“Determinants affecting customer intention to use chatbots in the banking sector”

AUTHORS	Irfan Abdul Karim Shaikh Sania Khan Shaha Faisal
ARTICLE INFO	Irfan Abdul Karim Shaikh, Sania Khan and Shaha Faisal (2023). Determinants affecting customer intention to use chatbots in the banking sector. *Innovative Marketing* , *19*(4), 257-268. doi:10.21511/im.19(4).2023.21
DOI	http://dx.doi.org/10.21511/im.19(4).2023.21
RELEASED ON	Monday, 18 December 2023
RECEIVED ON	Sunday, 01 October 2023
ACCEPTED ON	Tuesday, 05 December 2023
LICENSE	
JOURNAL	"Innovative Marketing "
ISSN PRINT	1814-2427
ISSN ONLINE	1816-6326
PUBLISHER	LLC “Consulting Publishing Company “Business Perspectives”
FOUNDER	LLC “Consulting Publishing Company “Business Perspectives”

NUMBER OF REFERENCES	NUMBER OF FIGURES	NUMBER OF TABLES
38	**2**	**5**

BUSINESS PERSPECTIVES

LLC "CPC "Business Perspectives"
Hryhorii Skovoroda lane, 10,
Sumy, 40022, Ukraine
www.businessperspectives.org

Irfan Abdul Karim Shaikh (Bahrain), **Sania Khan** (Saudi Arabia),
Shaha Faisal (Saudi Arabia)

DETERMINANTS AFFECTING CUSTOMER INTENTION TO USE CHATBOTS IN THE BANKING SECTOR

Abstract

The study aims to analyze the factors that influence customers' inclination to utilize chatbots in banking services. The paper employed the technology acceptance model and utilized structural equation modeling to examine the factors affecting consumers' willingness to embrace chatbot services. The survey evaluated various determinants, including perceived usefulness, perceived ease of use, trust, privacy concerns, and customer satisfaction. Data were collected from 250 bank customers in the Bombay region of India through an online survey employing a random sampling method. The collected data were analyzed using IBM SPSS AMOS. This study identifies the aspects of chatbot technology in the banking sector, such as user interface, content, security, and convenience, that influence customers' decisions to adopt this innovative technology. The results of the analysis revealed path coefficients indicating a significant relationship between information security and perceived usefulness ($\beta = 0.286$; $p = 0.005$) and between perceived usefulness and intention to use ($\beta = 0.489$; $p < 0.001$). Additionally, the path coefficients for design, security, and facilitating conditions were $\beta = 0.281$, $\beta = 0.193$, and $\beta = 0.136$, respectively, all of which held nearly equal significance in the study. The inter-correlations among the variables ranged from 0.346 to 0.854 and were statistically significant. In the banking sector, customers' intention to use chatbots is influenced by convenience, efficiency, trust, and personalized experiences. Customers are more likely to embrace chatbots when they provide seamless support and tailored solutions, ultimately enhancing customer satisfaction and engagement.

Received on: 1st of October, 2023
Accepted on: 5th of December, 2023
Published on: 18th of December, 2023

Irfan Abdul Karim Shaikh, Ph.D., Faculty of Business, Bahrain Polytechnic, Bahrain.

Sania Khan, Ph.D., Associate Professor, Human Resource Management Department, College of Business Administration, Prince Sattam Bin Abdulaziz University, Saudi Arabia. (Corresponding author)

Shaha Faisal, Ph.D., Assistant Professor, College of Business Administration, Prince Sattam Bin Abdulaziz University, Saudi Arabia.

Keywords design, information, security, facilities, chatbot, intention

JEL Classification M30, M31

INTRODUCTION

The banking industry has undergone a significant metamorphosis in recent times, mostly attributable to the swift progress of technology. Chatbots are a prominent technical breakthrough in this industry that has gained importance in customer service operations. Artificial intelligence and natural language processing-driven chatbots present a new means for banks to engage with their clientele, offering a variety of functions such as query resolution, transaction support, and customized financial counseling. Due to this paradigm change in customer service delivery, customers and banking institutions have a great opportunity. The use of chatbots in banking brings up several interesting issues and problems that need more research. One of the main concerns is understanding the factors that affect customers' inclination to utilize chatbots in their dealings with banks. Given that chatbots, when properly developed and deployed, can improve customer experiences, streamline operations, and save costs for financial institutions, this question becomes even more crucial.

Conflict of interest statement:
Author(s) reported no conflict of interest

The banking industry is undergoing a dynamic and ever-changing shift toward chatbot-assisted services. With chatbots, consumers can easily contact businesses using their mobile devices at any time and place. This technology makes it possible to quickly provide customized answers and solutions to particular questions and problems. Consequently, it is imperative to ascertain the attributes that impact users' inclination to engage with chatbots; yet, these findings may not be relevant to the financial services industry.

1. LITERATURE REVIEW AND HYPOTHESES DEVELOPMENT

The technology acceptance model is a widely recognized framework for analyzing why and how individuals adopt new technologies. This model is substantiated by a sequence that begins with the assessment of perceived ease of use and leads to perceived usefulness, collectively determining a user's perception of a product's utility and its user-friendliness (George & Kumar, 2013). Perceived ease of use measures the extent to which a potential customer believes using a specific system requires minimal effort. In contrast, perceived usefulness assesses how much a prospective customer believes using a particular system would improve his job performance (Davis, 1989).

Users can interact with computers or software programs using interactive user interfaces, which can be text- or graphical-based. They enable bidirectional information transmission, giving users a dynamic and user-friendly means to give commands and get feedback. These interfaces are essential to contemporary digital interactions and improve user engagement. Barakat and Dabbous (2019) addressed a research gap by investigating the factors contributing to the sustained usage of interactive user interfaces, enhancing the understanding of this crucial area. The research findings indicate that eight primary internal and external variables play a crucial role in facilitating the continued utilization of chatbots. Among these factors, the most significant ones include a positive relationship between humans and technology, a supportive corporate culture, a suitable regulatory framework, and the perceived high efficiency of the technology.

George and Kumar (2013) utilized the technology acceptance model (TAM) from the information technology literature (Silva, 2015) to examine the impact of TAM variables on customer satisfaction within the context of Internet banking. The findings revealed that perceived ease of use and perceived usefulness positively influence customer satisfaction, while public relations detrimentally impacts customer satisfaction. In a similar vein, Eren (2021) examined the correlation between customer happiness derived from the utilization of bank chatbots and the influence of perceived trust in chatbots, as well as the credibility of financial institutions on customer contentment. The study indicated a considerable impact of perceived performance, perceived trust, and company reputation on consumer satisfaction with chatbots. The influence of customer expectations and the validation of these expectations on customer satisfaction is not directly observable. However, it is essential to note that consumer expectations benefit the perceived performance of a product or service. The effect of consumer expectations on customer satisfaction is mediated through perceived performance. The confirmation of customer expectations is positively influenced by perceived performance, whereas the impact of customer expectations on the confirmation of customer expectations is not statistically significant.

Technology takes precedence as the preferred means in the quest for efficient and precise guidance. Most users were accustomed to the technology and preferred to utilize it at the start of the guidance process. Few participants in the Cardona et al. (2019) study stated they had no desire to utilize chatbots. According to Gupta and Sharma (2019), chatbots' perceived value, ease of use, and security threats correlate with customers' favorable attitudes toward them. Quah and Chua (2019) found that the technology was useful after researching the use of chatbots in Singapore's banking industry to see if its performance would meet client expectations. Customers ranked the banking chatbot's detailed information as its most valued quality, followed by user-friendliness, use-

http://dx.doi.org/10.21511/im.19(4).2023.21

fulness, interactivity, speed of response, and security of personal data. Trivedi (2019) examined how customers' perceptions of a banking chatbot can affect their loyalty to the bank using the information systems success model. Consumers' pleasant interactions with the chatbot contributed to their positive perceptions of the software's developer, and the program itself reassured them of its possible risks. Sarbabidya and Saha (2020) indicated that chatbots perform well in the customer service sector of the banking industry due to their advising services, ease of use, and convenience; they also perform well due to cost-effectiveness and efficiency, customization, relationship banking services, responsiveness, trustworthiness, and usefulness; they protect and preserve the security and privacy of their users.

Chatbots provide customers with 24/7 accessibility to businesses, enhancing customer service and support. These automated systems enable instant communication, answer queries, and streamline processes, ensuring that businesses are always within reach, regardless of the time, fostering improved customer satisfaction and engagement. Customers can contact businesses using chatbots on their mobile devices at any time, from any location, and receive prompt, personalized responses to their queries and concerns (Albayrak et al., 2018). It is also a widely used customer service strategy to provide customer services like one-on-one chats, personalized offers, and responsive customer care through 24/7/365 availability (Sarbabidya & Saha, 2020). Based on previous studies on the effects of chatbots on banking sector customer service (George & Kumar, 2013; Barakat & Dabbous, 2019; Eren, 2021), it is evident that service quality, security, convenience, sustainability, and problem handling are necessary to banking sector customers.

On the other hand, the behavioral intention was influenced by innovativeness, perceived usefulness, perceived simplicity of use, and attitude toward using the chatbot (Gangwar et al., 2014; Richad et al., 2019; Kasilingam, 2020). Almahri et al. (2020) have also looked into what might make customers more likely to embrace and use chatbots. Chatbots in the banking industry can assist customers with tasks like reviewing their accounts, reporting a stolen card, making a payment, renewing their insurance, and requesting a refund (Tarbal, 2020). Sathye (1999) cites the broadcast of information about unique technological advancements as a key component in the widespread deployment of such developments. Pikkarainen et al. (2004) show that consumer awareness plays a significant influence in predicting the frequency of online banking adoption. But, consumers are hesitant to switch to online banking because of concerns about security and privacy (Sathye, 1999). According to Hanafizadeh and Marjaie (2021), e-banking education also decreased generalized risk perception.

Chatbots revolutionized the financial sector, serving as trailblazers in their adoption. Their initial widespread use in the 21st century brought automation and efficiency to customer service, enabling instant responses to inquiries, transaction processing, and personalized financial advice. By harnessing AI and natural language processing, these early financial chatbots set the stage for broader applications across various industries, showcasing the immense potential of artificial intelligence in enhancing customer experiences and streamlining operations. Chatbots, short for "chat robots," are sophisticated AI programs designed to have conversations with humans. As defined by Adam et al. (2021), chatbots are computer programs that mimic human conversation using AI and natural language processing. According to Sarbabidya and Saha (2020), they are an innovative, forward-thinking, and easily adoptable technology that has proven effective in providing a wide range of client services. Gupta and Sharma (2019) apply the TAM model to learn how Indian banking clients feel about chatbots. Buhalis and Cheng (2020) shed light on creating and rolling out an SMS chatbot-based virtual assistant for hotel guests, with particular attention paid to their motives in entertainment, socializing, and interpersonal concerns. To better understand the appeal of chatbots, Brandtzaeg and Følstad (2017) successfully link users with quick and effective service. Access to complete, correct, sufficient, and timely information significantly impacts user happiness (Gupta & Sharma, 2019). Recent studies have also demonstrated that information quality is crucial to gaining consumers' trust (Gao & Waechter, 2017). Consumers spend considerable effort and time using chatbot services to get in-

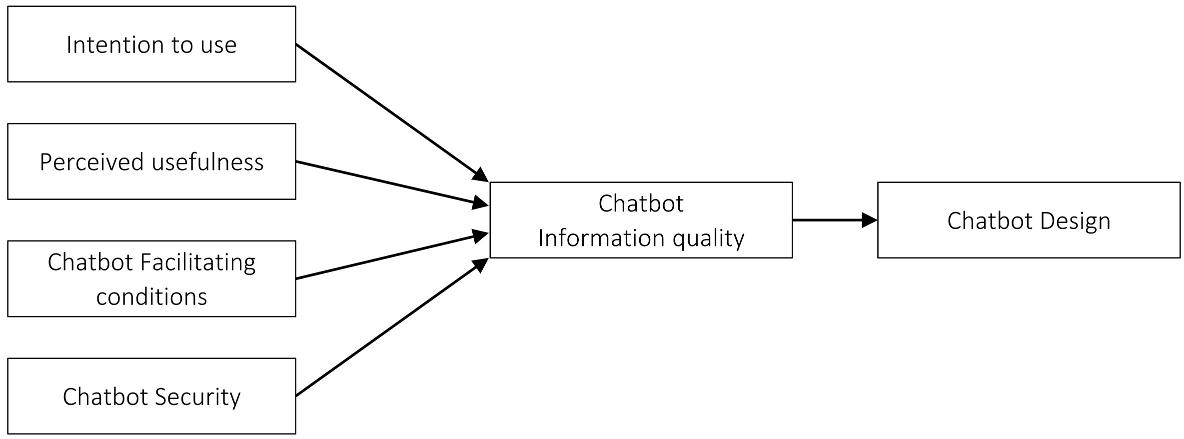

Figure 1. Conceptual framework

formation before making choices. Therefore, chatbot systems must provide accurate, understandable, relevant, and engaging information (Liao et al., 2009). Considering that a bank is a financial entity, the information it provides to its customers is crucial to ensure its accuracy because it can directly impact their finance-related behaviors and choices. If chatbots consistently mislead users with inaccurate or outdated information, people may quit using them altogether. This situation causes significant wasted time and effort for users (Juniper Research, 2019). For a chatbot to fulfill a user's requests, the user may need to reveal sensitive information occasionally. Service companies can win clients' confidence if they can guarantee the reliability and security of chatbot systems. Customers' trust in service providers declines when using information systems with poor interface design (Lee & Chung, 2009). Time savings, better knowledge, and faster responses are just a few of the benefits that users might hope to receive from interacting with chatbots. If the quality of the chatbot services matches or surpasses user expectations, they will be well received by users. Client satisfaction with chatbots is still fairly low despite the widespread use of chatbots by various companies in recent years. This may be due to issues associated with chatbots, such as skepticism about their efficacy, negative feelings, or privacy concerns (Luo et al., 2019). Little research has investigated why consumers are afraid to use chatbots even though user happiness and the intention to continue using chatbots are still fairly low.

Uncovering the underlying factors that shape customers' intentions to embrace and engage with chatbots in the banking context is necessary. In order to improve customer engagement and maximize the usage of chatbots in the banking industry, it is imperative to investigate the elements that encourage or impede customers' adoption of chatbots. In this regard, the goal is to thoroughly analyze the factors influencing consumers' propensity to utilize chatbots in the banking industry. By doing this, it is expected to add to the corpus of knowledge already available in banking, technology adoption, and consumer behavior. Based on the literature review, the study elaborates on the conceptual framework (Figure 1) and hypotheses:

H1: *Chatbot design significantly influences perceived usefulness.*

H2: *Chatbot information quality significantly influences perceived usefulness.*

H3: *Chatbot security significantly influences perceived usefulness.*

H4: *Chatbot facilitating conditions significantly influence perceived usefulness.*

H5: *Perceived usefulness significantly influences intention to use.*

2. METHODOLOGY

Davis (1989) proposed TAM to illuminate the realities of computer use. One's "perceived usefulness" of a system (like a single platform e-payment system) is the extent to which one anticipates using that system will improve one's action. According to Davis (1989), one's perceived ease of use of a system's usability is how confidently one assumes that it will be simple.

http://dx.doi.org/10.21511/im.19(4).2023.21

The banking sector in Mumbai served as the empirical study's sample. Customers who routinely use financial services and chatbots were randomly sampled as the study's respondents. A semi-structured questionnaire was developed, with one half containing questions about respondents and business information and the other half containing questions regarding study variables. Participants were given a Likert scale to indicate how much they agreed or disagreed with the statement, ranging from five (strongly agree) to one (strongly disagree). Missing values were removed from the initial pool of 275 completed questionnaires, and 250 samples were chosen for further analysis as part of the data screening process.

3. RESULTS

3.1. Respondent profile

Statistical Package for the Social Sciences and AMOS version 26 were used to test the data using descriptive and inferential statistics. To begin with, an exploratory factor analysis (EFA) was performed to ascertain the structure of the measurement data. The data's internal consistency was evaluated using Cronbach's alpha values. Then, to evaluate the research hypotheses, structural equation modeling (SEM) was performed.

Table 1. Details of respondents from selected SMEs

Measures	Items	Frequency	Percentage
Gender	Male	162	64.7
	Female	88	35.3
Age	Below 24	41	16.4
	25-30	98	39.2
	30-35	88	35.2
	35-40	49	19.6
	40 and above	15	6
Education	Secondary	27	10.8
	Undergraduate	108	43.2
	Postgraduate	67	26.8
	Others	48	19.2
Total		250	100

Table 1 shows that most respondents are male (64.7%) compared to female 38.3%. Most respondents are young individuals who are availing of chatbot services between 24 and 40 years (94%). Most of the respondents are well-educated.

3.2. Evaluation of normality

Prior to implementing structural equation modeling, the study employed a normality test to assess the suitability of the data distributions. The evaluation indicates that the data are considered within the accepted range, as the multivariate kurtosis value is 4.236, which falls below the recommended threshold of 5.0, as proposed by Hair et al. (2016) and Kline (2015). The critical ratio values observed in this study were all below the established cut-off value of ±8.0. Additionally, it is worth noting that all of the kurtosis values observed in the study fell within the permissible range of ±7.0, as established by Afthanorhan et al. (2020). The findings suggest that the collected data satisfied the requirements of the parametric approach, hence warranting the use of maximum likelihood-based structural equation modeling for subsequent analyses.

3.3. Exploratory and comformatory factor analyses

All the factor loading scores are over 0.5, and no cross-loading was seen in the preliminary exploratory factor analysis to ensure that selected scale items were suitably loaded, as shown in Table 2. Kaiser-Meyer-Olkin (KMO) values determine whether a sample size warrants more study. Bartlett's Test of Sphericity indicates that factor analysis is appropriate for the data due to its high KMO (0.924) and low significance (less than 0.05). The elements in the study were analyzed using Principal Component Analysis with the Promax Rotation technique. Eigenvalues greater than or equal to one were used to select the final factor extraction, yielding six factors. These variables can account for 72.483% of the total variance.

Confirmatory factor analysis (CFA) is a widely employed statistical technique in several research domains to assess the validity and reliability of measurement instruments before conducting hypothesis testing using a structural model. The CFA was employed as the initial and essential procedure to assess the dependability and accuracy of the measurement model utilized in the research. The output of the CFA can be categorized into two main approaches: 1) Individual CFA and 2) Pooled CFA. Both techniques, namely the utilization of first-order or second-order constructs, are gen-

Table 2. Factor loadings of variables

Factor	Items	Item loadings
Design	D1: Chatbot design is user-friendly	.806
	D2: Chatbots are designed to handle multiple queries	.836
	D3: Chatbots have a nice appearance	.796
	D4: Chatbots has a catchy name	.856
	D5: Chatbot tone is interesting	.834
Information quality	IQ1: The data offered by chatbots at banks can be trusted	.886
	IQ2: I think chatbots' information is reliable	.901
	IQ3: Information provided by chatbots is up-to-date	.787
	IQ4: I can get the data I need right when I need it, thanks to chatbots	.916
Facilitating conditions	FC1: I have the necessary resources for using chatbots	.817
	FC2: The ability to interact with chatbots is a skill I possess	.721
	FC3: I can utilize chatbots with the devices I already own	.765
Security	S1: Chatbot services keep my information confidential	.811
	S2: I believe my transactions using chatbots are secured	.747
	S3: Chatbots are secure enough to enhance the utilization of the service	.847
	S4: Chatbots complies with the regulatory standards	.760
Perceived usefulness	PU1: I can perform transactions efficiently with the help of chatbots	.780
	PU2: I have found that using chatbots allows me to get more done in less time	.888
	PU3: Chatbot advisory services are beneficial to me	.796
Intention to use	11: Eventually, I hope to make use of the chatbot	.722
	I2: Whenever possible, I use a chatbot service	.827
	I3: I think the bank's chatbot is fantastic and would recommend it to everyone	.775

erally recognized and accepted for measurement models. The measuring model employed a first-order construct for all constructs. The present study investigated the mediator constructs of perceived support and usefulness, with graduate employability as the endogenous construct. The analysis was conducted using AMOS version 26. The model was evaluated comprehensively by employing construct reliability, validity, and global fitness indices, as described by Byrne (2016).

Customers' levels of satisfaction with chatbot system-level characteristics such as design, information quality, security, and facilitating conditions, as well as their decisions regarding the perceived utility and intention to use chatbots, are detailed in Table 3. Mean values for all variables are more than 3 (the neutral value), indicating that respondents agree on the system-level causes responsible for adopting chatbots in financial services. The correlation of independent variables with one another and with the dependent variables is also shown in Table 3. All associations with the intention to use have positive and significant correlation coefficients, demonstrating that as indicators at the system level improve, so do consumers' perceptions of the utility of and desire to use chatbots in banking. Cronbach's alpha, a measure of inter-

Table 3. Cronbach's alpha and correlation of the variables

Description	Design	Information quality	Security	Facilitating conditions	Perceived usefulness	Intention to use
Reliability (Alpha value)	0.886	0.890	0.940	0.949	0.916	0.894
Mean	4.3213	4.6622	4.7296	4.2453	4.5669	4.4333
Standard deviation	.67538	.79533	.77554	.81197	.72713	.76730
Design	1	.728**	.717**	.619**	.739**	.363**
Information quality	.728**	1	.854**	.714**	.779**	.442**
Security	.717**	.854**	1	.662**	.744**	.426**
Facilitating conditions	.619**	.714**	.662**	1	.653**	.346**
Perceived usefulness	.739**	.779**	.744**	.653**	1	.533**
Intention to use	.363**	.442**	.426**	.346**	.533**	1

Note: ** Correlation is significant at the 0.01 level (2-tailed).

http://dx.doi.org/10.21511/im.19(4).2023.21

nal consistency, is displayed in Table 3 to conclude the analysis. All six components have an alpha value higher than 0.7, meeting the minimum criteria for reliability.

3.4. Assessment of the model fit

The study model was depicted in Figure 2 utilizing the Confirmatory Factor Analysis (CFA) technique. The maximum likelihood estimator was utilized to construct an output of the confirmatory factor analysis (CFA) model, with a limit of 50 iterations. The global fitness indicators are depicted in Figure 2. The results indicate that the Chi-square value normalized by the degree of freedom (Chisq/df) was 1.762. Additionally, the Comparative Fit Index (CFI) and Incremental Fit Index both had values of 0.967. The Tucker-Lewis Index (TLI) had a value of 0.962, and the Root Mean Square Error of Approximation (RMSEA) was 0.055. The results were deemed satisfactory as they met the recommended thresholds for various indices. Specifically, the incremental indices (CFI, IFI, and TLI) all exceeded the minimum threshold of 0.90.

Additionally, the absolute index (RMSEA) was lower than the suggested threshold of 0.08, and the parsimonious index (Chisq/df) was below the proposed threshold of 3.0. These thresholds are commonly advocated by Westland (2015). The items of each construct exhibited values greater than 0.60. Therefore, the adequacy of the measurement model fit was established, allowing for an additional evaluation of reliability and validity, which can serve as the foundation for the final step assessments.

Convergent and discriminant validity are fundamental aspects of validity assessment in academic research. Convergent validity refers to the extent to which different measures of the same construct are positively correlated, indicating that they measure the same underlying concept. Various approaches exist to evaluate the convergent validity, with the Average Variance Extracted (AVE) and Maximum Shared Variance (MSV) being the most frequently employed methods for this objective. The Average Variance Extracted (AVE) was computed by considering the factor loadings, while the Maximum Shared Variance (MSV) was assessed by considering the construct correlations. Furthermore, the study analyzed the Composite Reliability (CR) of each construct. All observed AVE (Average Variance Extracted) values exceeded the required threshold of 0.50, but the MSV (Maximum Shared Variance) values were lower than the corresponding AVE values. Therefore, the results confirmed the convergent validity of the constructs used in the study. According to Zaato et al. (2023), the composite reliability values obtained in the reliability tests were above the threshold value of 0.70. This suggests that the construct dependability has been established and may be considered dependable for subsequent assessments.

Discriminant validity is a method employed to assess the degree of correlation between constructs within a comprehensive model. Discriminant validity is said to be obtained, provided the construct associations exhibit values below the predetermined threshold of 0.85. Meanwhile, the outcomes of the square root of the average variance extracted (AVE) for the diagonal elements must surpass those of all the construct correlations utilized in the study. In this work, the correlation outcomes are presented in Figure 2 by establishing a first-order construct. The findings demonstrated that the correlation values of all constructs were below the established threshold of 0.85. The AVE values for each construct in the model are combined with construct correlations using the principal square root, as Afthanorhan et al. (2020) described. This standard was established based on the satisfaction of construct correlation and average variance extracted (AVE) values.

3.5. Hypotheses testing using structural equation modelling

The study runs SEM analysis employing a maximum likelihood approach to examine the potential for a causal association between the different variables. The study assessed the impact of four system-level indicators, design, information quality, security, and facilitating conditions, by considering exogenous variables (independent variables) on perceived usefulness and intent to employ chatbots as an endogenous dependent variable of the study. Critical ratios of 1.96 and p-values of less than 0.05 (at the 5% level of significance) are used to determine whether a study's hypothesized results are significant (Afthanorhan et al.,

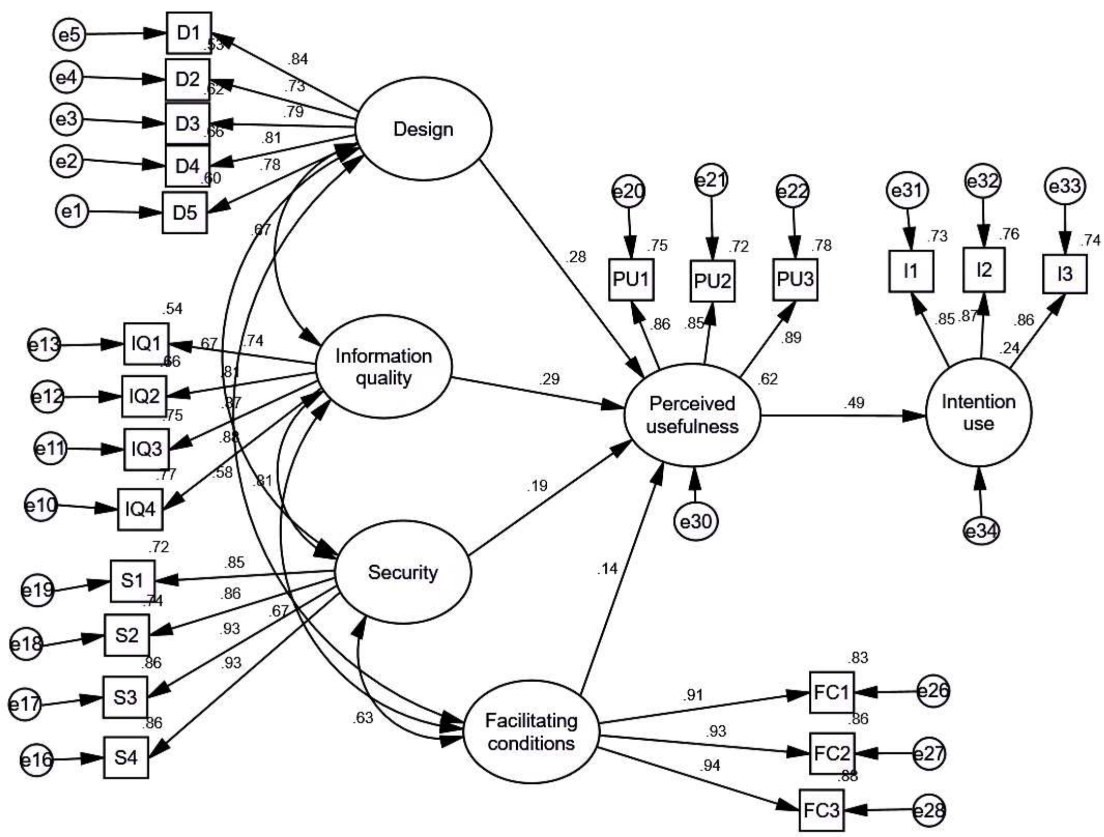

Figure 2. Casual model

2020; Byrne, 2016). The results of the path analysis and the testing of hypotheses are displayed in Table 4. Each relationship's standardized path coefficient and associated p-value are shown. The standardized path coefficient (beta) for all four system components is positive and statistically significant (p-value 0.05), as shown in Table 4 and Figure 2. The impact of chatbot design on perceived usefulness is positive and significant as $\beta = 0.281$ with $p = 0.000$. According to Byrne (2016) and Afthanorhan et al. (2020), $p < 0.05$ and CR (3.729) greater than 1.96 indicate the acceptance of H1.

The quality of information influenced by chatbots on perceived usefulness is positive and significant and resulted in $\beta = 0.286$, CR = 2.801, and $p = 0.005$ ($p < 0.05$), providing sufficient evidence to accept H2. Similarly, the perceived usefulness of chatbots in banking is positively influenced by security with $\beta = 0.193$, $p = 0.039$. A p-value of less than 0.05 indicates a significant relationship, supporting H3. In addition, facilitating conditions also result in a positive and significant impact on the perceived usefulness of chatbots. The β-value for this path is 0.136 with p-value = 0.048 ($p < 0.05$), confirming the acceptance of H4. Finally, the perceived usefulness of chatbots significantly influences customers' intention to use chatbots in the banking industry. The path coefficient value is 0.489 with p = 0.000; as the p-value is less than 0.05, this supports H5. Standardized regression weights indicate the robustness of the independent variable on the dependent variable.

The results showed that the quality of the information impacts the perceived usefulness of chatbots, followed by design, security, and facilitating conditions. The coefficient of determination (R^2) value is 0.62, demonstrating that 62% of variations in the perceived usefulness of chatbots by customers in banking are explained by four indicators of system-level variables, i.e., information quality, design, security, and facilitating conditions. In addition, perceived usefulness explains 24% of the variation in customers' intention to use chatbots in the banking industry. CMIN/df =1.762, RMSEA = 0.055, CFI = 0.967, TFI = 0.962, and AGFI = 0.866 are the fit indices for the measurement model. Prediction and interpretation are consistent with the structure model.

http://dx.doi.org/10.21511/im.19(4).2023.21

Table 4. Structural model path coefficients

Hypotheses	Outcome variables	Path	Causal Variables	SE	CR	p-value	Path coefficient	Result
H1	Perceived usefulness	←	Design	.085	3.729	***	0.281	Accepted
H2	Perceived usefulness	←	Information quality	.098	2.801	.005	0.286	Accepted
H3	Perceived usefulness	←	Security	.092	2.064	.039	0.193	Accepted
H4	Perceived usefulness	←	Facilitating conditions	.067	1.980	.048	0.136	Accepted
H5	Intention to use	←	Perceived usefulness	.068	7.234	***	0.489	Accepted

Note: S.E; Standard error, C.R; Critical ratio, Path coefficient, p-value: probability of significance. *** indicates p < 0.000.

Table 5. Overall model fit

Indices	Recommended criteria	Model values
Normed chi-square	$1<\chi2/df<3$	1.762
Goodness-of-fit index	>0.90	0.916
Adjusted GFI	>0.80	0.866
Comparative fit index	>0.95	0.967
Root mean square error approximation	<0.05 good fit <0.08 acceptable fit	0.055
Tucker-Lewis index	0<TLI<1	0.962

Note: Threshold criteria suggested by Hair et al. (2016).

4. DISCUSSION

Financial institutions and banking sectors are adopting AI-powered chatbots to better serve their consumers. Utilizing a structural equation modeling strategy, this study aimed to analyze the connections between four system-level properties of chatbots (chatbot design, information quality, security, and enabling conditions) and customers' intention to use them in the financial sector. Results from the research demonstrated that all system-level factors affecting chatbot acceptability are crucial. As a result, financial institutions and programmers working on chatbots for financial institutions need considerable resources to perfect each of these features. The study concludes that the quality of the information offered by a banking chatbot has a significant impact on customers' decisions to embrace the chatbot. This is why customers need to receive up-to-date information from their institutions. Customers prioritize chatbot safety; thus, financial institutions need to develop guidelines in this area. The way chatbots are programmed is crucial to their success. Designing a chatbot with the end user in mind ensures it will be easy to learn and utilize. The study's results also showed that favorable settings encourage chatbot adoption, consistent with previous research findings (Ponte et al., 2015; Schierz et al., 2010; Shaikh & Karjaluoto, 2015; Shankar, 2016). When teaching individuals how to use chatbots, managers are recommended to emphasize customer service.

It is realistic to expect useful responses from a chatbot because it employs AI to simulate human conversation. Providers of chatbots should ensure the high quality of their services and the data they deliver to avoid planting seeds of doubt and leading to a loss of faith, which can result from an unfavorable first contact. Professional connections, the quality of questions asked and advice offered, and the safekeeping of private information can all contribute to a more trusting atmosphere. Management considerations for chatbot vendors are derived from research findings on user perceptions of risk and trust. In order to give people the sense of security they deserve while doing financial transactions online, it is vital to hold awareness campaigns to inform them of what information is collected, how it is stored, and how it is analyzed. Financial institutions are increasingly using AI-enabled chatbots to better serve their customers. Rather than talking to a human, customers would rather interact with a consumer acquisition system. For these reasons, curiosity, ease, and technical advancement stand to reason that banking customers are keen to adopt chatbots. As a result, financial institutions should begin testing and deploying AI chatbots as a primary method of client acquisition and interaction. Making use of chatbots to maintain up-to-date client information also shows great promise. They can also raise the bar of service quality supplied to customers. Thus, financial institutions would do well to prepare for this shift. Users would be able to vouch for the platform's safety, and the platform's administrators might use promotions and cash back to attract new users. The managerial implications of this study show that service providers should pay particular attention to elements such as users' views of chatbots' utility and danger to increase their customers' satisfaction and intention to utilize chatbots.

Like any other study, this one includes caveats suggesting new research avenues. The small size of the sample is the first and most glaring issue. The study's sample size is high enough to pass the minimum threshold, but more participants would improve the quality of the results. This is especially true given the size and relevance of the millennial generation. Information on chatbots would be strengthened by contrasting the experiences of millennial and Generation Z users.

CONCLUSION

This study has endeavored to use the technology acceptance model through structural equation modeling to examine aspects influencing consumers' inclination to adopt chatbot services. In a nutshell, this study emphasized the significance of perceived utility, perceived usability, trust, privacy concerns, and customer satisfaction in influencing customer desire to use chatbots in banks. The study factors have demonstrated a statistically significant positive association with one another, indicating their influence on predicting the desire to utilize chatbots in the banking sector. The results illustrated Chatbot design significantly impacts user perception. High information quality, robust security measures, and favorable facilitating conditions enhance user experience. The perceived usefulness of a chatbot, influenced by these design aspects, strongly correlates with users' intention to use the chatbot, emphasizing the importance of a well-crafted and secure chatbot design in fostering user acceptance. Facilitating conditions, such as user-friendly interfaces and seamless integration into daily tasks, enhance the overall usability of the chatbot, positively impacting user satisfaction. A chatbot that effectively addresses user needs, provides valuable information, and simplifies tasks is more likely to be adopted, highlighting the direct link between perceived usefulness and user acceptance. The study recommends a successful chatbot design should prioritize delivering high-quality information, ensuring robust security measures, and creating facilitating conditions that make the interaction seamless. The perceived usefulness stemming from these design elements significantly influences users' intentions to engage with and adopt chatbot services in various contexts.

Banking institutions can use this study to help them create efficient strategies for implementing chatbots and enhancing customer service. By taking care of these issues, banks may increase customer acceptance of and engagement with chatbot technology, thus increasing the overall customer experience in the banking industry. Overall, this study adds to the knowledge of chatbot adoption in the banking industry and offers valuable recommendations for banks looking to use chatbot technology efficiently. Banks should use the potential of chatbots to create improved customer experiences and streamline their financial services by comprehending and addressing the factors impacting client intention.

AUTHOR CONTRIBUTIONS

Conceptualization: Irfan Abdul Karim Shaikh, Sania Khan, Shaha Faisal.
Data curation: Irfan Abdul Karim Shaikh.
Formal analysis: Irfan Abdul Karim Shaikh.
Funding acquisition: Sania Khan.
Investigation: Irfan Abdul Karim Shaikh.
Methodology: Irfan Abdul Karim Shaikh, Sania Khan.
Project administration: Irfan Abdul Karim Shaikh, Sania Khan.
Resources: Irfan Abdul Karim Shaikh, Sania Khan, Shaha Faisal.

http://dx.doi.org/10.21511/im.19(4).2023.21

Software: Sania Khan, Shaha Faisal.
Supervision: Sania Khan.
Validation: Irfan Abdul Karim Shaikh.
Visualization: Irfan Abdul Karim Shaikh, Sania Khan.
Writing – original draft: Irfan Abdul Karim Shaikh, Sania Khan.
Writing – review & editing: Sania Khan, Shaha Faisal.

ACKNOWLEDGMENT

This study is supported via funding from Prince Sattam Bin Abdulaziz University project number (PSAU/2023/R/1445).

REFERENCES

1. Adam, M., Wessel, M., & Benlian, A. (2021). AI-based chatbots in customer service and their effects on user compliance. *Electronic Markets, 31*(2), 427-445. https://doi.org/10.1007/s12525-020-00414-7
2. Afthanorhan, A., Awang, Z., & Aimran, N. (2020). An extensive comparison of CB-SEM and PLS-SEM for reliability and validity. *International Journal of Data and Network Science, 4*(4), 357-364. http://dx.doi.org/10.5267/j.ijdns.2020.9.003
3. Ahmad, S., Bhatti, S. H., & Hwang, Y. (2020). E-service quality and actual use of e-banking: Explanation through the technology acceptance model. *Information Development, 36*(4), 503-519. https://doi.org/10.1177/0266666919871611
4. Albayrak, N., Özdemir, A., & Zeydan, E. (2018). An overview of artificial intelligence based chatbots and an example chatbot application. *2018 26th signal processing and communications applications conference (SIU)* (pp. 1-4). IEEE. https://doi.org/10.1109/SIU.2018.8404430
5. Almahri, F. A. J., Bell, D., & Merhi, M. (2020). Understanding student acceptance and use of chatbots in the United Kingdom universities: A structural equation modelling approach. *6th International Conference on Information Management (ICIM)* (pp. 284-288). London, UK. Retrieved from https://ieeexplore.ieee.org/document/9081419
6. Barakat, K. A., & Dabbous, A. (2019). Understanding the factors that affect the sustained use of chatbots within organizations. *IADIS International Journal on WWW/Internet, 17*(2), 71-84. Retrieved from https://www.iadisportal.org/ijwi/papers/2019172106.pdf
7. Brandtzaeg, P. B., & Følstad, A. (2017). Why people use chatbots. In I. Kompatsiaris, J. Cave, A. Satsiou, G. Carle, A. Passani, E. Kontopoulos, S. Diplaris, & D. McMillan (Eds.), *Internet Science* (pp. 377-392). Springer International Publishing. https://doi.org/10.1007/978-3-319-70284-1_30
8. Buhalis, D., & Cheng, E. S. Y. (2020). Exploring the use of chatbots in hotels: technology providers' perspective. In J. Neidhardt & W. Wörndl (Eds.), *Information and Communication Technologies in Tourism 2020* (pp. 231-242). Springer International Publishing. https://doi.org/10.1007/978-3-030-36737-4_19
9. Byrne, B. M. (2016). *Structural equation modeling with AMOS: Basic concepts, applications, and programming* (3rd ed.). Routledge.
10. Cardona, R. D., Werth, O., Schönborn, S., & Breitner. (2019). A mixed methods analysis of the adoption and diffusion of chatbot technology in the German insurance sector. *25th Americas Conference on Information Systems (AMCIS).* Retrieved from https://aisel.aisnet.org/amcis2019/adoption_diffusion_IT/adoption_diffusion_IT/18/
11. Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly, 13*(3), 319-340. https://doi.org/10.2307/249008
12. Eren, B. A. (2021). Determinants of customer satisfaction in chatbot use: Evidence from a banking application in Turkey. *International Journal of Bank Marketing, 39*(2), 294-311. https://doi.org/10.1108/IJBM-02-2020-0056
13. Gangwar, H., Date, H., & Raoot, A. D. (2014). Review on IT adoption: Insights from recent technologies. *Journal of Enterprise Information Management, 27*(4), 488-502. https://doi.org/10.1108/JEIM-08-2012-0047
14. Gao, L., & Waechter, K. A. (2017). Examining the role of initial trust in user adoption of mobile payment services: An empirical investigation. *Information Systems Frontiers, 19,* 525-548. https://doi.org/10.1007/s10796-015-9611-0
15. George, A., & Kumar, G. G. (2013). Antecedents of customer satisfaction in internet banking: Technology acceptance model (TAM) redefined. *Global Business Review, 14*(4), 627-638. http://dx.doi.org/10.1177/0972150913501602
16. Gupta, A., & Sharma, D. (2019). Customers' attitude towards

chatbots in banking industry of India. *International Journal of Innovative Technology and Exploring Engineering, 8*(11), 1222-1225. Retrieved from https://www.ijitee.org/wp-content/uploads/papers/v8i11/J93660881019.pdf

17. Hair Jr, J. F., Sarstedt, M., Matthews, L. M., & Ringle, C. M. (2016). Identifying and treating unobserved heterogeneity with FIMIX-PLS: Part I–method. *European Business Review, 28*(1), 63-76. https://doi.org/10.1108/EBR-09-2015-0094
18. Hanafizadeh, P., & Marjaie, S. (2021). Exploring banking business model types: A cognitive view. *Digital Business, 1*(2), 100012. https://doi.org/10.1016/j.digbus.2021.100012
19. Juniper Research. (2019). *Bank Cost Savings via Chatbots to Reach $7.3 Billion by 2023, as Automated Customer Experience Evolves.* Retrieved from https://www.juniperresearch.com/press/bank-cost-savings-via-chatbots-reach-7-3bn-2023
20. Kasilingam, D. L. (2020). Understanding the attitude and intention to use smartphone chatbots for shopping. *Technology in Society, 62*, 101280. https://doi.org/10.1016/j.techsoc.2020.101280
21. Kline, R. B. (2015). *Principles and practice of structural equation modeling.* Guilford Publications.
22. Lee, K. C., & Chung, N. (2009). Understanding factors affecting trust in and satisfaction with mobile banking in Korea: A modified DeLone and McLean's model perspective. *Interacting with Computers, 21*(5-6), 385-392. https://doi.org/10.1016/j.intcom.2009.06.004
23. Liao, C., Palvia, P., & Chen, J.-L. (2009). Information technology intention to use behavior life cycle: Toward a technology continuance theory (TCT). *International Journal of Information Management, 29*(4), 309-320. http://dx.doi.org/10.1016/j.ijinfomgt.2009.03.004
24. Luo, X., Tong, S., Fang, Z., & Qu, Z. (2019). Frontiers: Machines vs. humans: The impact of artificial intelligence chatbot disclosure on customer purchases. *Marketing Science, 38*(6), 937-947. https://doi.org/10.1287/mksc.2019.1192
25. Pikkarainen, T., Pikkarainen, K., Karjaluoto, H., & Pahnila, S. (2004). Consumer acceptance of online banking: An extension of the technology acceptance model. *Internet Research, 14*(3), 224-235. https://doi.org/10.1108/10662240410542652
26. Ponte, E. B., Carvajal-Trujillo, E., & Escobar-Rodríguez, T. (2015). Influence of trust and perceived value on the intention to purchase travel online: Integrating the effects of assurance on trust antecedents. *Tourism Management, 47,* 286-302. https://doi.org/10.1016/j.tourman.2014.10.009
27. Quah, J. T., & Chua, Y. W. (2019). Chatbot assisted marketing in financial service industry. In J. Ferreira, A. Musaev, & L. J. Zhang (Eds.), *Services Computing – SCC 2019* (pp. 107-114). Springer International Publishing. https://doi.org/10.1007/978-3-030-23554-3_8
28. Richad, R., Vivensius, V., Sfenrianto, S., & Kaburuan, E. R. (2019). Analysis of factors influencing millennial's technology acceptance of chatbot in the banking industry in Indonesia. *International Journal of Management, 10*(3), 107-118. http://dx.doi.org/10.34218/IJM.10.3.2019.011
29. Sarbabidya, S., & Saha, T. (2020). Role of chatbot in customer service: A study from the perspectives of the banking industry of Bangladesh. *International Review of Business Research Papers, 16*(1), 231-248. Retrieved from https://zantworldpress.com/wp-content/uploads/2020/03/13.-601-Tama-Saha.pdf
30. Sathye, M. (1999). Intention to use of Internet banking by Australian consumers: An empirical investigation. *International Journal of Bank Marketing, 17*(7), 324-334. http://dx.doi.org/10.1108/02652329910305689
31. Schierz, P. G., Schilke, O., & Wirtz, B. W. (2010). Understanding consumer acceptance of mobile payment services: An empirical analysis. *Electronic Commerce Research and Applications, 9*(3), 209-21. https://doi.org/10.1016/j.elerap.2009.07.005
32. Shaikh, A. A., & Karjaluoto, H. (2015). Mobile banking adoption: A literature review. *Telematics and Informatics, 32*(1), 129-142. https://doi.org/10.1016/j.tele.2014.05.003
33. Shankar, A. (2016). Factors affecting mobile banking adoption behavior in India. *Journal of Internet Banking and Commerce, 21*(1). Retrieved from https://www.icommercecentral.com/open-access/factors-affecting-mobile-banking-adoption-behavior-in-india.php?aid=70187
34. Silva, P. (2015). Davis' technology acceptance model (TAM) (1989). In M. Al-Suqri & A. Al-Aufi (Eds.), *Information Seeking Behavior and Technology Adoption: Theories and Trends* (pp. 205-219). IGI Global. https://doi.org/10.4018/978-1-4666-8156-9.ch013
35. Tarbal, J. (2020). *Chatbots in financial services: Benefits, use cases and key features.*
36. Trivedi, J. (2019). Examining the customer experience of using banking chatbots and its impact on brand love: The moderating role of perceived risk. *Journal of Internet Commerce, 18*(1), 91-111. https://doi.org/10.1080/15332861.2019.1567188
37. Westland, J. C. (2015). An introduction to structural equation models. In *Structural Equation Models* (pp. 1-8). Cham: Springer. https://doi.org/10.1007/978-3-319-16507-3_1
38. Zaato, S. G., Zainol, N. R., Khan, S., Rehman, A. U., Faridi, M. R., & Khan, A. A. (2023). The mediating role of customer satisfaction between antecedent factors and brand loyalty for the Shopee application. *Behavioral Sciences, 13*(7), 563. https://doi.org/10.3390/bs13070563

http://dx.doi.org/10.21511/im.19(4).2023.21