American Journal of Industrial and Business Management, 2023, 13, 195-214
https://www.scirp.org/journal/ajibm
ISSN Online: 2164-5175
ISSN Print: 2164-5167

Factors Affecting Consumers Adoption of AI-Based Chatbots: The Role of Anthropomorphism

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How to cite this paper: Alboqami, H. (2023). Factors Affecting Consumers Adoption of AI-Based Chatbots: The Role of Anthropomorphism. *American Journal of Industrial and Business Management, 13,* 195-214.
https://doi.org/10.4236/ajibm.2023.134014

Received: March 14, 2023
Accepted: April 17, 2023
Published: April 20, 2023

Abstract

Previous studies paid more attention to factors affecting consumers intentions and behaviors to adopt IT in the retail industry; however, little attention has been paid to factors affecting consumer intentions to adopt chatbots in the retails industry. This study utilizes technology acceptance models to explore these factors. Quantitative approach method using online survey was adopted to collect data from consumers in Saudi Arabia retail industry. We collected data from 903 consumers and analyzed it using structural equation modeling technique. The findings indicated that perceived intelligence, perceived ease of use, and perceived usefulness have a significant positive influence on consumers intentions to adopt chatbots. It also indicated that technological anxiety has a negative influence on intentions. Our study indicated that anthropomorphism plays a moderating role on these relationships. Our study offers meaningful implications for retailers and marketer to develop their marketing plan and strategy.

Keywords

Chatbots Adoption, Technological Anxiety, Perceived Intelligence, Perceived Ease of Use, Anthropomorphism, Saudi Arabia

1. Introduction

Conversational chatbots are software applications that employ natural language processing to simulate human conversations (Pillai & Sivathanu, 2020). Based on their research, Sheehan et al. (2020) view chatbots as automated advice givers that can help people make decisions. Voice-activated digital assistants (such as Siri, Cortana, Alexa, and Google Home) and text-based systems integrated into messaging apps make up the chatbot ecosystem. Melián-González et al. (2021) predict that by 2024, one-quarter of all customer support operations would include chatbot technology, and that by 2024, the average individual will have more chats per day with a chatbot than with their spouse (Mogaji et al., 2021). Chatbots can be thought of as a self-service technology (SST) when they provide client support without the need for a human service person (Jang et al., 2021).

Intelligent backend systems support chatbot interactions, streamlining the process for end users (Agag, 2019; Wang et al., 2022). Sales, marketing, and customer support can all benefit from the conversational system capabilities offered by the rise of digital intelligent assistants and chatbots. Machine learning and smart software algorithms allow for more engaging, conversational interactions with clients (Abdelmoety et al., 2022; Aboul-Dahab et al., 2021; Jenneboer et al., 2022). The latest generation of chatbots is powered by artificial intelligence, making them far more advanced, powerful, and capable than their simpler predecessors (Agag et al., 2022; Kasilingam, 2020). Chatbots are increasingly being employed in the hotel and tourism business for a variety of purposes, including but not limited to customer research, customer service, customer booking, and consumer recommendation and suggestion. Chatbots are useful for tourism businesses, because they enable round-the-clock customer service, increased revenue and engagement, automatic lead capture, lower operating costs, a competitive advantage, and significant time savings (Agag et al., 2020a; Sugumar & Chandra, 2021). Makemytrip, Expedia, Kayak, Skyscanner, and Cheapflights are just some of the travel companies that have adopted chatbots as a consumer care tool (Agag & El-Masry, 2016a; Malik et al., 2021). Aspect research software's poll found that over half of consumers are eager to replace human consumers service representatives with AI-based chatbots (Agag & Eid, 2019; Cai et al., 2022). Prior research explored factors affecting consumers' attitudes and behaviours towards IT adoption in the tourism and hopsitality industry (Agag & Colmekcioglu, 2020; Pillai et al., 2023).

Due to customers' increasing reliance on digital channels, e-service agents have become an indispensable part of modern businesses. There has been a shift away from using human agents to communicate with customers and create connections in favor of e-service agents, often known as chatbots. Chatbots have various applications in business, but the most common are in customer service and sales (Agag & El-Masry, 2017; Kwangsawad & Jattamart, 2022). Business of all sizes, from startups to multinationals, may benefit from having a strong customer service and support infrastructure in place, and this is especially true for online enterprises. A chatbot's interactions consist of several interrelated parts that all contribute to the overall customer experience, such as the initial greeting and introduction of the bot's capabilities, the provision of alternate paths for frequently used requests, the development of natural-sounding dialogues, and the resolution of questions and complaints (Agag et al., 2020b; Wang et al., 2023).

Despite the widespread availability of chatbots, they frequently fail to meet customers' expectations due of a lack of comprehension of input. According to

Chen et al. (2021), Facebook's Project M (a text-based virtual assistant) is estimated to have failed in over 70% of encounters, necessitating human intervention. A negative public opinion of chatbots may result from instances like the media's coverage of two children's mental health chatbots that failed to identify sexual assault (Alsuwaidi et al., 2022; Lee et al., 2022). It's been proven that even the most advanced chatbots make mistakes in their communication. Misunderstandings between humans and chatbots are prevalent, as evidenced by an analysis of transcripts from the Loebner Prize, one of the most prestigious chatbot competitions in the world (Alyahya et al., 2022; Rapp et al., 2021).

The following research questions (RQs) were developed to address the aforementioned knowledge gap and pave the way for more substantial study.

RQ1. What factors lead to consumers using chatbots powered by artificial intelligence (AI)?

RQ2. What is the role of anthropomorphism on the acceptance of chatbots powered by artificial intelligence?

A proposed model is developed to examine the predictors for the adoption of chatbots by consumers, and it integrates "Technology acceptance model" (TAM) along with "the contextual constructs anthropomorphism" (ANM), "perceived intelligence" (PNT), PTR, and "technology anxiety").

2. Literature Review and Hypotheses Development

2.1. Chatbot Adoption

Invigorated by advancements in artificial intelligence and machine learning, chatbots are a rapidly growing industry that offers unrivalled commercial possibilities. Several services have found use for chatbots, including those aimed at facilitating student-teacher interactions, tourist-visitor interactions, and online shopper interactions (Lin et al., 2022). A chatbot is a service agent powered by artificial intelligence (AI) that has the ability to have "natural" conversations with customers in order to gather specific details about their needs (Gümüş & Çark, 2021). The word "bot" in "chatbot" is short for "robot", which suggests that chatbots are computer programs or systems that simulate human conversation with others.

Throughout their experience, clients can communicate with chatbots (Alyahya et al., 2023a; Kecht et al., 2023). By utilizing learning algorithms and predictive modelling, chatbots may instantaneously match a customer's enquiry with accessible products that fulfil their needs (Alyahya et al., 2023b; Brachten et al., 2021). When a customer is ready to buy, a chatbot can point them to relevant shopping platforms or present them with relevant discount offers (Chen et al., 2023; Selim et al., 2022). Customers can continue interacting with the chatbot even after the purchase has been made to monitor the shipping status and receive after-sale support. As a result, chatbots can be quite helpful for small and medium-sized enterprises (SMEs), who are particularly susceptible to losing customers.

Earlier chatbot marketing apps were utilized to successfully guide users through websites and make online purchases (Chen et al., 2023; Youssef et al., 2022). There has been a dramatic development in chatbot technology ever since. To the point that clients may not even realize they are interacting with a chatbot and not a real person, modern chatbots are distinguished by conversational interfaces that allow them to mimic human discussions. Chatbots can conduct interviews with customers and use consumers' expertise adaptively to deliver tailored solutions (Pantano & Pizzi, 2020; Shaalan et al., 2023), allowing them to function not just as a virtual assistant but also as a virtual buddy. In addition, chatbots have evolved to become more interactive and helpful in areas such as reading product reviews, searching for and researching products, comparing products, accessing stored coupons, making purchases, monitoring orders, and getting rewards and loyalty points (Safi et al., 2020). The research summarized here covers the last five years of published material in an effort to discover cutting-edge, service-oriented additions to chatbots.

2.2. Technology Acceptance Model

The Technology Acceptance Model (TAM) explores the behavioral intention to accept new technology and is a widely used and recognized model in the field of technology adoption research. The user's purpose is affected by how confident they are in the new technology's PEA and PUL (Davis & Venkatesh, 1996). Multiple studies have used TAM, including one on the use of social media in choosing a vacation spot (Al-Qaysi et al., 2020), another on self-service hotel technology (Unal & Uzun, 2021), yet another on Web-based self-service technology in the hospitality industry (Chen et al., 2023), and yet another on e-tourism in Egyptian travel agencies (Park & Park, 2020). Since chatbots are a relatively new innovation in the tourism sector, this study takes TAM into account in order to better comprehend travelers' motivations for adopting them in the context of trip preparation.

2.3. Anthropomorphism

The uncanny valley notion is widely applied in the field of robotics research. The uncanny valley theory, first proposed by Blut et al. (2021) and later developed by Crolic et al. (2022), argues that people are more likely to like products that display anthropomorphic traits, but that this positive attitude is not always proportional to the level of resemblance between the two. Consumers' Artificial Human Likeness (ANM) is defined as the level to which they attribute human characteristics to robots and other inanimate objects (Sheehan et al., 2020). Researchers in these articles focused on how chatbots and robots can appear human (Balakrishnan et al., 2022; Han, 2021). It is examined how users' impressions of chatbots' intelligence, dependability, and trustworthiness have shifted as a result of their use in casual conversation (Adam et al., 2021). Because ANM boosts customers' self-assurance and sense of agency, it encourages a more favorable emotional reaction (Jin & Youn, 2021). Because of this, ANM is taken into account in this work to evaluate the usage of chatbots in tourism planning for HRI to find out how human-like its users find it to be.

2.4. Hypotheses Development

Because TAM is all-encompassing and commonly used to investigate the adoption of technology, it is being applied to the study of chatbot adoption (Jin & Youn, 2021; Schanke et al., 2021). More explanatory power may be found in combining TAM with context-specific variables pertaining to HRI (Roy & Naidoo, 2021; Schanke et al., 2021). A schematic representation of the model we propose to use in this research is presented in **Figure 1**.

An individual's level of technological anxiety (TXN) can be defined as the degree to which they worry about potential risks associated with using various forms of technology (Fotheringham & Wiles, 2022). The Technology Acceptance Model (TXN) is one of the factors recognized as a crucial psychological antecedent of technology adoption (Han, 2021). TXN's potential demotivating effect on task performance stems from its ability to muddle priorities (Li et al., 2021). Individuals' TXN has been shown to prevent them from making use of technological resources (Blut et al., 2021), hence preventing the widespread adoption of innovative technologies (Pillai & Sivathanu, 2020). Because of this, it has a chilling effect on the spread of new technologies (Rajaobelina et al., 2021; Selamat & Windasari, 2021). Chatbots are a relatively new technology in the retail sector, and consumers are using them in a variety of ways to aid in their buying planning. Thus, we suggest the following hypothesis:

H1: "Technological anxiety has a negative influence on consumers Intention to adopt AI-based chatbots".

An experiment in which participants interpreted characteristics of a robot's speech, voice, and appearance as indicators of its intelligence has been described in the literature (Rajaobelina et al., 2021). Competence, efficiency, use, and the ability to provide effective output are all taken into account when determining a

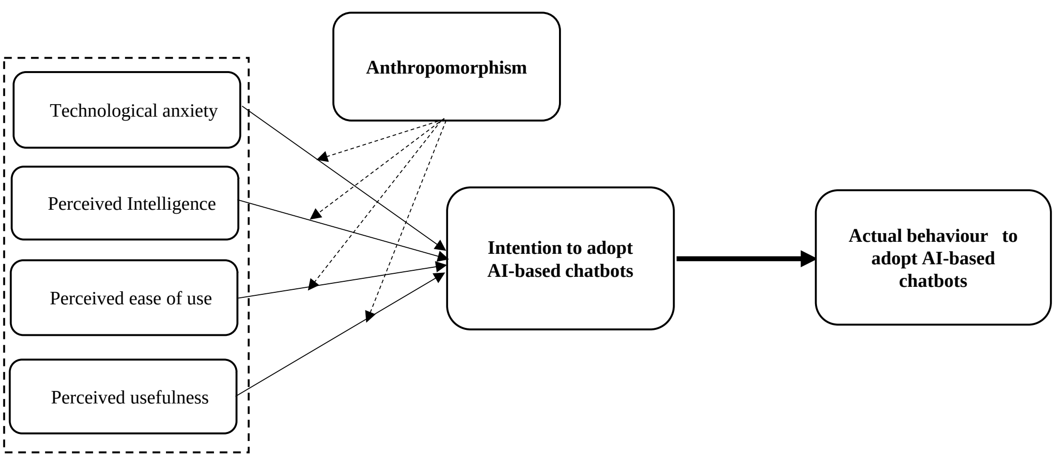

Figure 1. Research model.

chatbot's or robot's PNT (Li et al., 2021), which in turn determines how effectively it solves customers' problems with minimal input from the human side (Kwangsawad & Jattamart, 2022). Intelligent robots are viewed as more alive in the literature (Pillai et al., 2023), and research shows that robots that provide personalised information and interact with their users are more likely to be adopted (Zhang et al., 2022a). One of the forerunners of the Artificial Intelligence (AIN) used by retail service robots (Wang & Shao, 2022) and individual intelligent agents is the field of PNT (Zhang et al., 2022b). Retail chatbots engage in two-way conversation with customers while offering individualized assistance with trip preparation in real time. If you're having trouble figuring out when and where to go shopping, a chatbot can help with that, too. Thus, it is important to investigate whether or not PNT is linked to AIN:

H2: "Perceived intelligence has a significant influence on consumers Intention to adopt AI-based chatbots".

How simple and uncomplicated a consumer envisions a system to be is its perceived ease of use (PEU). As previously mentioned (Dinh & Park, 2023), prior experiential acquisition (PEU) is a precursor to behavioral intention to utilize technology associated with tourism. The study of app usage in tourism also indicated that PEU has no bearing on AIN (Mokmin & Ibrahim, 2021). If consumers believe that technology is straightforward and useful, they are more likely to adopt it. Hypothesis formed as follows due to the intended simplicity of chatbots for use in pre-purchase research and planning:

H3: "Perceived ease of use has a significant influence on consumers intention to adopt AI-based chatbots".

A system's perceived usefulness (PUS) is the extent to which a consumer believes that adopting the system would improve his or her ability to do a certain job or carry out a given task (Davis, 1989). Research on B2C airline websites (Ragheb et al., 2022), tourism apps (Iancu & Iancu, 2022), the Lonely Planet (Alqaidi et al., 2021), travel search engines (Ren, 2020), and self-service technology in resort hotels (Ragheb et al., 2022) all corroborate that technology's usefulness to retailers influences AIN (Ragheb et al., 2022). Chatbots and other forms of artificial intelligence are streamlining the shopping experience and improving customer service. Shoppers can get help from retail chatbots whenever they need it. For this reason, we can formulate a hypothesis:

H4: "Perceived usefulness has a significant influence on consumers intention to adopt AI-based chatbots".

Anthropomorphism (ANM) refers to the tendency for humans to attribute human traits and actions to inanimate objects like robots and chatbots (Oh et al., 2020). When a human interacts with something that isn't human, they tend to look for similarities between the two (Jin, & Youn, 2022). When consumers use chatbots for purposes like shopping trip planning, for instance, such people often equate it with real-life customer service representatives. In the literature, it is stated that users' perceptions of a chatbot's credibility, intelligence, trust, and engagement have improved as a result of its use in casual conversation (Abd-Alrazaq et al., 2019). Chen et al. (2023) verifies the link between ANM and the intent to employ chatbots in daily life. According to the existing literature, computers and machines can be compared to humans (Chen et al., 2023). Chatbots designed to assist with retail research should also be evaluated on how well they mimic real human interaction, including in terms of voice quality, conversational ability, and replies. As a result, we put up the following hypothesis:

H5: "Anthropomorphism has a moderating effect on the link between technological anxiety, perceived intelligence, perceived ease of use, perceived usefulness, and intention to adopt AI-based chatbots".

Intention to embrace AI-based chatbots among consumers is the subjective probability of a given behavior (Chhikara et al., 2022). The goal of studying users' behavioral intentions is to shed light on and predict how they will interact with emerging technologies (Chatterjee et al., 2021). The acronym AUE stands for "assistance from technology used to accomplish goals" (Scherer et al., 2019). The current study on tech adoption verifies the link between AIN and customer usage behavior (Sciarelli et al., 2022). The current literature suggests that AIN has an impact on the AUE of retail technologies (Chatterjee et al., 2021). Customers can now organize their shopping trips with the help of chatbots, a relatively new form of technology. Even though they want to implement this chatbot technology, there is no evidence yet that it will increase actual behavior to adopt AI-based chatbots. Hence, we propose the following hypothesis:

H6: "Consumers intention to adopt AI-based chatbots has a significant influence on actual behavior to adopt AI-based chatbots".

3. Research Methodology

3.1. Sampling and Data Collection

This research used a quantitative strategy, an online survey administered in Saudi Arabia, to test the proposed research model. In December of 2022, we used an internet survey to compile our statistics. All consumers who have heard of chatbots and made purchases with them in the past year make up our study population. We utilized an established online survey organization in Saudi Arabia that has access to 1.7 million people. 2000 clients were randomly selected from the company's database and sent the link. The email invitation included the study's stated purpose, the primary URL link, and the estimated time required to complete the survey. There were a total of 914 usable responses, 11 of which couldn't be used because of missing information. As a result, we were able to proceed with our analysis thanks to the 903 usable responses we received. The majority of the participants are male (63%), while only 47% are female. Participants between the ages of 18 and 60 were polled. Average respondent age was 39.5 years old. The majority of respondents (43.50%) reported earning between $20,000 and $30,000 annually. Most respondents (48%) said they had completed at least a bachelor's degree. The survey was pilot tested with 80 consumers to increase clarity, readability, and decrease errors and ambiguity; their feedback was incorporated into the final form.

3.2. Measurements

The research variables in our study were evaluated using established scales. Three items adapted from Pillai and Sivathanu (2020) were used to evaluate people's actual behavior to adopt AI-based chatbots. Three items adapted from prior research were used to assess intent to adopt AI-based chatbots (e.g., Kaushik et al., 2015). The level of technological anxiety was measured with three items taken from other studies (Evanschitzky et al., 2015). The concept of "perceived intelligence" was borrowed from earlier studies (e.g., Roy et al., 2001; Ponte et al., 2015). Measures of perceived ease of use and usefulness were borrowed from earlier studies (e.g., Oh et al., 2013; Davis, 1989; Kaushik et al., 2015). A total of three items from Pillai and Sivathanu (2020) were used to assess anthropomorphism. A 5-point Likert scale was used to rate all of the factors. We also included in age, gender, level of education, and income as control variables because these factors have been shown to affect the spread of new technologies.

3.3. Common Method Bias

We are aware of the possibility of common method bias because the same information source was used for both the independent and dependent constructs. Then, we utilized a marker variable (MV), as proposed by Lindell and Whitney (2001). An MV is a question on the survey that, in principle, won't have any bearing on the results. If there is a correlation between the MV and one of the study's constructs, we will use it to determine the significance of our observed correlations (Tehseen et al., 2017). As a whole, the correlations between the MV and the main factors averaged 0.02. The numbers varied from −0.15 to 0.09. Insignificant results ($p > 0.01$) were found for all of them. The potential for bias due to the study's methodology is somewhat dampened by a number of considerations. Using educated respondents and guaranteeing full anonymity are two of these. This suggests that the typical method bias is not a serious issue in our research.

4. Data Analysis and Results

Using PLS analysis, there are two stages to assessing a conceptual framework. The first stage entails checking the outside measurement model. Step two entails making a structural review (inner).

4.1. Measurement Model

Skewness, kurtosis, and Mahalanobis distance statistics (Bagozzi & Yi, 1988) were calculated to ensure that all of the constructs met the criterion of multivariate normality. They showed no abnormality whatsoever. While evaluating the psychometric qualities of the constructs, the Cronbach's alpha reliability coefficient was computed (Hair et al., 2021). The results of the measuring model, including checks for convergent validity, discriminant validity, and internal consistency reliability of the indicators, are presented as the first phase in the evaluation of a research model. Based on Hair et al. (2021), Cronbach's alpha for all measurements is greater than 0.70, as indicated in **Table 1** (Hair et al., 2021). As a result, there is a high degree of reliability across the board for all measurements. According to Hair et al. (2021), PLS-SEM works better with composite dependability. Our research shows that composite reliabilities can be anywhere from 0.81 to 0.94, much beyond the threshold of 0.70 (Bagozzi & Yi, 1988). Last

Table 1. Measurement statistics of construct scales.

Construct/Indicators	SFL	Mean	Standard deviation	Cronbach's α	CR	AVE	t-values	Skewness	Kurtosis
Actual behaviour (ACT)									
ACT1	0.934	2.128	1.439	0.939	0.950	0.540	14.302	−1.91	1.34
ACT2	0.949	2.039	1.320				21.230	−1.02	1.64
ACT3	0.903	3.244	1.127				29.357	−1.56	1.20
Intentions (INT)									
INT1	0.942	2.128	1.310	0.921	0.940	0.608	12.309	−1.56	1.39
INT2	0.959	2.084	1.354				19.349	−1.76	1.39
INT3	0.908	2.527	1.750				31.203	−1.30	1.54
Technological anxiety (TAN)									
TAN1	0.930	2.489	1.329	0.932	0.954	0.659	23.230	−1.50	1.23
TAN2	0.923	2.409	1.280				24..309	−1.65	1.56
TAN3	0.960	2.167	1.289				11.203	−169	1.67
TAN4	0.917	3.039	1.457				25.309	−1.04	1.34
Perceived intelligence (PIT)									
PIT1	0.913	2.345	1.102	0.906	0.921	0.688	19.304	−1.46	1.85
PIT2	0.956	2.123	1.346				21.209	−1.59	1.35
PIT3	0.967	2.498	1.674				25.405	−1.34	1.67
	0.904	2.534	1.230				11.209	−1.50	1.70
Perceived ease of us (PEU)									
PEU1	0.930	2.896	1.452	0.920	0.943	0.604	12.340	−1.45	1.46
PEU2	0.923	2.450	1.129				19.456	−1.67	1.34
PEU3	0.940	2.549	1.458				21.234	−1.30	1.49
	0.965	2.530	1.354				16.405	−1.45	1.56
Perceived usefulness (PUS)									
PUS1	0.932	2.203	1.487	0.932	0.954	0.598	23.203	−1.43	1.59
PUS2	0.909	2.453	1.490				18.403	−1.59	1.34
PUS3	0.949	2.920	1.120				25.409	−1.12	1.56
Anthropomorphism (ANP)									
ANP1	0.894	2.345	1.029	0.926	0.948	0.610	27.409	−1.20	1.04
ANP2	0.943	2.120	1.348				21.256	−1.48	1.28
ANP3	0.910	2.564	1.208				18.257	−1.06	1.29

Notes: SFL: standardized factor loading; **SFL** is significant at the0.001 level; **AVE** = Average variance extracted; **CR** = Composite reliability.

but not least, all indicator loadings are more than the 0.60 cutoff (Hair et al., 2021). Convergent validity was determined by calculating AVE for each construct in our proposed model, as recommended by Fornell and Larcker (1981) (see **Table 1**). The results provide evidence for convergent validity because all AVEs for the constructs are more than the threshold of 0.50. It is a two-stage process to evaluate discriminant validity. To begin, the square root of an AVE is compared to the correlations between all other constructs in the model using the Fornell and Larcker criterion to determine if there is a significant difference. **Table 2** displays the degree to which individual constructs are correlated with their respective sets of indicators. Second, a non-construct item's loading on a construct should be lower than that of the item that measures that construct.

4.2. Structural Model Assessment

There was proof of reliability and validity from the assessment of the measurement model, thus the structural model was looked at to test the hypothesized connections between the constructs in the research model (Hair et al., 2021). The structural model provided in this work was assessed using a number of criteria, as recommended by Hair et al. (2021). Subgroup analysis was used to examine whether or not anthropomorphism acts as a moderator, building off of the work of Hair et al. (2021). Using the median, we separated the groups into two categories: those with a high degree of anthropomorphism and those with a low degree of anthropomorphism in our study (Hair et al., 2021).

The model accounts for 58% of the variation in intentions to embrace AI-based chatbots and 51% of the variation in actual behavior. The structural equation model was used to test hypotheses (H1-H6). Acceptable global fit metrics were found to be APC = (0.179, $p < 0.001$), ARS = (0.805, $p < 0.001$), AARS = (0.793, $p < 0.001$), AVIF = (2.10), and GOF = (0.797).

All predicted associations hold, as evidenced by the findings. As a result, H1 is supported by the statistical significance of the negative correlation between

Table 2. Discriminant validity of the correlations between constructs.

Construct	Correlations and square roots of AVE						
	ACT	INT	TAN	PIT	PEU	ANP	PUS
ACT	**0.735a**						
INT	0.304b	**0.779**					
TAN	0.348	0.297	**0.812**				
PIT	0.530	0.458	0.519	**0.829**			
PEU	0.329	0.409	0.434	0.335	**0.777**		
PUS	0.430	0.332	0.328	0.257	0.456	**0.772**	
ANP	0.549	0.437	0.503	0.531	0.230	0.439	**0.781**

Note: a: Composite reliability is along the diagonal, b: Correlation.

technological anxiety and the intention to adopt AI-based chatbots (β = −0.23, $p < 0.001$). H2 is supported by the data (β = 0.43, $p < 0.001$), showing that consumers' perceptions of a chatbot's intelligence have a considerable impact on their intentions to use such technologies. Support for H3 comes from a significant positive correlation between perceived ease of use and intentions (β = 0.37, $p < 0.001$). Support for H4 comes from the fact that perceived usefulness significantly affects intentions (β = 0.21, $p < 0.001$). H5 is confirmed by the data, which shows that intentions significantly affect actual behaviors (β = 0.59, $p < 0.001$).

Using the method proposed by Agag and El-Masry (2016a), we calculated t-statistics to compare the path coefficients of the high-anthropomorphism subgroup model to those of the low-anthropomorphism subgroup model. This allows us to further evaluate the moderating function of anthropomorphism. Consumers with a low level of anthropomorphism were found to be more influenced by chatbots' perceived intelligence, perceived ease of use, and usefulness when deciding whether or not to embrace them. Nevertheless, H6 is backed by evidence that shows technology anxiety has a greater impact on intentions for customers with a higher level of anthropomorphism.

5. Discussion and Conclusion

5.1. Key Findings

This study investigated the factors that have led Saudi Arabian consumers to embrace the use of chatbots for strategic retail purchasing. The chatbots for planning purchases are user-friendly and can be used from any computer, tablet, or smartphone. As a result of the instantaneous suggestions and real-time solutions provided by chatbots, users can save time and effort while purchasing. Consistent with previous research on the topic of consumer acceptance of new shopping technologies (Chen et al., 2023; Pillai & Sivathanu, 2020; Tehseen et al., 2017), this study concludes that consumers' perceptions of chatbots' ease of use and usefulness have an impact on their intentions to adopt them. Chatbots are popular with users, because they are simple to access and use. Anxiety over using technology can make people reluctant to do so (Chen et al., 2023). Customers are savvy when it comes to using various forms of e-commerce technology. That won't happen if chatbots can be set to move at a rate that's suitable for each unique user. Customers' perceptions of chatbots' level of intelligence indicate that they believe the services delivered by these programs to be genuine and trustworthy. Customers agree that chatbots can be trusted to deliver accurate forecasts for their purchases.

Researchers have looked into the anthropomorphic traits of robots in a variety of contexts (Iancu & Iancu, 2022; Ragheb et al., 2022). This research backs up the hypothesis that anthropomorphic features of chatbots influence people's willingness to adopt them in a retail setting. Customers use chatbots to make purchases, because they believe they are real, alive, and possess human-like features. The perceived intelligence literature explores how clever, knowledgeable, rational, and reliable shopping chatbots are. Artificial intelligence allows chatbots to be preprogrammed with these abilities.

5.2. Theoretical Contributions

A theoretical model is proposed for the widespread implementation of chatbots, a potentially game-changing advancement in the retail sector. The theoretical framework is based on previously published works (Chen et al., 2023; Oh et al., 2020; Ren, 2020). As there is currently a dearth of studies that explore the shift in retail performance due to the mediation of emerging technologies like AI and robotics, this work responds to the call for further research and empirical studies on intelligent automation in the retail sector by providing a conceptual model for the adoption of chatbots (Agag et al., 2020c; Dinh & Park, 2023). It helps fill in some of the blanks in the current literature on the use of chatbots in retail. This research contributes to the body of knowledge by shedding light on how consumers' attitudes towards chatbots in retail might be better understood by practitioners and academics.

Technological apprehension, perceived intelligence, perceived ease of use, and perceived usefulness are the indicators of intentions to embrace chatbots provided by the model. The mediating influence of on consumers' intentions to adopt chatbots is also investigated. Anxiety about new technologies was revealed to be an important predictor. This research builds on prior work on the anthropomorphism adoption of robots to show that technological concern is a predictor of chatbot adoption. This makes a theoretical contribution by providing empirical support for the uncanny valley hypothesis as it pertains to chatbots. The extent to which chatbots are perceived as intelligent influences people's willingness to use them. This study contributed significantly to the literature of the retail domain by empirically testing and validating the moderation effect of anthropomorphism on the relation between study variables and intentions to adopt chatbots. This framework can be used by academics interested in the deployment of artificial intelligence (AI) chatbots and robotics in retail to analyze consumer preferences and trends. In this article, we look at how anthropomorphism affects people's perceptions of chatbots and their willingness to use them.

5.3. Managerial Contributions

This study sheds light on the factors that influence businesses' decisions to deploy chatbots in the retail sector in Saudi Arabia, offering useful information for practitioners and managers. This research sheds insight on the perspectives of shoppers that might be taken into account when trying to fathom the use of chatbots in the retail sector. Marketers and developers of retail chatbots should make them intuitive and user-friendly, as well as practical for tasks like trip preparation and inventory control. For the sake of Hypotheses 1, 2, 3, 4, 5, and 6, it is imperative that those working on retail chatbots ensure that their creations are trustworthy sources of information and intelligently automate the retail sector through the provision of timely, relevant solutions.

Trust needs to be ensured by delivering genuine service through chatbots for the tourism industry because perceived intelligence is a key factor in intents to embrace chatbots (Iancu & Iancu, 2022). Developers of chatbots also need to make sure that chatbots have anthropomorphic traits so that consumers feel that chatbots are real, living, and human-like. Assuring that chatbots can speak in multiple languages is a simple task for designers and developers, who can then offer their clients a more welcoming experience. It is the responsibility of practitioners to guarantee that chatbots do not give users technological concern. Designers must create chatbots that are simple to use if they want to ease clients' fears of new technologies.

Limitations and Directions for Future Studies

Because of its limitations, our work can serve as a springboard for further research. Firstly, there was no attempt to account for cultural differences; comparison research between a developed and developing country would be an important addition to the existing body of literature. Two, this study has one major limitation: all of the variables have been measured at the same instant. Hence, longitudinal analysis will be necessary in future studies to verify the suggested model. Third, we employed a quantitative methodology to analyze the data we collected from the respondents. Further information on what influences people's decisions to embrace chatbots can be gleaned from qualitative research methods in future studies. Last but not least, while the antecedents of consumer intents to adopt chatbots in a retail environment explained a large portion of its variance, there are some additional key characteristics which have not been included in the research model, representing opportunities for further research (e.g., satisfaction, perceived value, consumer experience of with the internet and consumers shopping orientations).

Conflicts of Interest

The author declares no conflicts of interest regarding the publication of this paper.

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Appendix A

Variable	Items	Source
Actual behavior to adopt AI-based chatbots	I frequently use to chatbots for my shopping planning I would like to plan my shopping through my agent always than chatbots for shopping. I always prefer that my human shopping planner plans my shopping.	Pillai and Sivathanu (2020)
Behaviour intentions	I intend the usage of chatbots in shopping for future shopping plan There is a possibility that I will suggest my friends to use chatbots for shopping planning I use chatbots for my shopping suggestions and planning	Kaushik et al. (2015)
Technological anxiety	I might somehow face a problem when I use technology such as chatbots for shopping I am unable to keep a pace with new technological advances Using technology such as chatbots for shopping is makes me anxious Technology-related words are difficult to understand I feel difficult to understand technology-related matters	Kaushik et al. (2015)
Perceived intelligence	I feel that chatbots for shopping are competent I feel that chatbots for shoppingare knowledgeable I feel that chatbots for shopping are responsible	(e.g., Roy et al., 2001; Ponte et al., 2015).
Perceived ease of use	Chatbots for shopping requires little mental efforts. It is easy to use chatbots for shopping for my shopping plan My interaction with chatbots for shopping is clear and understandable for planning my shopping	(e.g., Oh et al., 2013; Davis, 1989; Kaushik et al., 2015).
Perceived usefulness	Chatbots for shopping are useful for my shopping planning Chatbots for shopping improve the efficiency of myshopping planning Chatbots for shopping improve my performance of shopping planning	(e.g., Oh et al., 2013; Davis, 1989; Kaushik et al., 2015).
Anthropomorphism	Chatbots for shopping have their own mind Chatbots for shopping can experience emotions I fell chatbots for shopping are computer-animated: real	Pillai and Sivathanu (2020)