile of the users to increase the acceptance and usage of chatbots for mobiles shopping. As perceived ease of use is one of the most significant factors affecting the intention to use chatbots for mobile shopping, marketers and retailers must, when designing their chatbots, focus on features that would provide users with reliable and quality information regarding products and trends and exploit to the fullest unique features, such as the ability to shop and browse anytime and anywhere, use the bar scanner, use GPS to set shipping address, provide auto pay options, help locate the nearest stores, and provide personalized chat notifications regarding the latest products. This can attract women users and consumers with low experience as these groups are tricky to handle and low in numbers. Moreover, doing so will naturally increase the intentions and attitudes of the other groups as they are more innovative than the aforementioned groups. The better the chatbot support in shopping activities, the more attractive they would be.

Managers should ensure that chatbots add value to their users by guaranteeing that they optimize their output by saving shopping time, obtaining promotion information, and obtaining customized products information. Furthermore, previous experience in using mobile shopping is an essential factor. Therefore, managers could refer to the design of a prevalent computer software and popular shopping websites as the more familiar the people are with using a particular technology, the quicker it becomes a habit. Chatbot being a relatively new technology, marketers should provide online and offline support for using the apps, tutorials, and FAQs as these facilitate chatbot use. Likewise, for perceived enjoyment construct, managers could enforce appropriate functions on chatbots to create an enjoyable and entertaining shopping experience. For instance, enjoyment can be enhanced through animated features, fun content, and non-conventional interaction with the chatbots. As chatbots use advanced data mining and big data analytics as an integral part, respondents can be profiles to create a personalized and self-catered experience for them, thereby retaining user adoption levels.

5. Conclusion

In the context of chatbots for mobile shopping, a relatively new technology that is yet to be released in the market, TAM and DOI continue to be robust theories for explaining attitude and usage intentions. The study results can be generalized across the county, mainly because of the diversity of the sample. Moreover, it can be generalized for developing markets. However, empirical validation may be necessary for developed markets, mainly due to cultural and economic variations. Although the study explains >72% of the variance associated with adoption, variables can differ over time as people begin to adopt and use the technology, and hence, a longitudinal research would certainly provide interesting results. Although the sample was presumed to represent the population, a large sample size can reduce the probability of error in the estimation, and hence, future researchers can attempt to validate the model with larger datasets. Chatbot application in business is truly immense, and this study analyzed chatbot application in mobile-based commerce. Identifying applications of mobile chatbots in a B2B perspective and understanding adoption would indeed be interesting. Variables such as internet speed and mobile device used for chatbot functions may significantly moderate the relationships in the model, and hence, future researchers can explore these dimensions. Overall, this research is one of the first to propose a generic model that captures a vast variance in technology adoption specific to a futuristic technology. Organizations can hence use this model to develop and pivot their strategies accordingly.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.techsoc.2020.101280.

Appendix

Perceived Risk—Featherman and Pavlou [62].

Chatbots for shopping may not perform well and process payments incorrectly.
Using chatbots would lead to payment uncertainty.
The security systems built into the chatbots may not be strong enough to protect my account.
Internet hackers (criminals) might take control of my account if I used chatbots for shopping.
My decision to use chatbots for shopping involves a high risk.

Perceived Usefulness—Davis [10].

Chatbots for shopping will be useful to me.
Using chatbots for shopping will enable me to accomplish transactions quickly.
Using chatbots for shopping will increase my productivity.
Using chatbots for shopping will enhance my effectiveness.
Using chatbots for shopping would enable me to accomplish shopping tasks fast.

Perceived Ease of Use—Davis [10].

Shopping using chatbots does not require great mental effort.
Ithink I will be able to shop using chatbots without the help of an expert.
Learning to operate chatbots for shopping will be easy for me.
Overall, I believe that using chatbots for shopping is easy.
Working with chatbots is not complicated; it is easy to understand what is going on.

Perceived Enjoyment—Davis, Bagozzi and Warshaw [129].

Ifind using chatbots for shopping enjoyable.
The actual process of using chatbots for shopping is pleasant.
Iwill have fun while using chatbots for shopping.

Personal Innovativeness—Goldsmith and Hofacker [130].

Ithink I know more about chatbots than my circle of friends

If I heard about a new application/technology like chatbots, and I would look for ways to experiment with it.

Among my peers, I am usually the first to try out new applications/ technologies such as chatbots.

In general, I am hesitant to try out new applications/technologies such as chatbots.
Ilike to experiment with new applications/technologies such as chatbots.

Trust—Chong, Chan and Ooi [131] and Tsu Wei, Marthandan, Yee Loong Chong, Ooi and Arumugam [33].

Ibelieve payments made through chatbots will be processed securely.
Ibelieve transactions conducted through chatbots will be secure.
Ibelieve my personal information will be kept confidential while using chatbots.
Iam confident regarding the security measurements offered by chatbots.
Privacy chatbots are well protected.
Ido not worry about providing credit card information to chatbots.
Chatbots is as secure as any e-commerce or m-commerce website.

Price Consciousness—Dickinger and Kleijnen [132], Lichtenstein, Ridgway and Netemeyer [133], and Swaminathan and Bawa [134].

Ifind myself checking prices in stores even for small items.
A person can save ample money by shopping around for bargains.
Iam not willing to put extra efforts to find items with lower prices.
Itry to buy inexpensive products.
A low price is the most important factor influencing my purchasing decisions.
Ivalue low prices for various products.

Attitude—Taylor and Todd [135].

Using chatbots for shopping is a good idea.
Ilike using chatbots for shopping.
Using chatbots for shopping would be pleasant.

Intention to Use—Kim, Mirusmonov and Lee [11].

Now I intend to use chatbots to shop and procure products.
Assuming that I have access to chatbots, I intend to use it.
During the next 6 months, I intend to use chatbots for shopping.
Iintend to use chatbots for shopping after 5 years.

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