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Investigating Factors Impacting Customer Acceptance of Artificial Intelligence Chatbot: Banking Sector of Kuwait

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ABSTRACT

The Purpose: This study investigates the role of Artificial Intelligence- chatbot (AI chatbot) quality and AI chatbot users across various banking needs and its impact on customer acceptance of AI chatbots through the mediating role of perceived usefulness and ease of use. **Design/methodology/approach** – This quantitative study uses a cross-sectional time dimension. The questionnaire of this study was developed using multiple academic sources. Partial least square structural equation modeling was used to analyze the data, and the SmartPLS 4 software was used for the calculation. **Finding -** The findings indicated a significant positive direct relationship between AI chatbot quality and acceptance of AI chatbot (path coefficient of 0.138 and p-value of 0.022). At the same time, the direct relationship between the AI-chatbot user and the acceptance of the AI chatbot was insignificant (path coefficient = 0.0.096, and p-value = 0.246). While the results of the indirect relationship reveal that perceived usefulness and ease of use partially mediated the relationship between AI chatbot quality and acceptance of AI chatbots. The perceived usefulness and ease of use fully mediated the relationship between AI chatbot users and acceptance of the AI chatbot. **Originality/value** – The results of this study developed a framework for banking and other customer-oriented businesses in understanding and developing AI chatbots to address customer needs.

1. Introduction

Recent technological developments have transformed the way consumers and financial institutions interact with each other. Technology is evolving, impacting consumer and financial institution interaction. The rise of AI-based technology contributes extensively to this transformation. A chatbot is a Human-Computer Interaction model and an AI program (Bansal & Khan, 2018). AI chatbots, commonly referred to as conversational agents (CA), are software programs that can converse in natural language (Nicolescu & Tudorache, 2022). Also, it stands for interactive systems that enable human-computer interaction & wing to more recent advancements in AI and machine learning; CA has begun to be employed widely.

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Conversational agents have been used in various contexts and fields, including education, marketing, and support systems (Adamopoulou & Moussiades, 2020). Now, AI-enabled chatbots can simulate human behavior and engage in conversation thanks to machine learning and AI advancements (Følstad, Nordheim, & Bjørkli, 2018). Nicolescu and Tudorache (2022) maintain that client service is a crucial area where CA-chatbots are employed; nevertheless, AI-enabled chatbots are viewed as groundbreaking tools for service providers because they offer fully automated customer assistance. The appearance of such bank-customer interaction has transformed with the emergence of AI-powered chatbots. Suhel, Shukla, Vyas, and Mishra (2020) argue that chatbots powered by AI can respond to even uncertain questions and generate a response through the processing technology embedded within natural language.

The use of chatbots in customer care has received increasing attention, which is suitable for both businesses and clients. This leads to a shortage of service staff. Clients typically experience queuing and awaiting a response to resolve their problems with conventional customer service, which might result in a horrible service experience (McLean & Wilson, 2016). Virtual agents, like chatbots, are equipped to respond to clients' issues immediately and provide pertinent information (McLean & Wilson, 2016; van Esch & Mente, 2018). Furthermore, Dospinescu, Anastasiei, and Dospinescu (2019) claim that the most crucial elements affecting customer satisfaction in their interactions involving service providers were long waits, transaction fees, and competing services.

Implementing AI-based chatbot technology is an impactful form of technological development in the financial sector. It has been reported that 29% think offering products and services through assistants or messaging bots will be essential in the future, and 76% believe that AI interfaces will become the primary interaction point between banks and customers in the following years (Wilson, Daugherty, & Bianzino, 2017). However, companies and banks may be strikingly enthusiastic about chatbots they often need to meet customer requirements (Adam, Wessel, & Benlian, 2021), mainly concerning personal data protection (Rese, Ganster, & Baier, 2020). However, the empirical studies about factors underlying the potential experienced users' behavior intentions to interact with bank chatbots are bounded. So, this study aims to investigate the role of AI-chatbot quality and users across various banking needs and its impact on customer acceptance of AI chatbots through the mediating role of perceived usefulness and ease of use.

2. Theoretical Background and Hypotheses

This study's theoretical framework guides the research's paths and offers the foundation for establishing its credibility.

2.1. Chatbot Technology

Digital services in the banking and insurance sectors have entirely changed how customers are served (Sahu, Deng, & Mollah, 2018). AI chatbots are one of the many digital service technological options accessible and the most widely used internet services for conducting business in the modern era. Lester, Branting, and Mott (2004, p. 220) argue that chatbots can "*understand natural language and respond in natural language to a user request*," relying on artificial intelligence algorithms. Also, chatbots can make real-time responses to user questions that are task- or information-oriented.

2.2. AI Chatbot Quality

This study uses service and information quality to examine the effectiveness of the AI chatbot.

2.2.1. Information Quality

Information quality could be described as "the accuracy, format, completeness, and currency of information produced by digital technologies" (Setia, Setia, Venkatesh, & Joglekar, 2013, p. 268). The degree to which consumers are satisfied is directly related to their ability to get sufficient, accurate, comprehensive, updated, and reliable information (Veeramootoo, Nunkoo, & Dwivedi, 2018).

2.2.2. Service Quality

A creative service approach and a new type of service provider can be found in AI chatbot services. AI chatbots are distinct from conventional interactive computer avatars, which feature live people providing customer care. Additionally, AI chatbot services differ from information system-based self-service technology (SST). The AI chatbot is portrayed as a distinct species, yet it is more intelligent than humans in several ways, like storing information, computer capability, and learning capacity. It briefly lags below humans in several areas, like emotional intelligence (Chen, Gong, Lu, & Tang, 2022). The essential qualities, service delivery mechanisms, and service outcome contents of AI chatbots are distinctive.

2.3. AI Chatbot User

Trust and awareness were used to examine the AI, chatbot users.

2.3.1. Awareness

Technology awareness can sometimes be linked to the idea of awareness (Saffarizadeh, Boodraj, & Alashoor, 2017). Li (2014) claimed that awareness provides both intellectual and expressive purposes. The first can be characterized as awareness of the data gathered about the person, including technology usage. In contrast, the second is seen as the intimacy experienced by the person. Because of this familiarity, people feel shielded from hazards that could intrude on their privacy. Their expertise and awareness of technologies negatively influence individuals' privacy concerns. In other terms, a greater understanding of technology and an awareness of it reduces privacy issues (Bouhia, Rajaobelina, PromTep, Arcand, & Ricard, 2022).

2.3.2. Trust

Trust has indeed been regarded as one of the key factors affecting consumers' engagement in e-commerce since it might lessen the uncertainty and apparent risk (Seo & Lee, 2021). In this study, users' confidence level in the dependability and caliber of chatbot systems is their level of trust (Caceres & Paparoidamis, 2007). Users of AI chatbots are advised to think about the hazards involved before chatting with them because they are designed to mimic human conversational behavior. Trust is a crucial factor influencing users' behavioral intent regarding AI chatbot services, given the potential uncertainties and dangers (Nguyen, Chiu, & Le, 2021).

2.4. User Perception of AI Chatbots

The current study uses perceived usefulness and ease of use to measure user perception of AI chatbots.

2.4.1. Perceived Usefulness (PU)

Perceived usefulness is "the degree to which a person believes that using a particular system would enhance his or her job performance" (Davis, 1989).

Operational factors like chatbots' capacity for problem-solving can influence how willing consumers are to engage with chatbots (Wuenderlich & Paluch, 2017). Recent studies on the purpose of using financial technology innovative ideas like blockchain, biometric authentication, Robo-advisors, and peer-to-peer platforms found that a higher synchronism readiness, or the technology's capacity to facilitate better efficiency levels for the users through smooth, quick, or immediate exchanges impartial from human staff handling, is necessary (Verbovetska, 2019). Therefore, an AI chatbot is more frequently used if the user gives it a highly subjective good rating because of the operational characteristics that effectively support the user to complete an insurance-related task by providing quicker and more accurate guidance without time restrictions or geographic area (Rodríguez Cardona, Janssen, Guhr, Breitner, & Milde, 2021).

2.4.2. Perceived Ease-of-Use (PU)

Perceived ease of use is one of the critical factors in the acceptance of new technologies. It would be described as the user's simplicity, convenience, or effort-free evaluation while using the electronic gadget (Selamat & Windasari, 2021). Perceived ease of use is a feature that significantly influences customers' interest and motivation (Zarouali, Van den Broeck, Walrave, & Poels, 2018). Perceived ease of use is valued highly when using chatbots in a professional setting (Rietz, Benke, & Maedche, 2019).

2.5. Acceptance of AI Chatbot

Service AI chatbots are multi-intelligent platforms that enable effective and exact user communication (McLean & Osei-Frimpong, 2019). Chatbots can accommodate users' evolving needs considering the nature of AI and its revolutionary self-learning capabilities (Montes & Goertzel, 2019). When people engage with chatbots, they can experience the very same thing. To answer or engage effectively, chatbots can self-learn from their surroundings. Equivalent frameworks might encourage users to keep utilizing chatbots for services. This theoretical claim, nevertheless, needs to be investigated. Accordingly, we have adopted the following variables in the development of hypotheses:

Table 1.
Variables and Its sources

Variable Type	Variables	Sources
Independent Variables	AI chabot Quality AI chabot Users	Alt et al. (2021), Nguyen et al. (2021) and Cardona et al. (2021)
Dependent Variable	AI chatbot Acceptance	Alt et al. (2021), Nguyen et al. (2021) and Cardona et al. (2021)
Moderating Variables	Perceived usefulness (PE) Perceived usefulness (PE)	Alt et al. (2021), Nguyen et al. (2021) and Cardona et al. (2021)

Source: (Authors)

Based on the theoretical framework discussion above, the following hypotheses are proposed:

- H1: AI chatbot quality positively impacts acceptance of AI chatbot
- H2: AI chatbot user positively impacts on acceptance of AI chatbot.
- H3: AI chatbot quality positively impacts acceptance of AI chatbot mediated by perceived usefulness.
- H4: AI chatbot quality positively impacts acceptance of AI chatbot mediated by perceived ease-of-use.

- H5: AI chatbot user positively impacts acceptance of AI chatbot mediated by perceived usefulness.
- H6: AI chatbot user positively impacts acceptance of AI chatbot mediated by perceived ease-of-use.

In this way, the conceptual framework of this research is presented in the Figure 1.

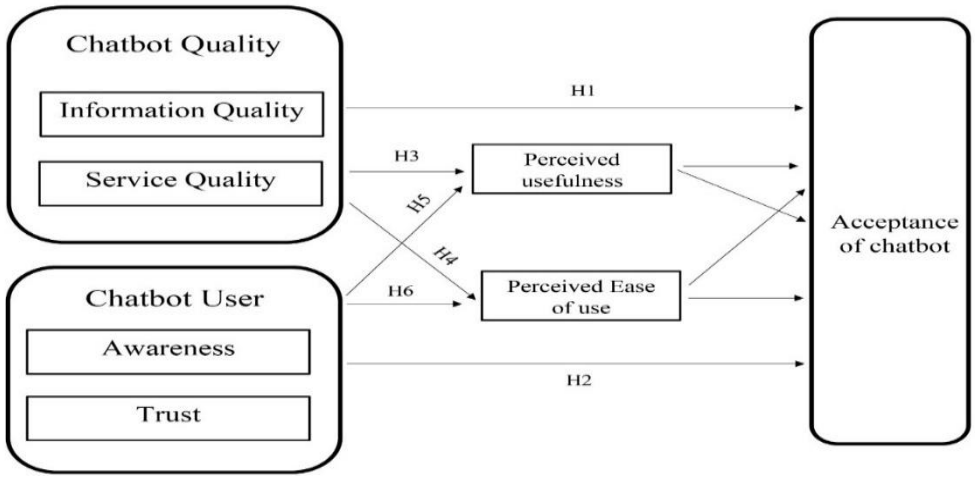

Figure 1. Study Conceptual Framework
Source: (Authors)

3. Methods

3.1. Measurement Tool

The current study adopts the quantitative research approach by using a questionnaire survey. The questionnaire of this study was developed using multiple sources (Kwangsawad & Jattamart, 2022; Mostafa & Kasamani, 2021; Nguyen et al., 2021; *Traditional retail segments show positive trends, while Kuwait's e-commerce market undergoes rapid expansion (Kuwait Retail).* , 2018) to measure the dependent, independent, and mediator variables. The developed questionnaire comprised three main sections. The first section covered questions about using chatbots earlier and the frequency of using banks' chatbots by the participants. Only those who have interacted with chatbots are allowed to participate. This section is followed by demographic characteristics questions such as gender, age, education, and monthly income. The second section covered questions that measure all the studied variables, which consist of 30 questions distributed as follows: information quality (four items), service quality (four items), awareness (four items), trust (four items), perceived usefulness (four items), perceived ease of use (four items), and acceptance of AI chatbot (six items). All questions are measured with a 5-point Likert scale, which is strongly Disagree, Disagree, Neither Disagree nor Agree, Agree, and Strongly Agree. In addition, A cover letter was attached to the questionnaire, which included information about the study's purpose, instructions for completing and returning the questionnaire, and the ethical consideration of confidentiality and anonymity.

3.1.1. Pilot Study

The questionnaire was administered to 10 participants to determine whether the questions were clear to them. After the pilot study, some items were modified before incorporating into the final version. The data collected from the 10 participants in the pilot study were excluded when further analysis was conducted.

3.2. Sampling and Population

This research used stratified random sampling, which comes under probability sampling. Stratified random sampling refers to dividing the entire population into groups. In this research, the population is banking customers. The strata are based on customers that have used Chatbots. This is achieved based on the questionnaire's classification question, "Have you used Chatbot for banking services before?". Those that answered "yes" were presented with the questionnaire, and those that answered "no" were taken to the closing screen. Because the majority of the working population in Kuwait is expected to have a bank account per government regulations. The working population was collected from the World Bank database. As of 2021, there were 2,405,946 people in the labor force (World Bank, 2022). Therefore, the recommended sample size is 385 participants based on a 95% confidence level and a 5% margin of error.

3.3. Data Collection

A cross-sectional time frame was adopted in this study. The questionnaire was designed on survey monkey Forms. The questionnaire link was distributed to 750 banking customers on May 2022. Three weeks were given to gather customer feedback. The total number of responses used in this study was 401 after removing the incomplete questionnaires and those that answered “no” to using Chatbot.

3.4. Data Analysis

Partial least square structural equation modeling (PLS-SEM) was used to analyze the data. PLS-SEM is a multivariate statistical technique widely used to analyze the relationships between variables. It provides a flexible method for assessing complicated models and can address reflective and formative measurement models (Abdallah, Johnson, Nitzl, & Mohammed, 2019; Hair Jr, Hult, Ringle, & Sarstedt, 2016). For the calculations, the SmartPLS 4 software was used. A two-step process was used to analyze the current research models. The measurement model was used to assess the validity and reliability of the questionnaire, and the structural model was used to test the relationship between the studied variables. Internal consistency reliability, convergent validity, and discriminant validity were used in the reflective measurement model analysis. Internal consistency includes Cronbach alpha analysis, which should be ≥ 0.7, and composite reliability analysis, which should be ≥ 0.6. At the same time, convergent validity has outer loading, which should be ≥ 0.7, and average variance extracted (AVE), which should be ≥ 0.5. At the same time, discriminant validity includes the Heterotrait-monotrait ratio (HTMT), in which all correlations of indicators across constructs should be below 0.9. Moreover, the Fornell-Larcker criterion should be greater than its highest correlation with any other construct. Variance inflation factor (VIF), which assess the level of collinearity, Relevance of outer weight, and p-value of each outer weight, were used in the formative measurement model analysis. However, using a bootstrapping procedure, the outer weight should be significantly different from zero, the p-value should be less than 0.05, and VIF should be less than 5. To evaluate the structural model, the bootstrapping procedure with 5,000 bootstraps without sign changes was used for calculating the path coefficient, which has standardized values between -1 and +1 (values close to +1 and -1 represent strong positive and negative relationships, respectively), the p-values that should be less than 0.05, and R^2 that range between 0 and 1 (the higher R^2, the better). Next, the global model fit was assessed using standardized root means square residual (SRMR), which should be <0.085 (Hair Jr et al., 2016).

4. Results

4.1. Demographic Characteristics

Of 750 distributed questionnaires, 401 (53.4% response rate) were completed and returned. Demographic characteristics show higher participation from males (72%). At the same time, the participant's ages ranged between the age group of 31-40 years (39%) and 20-30 years (32%), with most of them having Bachelor's degrees (69%) and earning an income between KD 500-1000 (44%).

4.2. Descriptive Analysis

The mean and standard deviation of all variables and items were calculated. As presented in Table 2. The mean score of all variables is higher than 3, which indicates a positive response from the participants about chatbot quality, chatbot users, acceptance of chatbot, perceived usefulness, and perceived ease of use. The highest observed mean of 3.806 was for the variable "perceived usefulness"; this refers to getting faster information using chatbots and improving customer productivity in transactions.

Table 2.
Results of Descriptive Analysis

Variables	**Mean**	**Standard Deviation**
Information Quality (IQ)	3.676	0.914
Service Quality (SQ)	3.443	0.944
Awareness (AW)	3.38	0.998
Trust (TR)	3.56	0.980
Perceived Usefulness (PU)	3.806	0.806
Perceived Ease of use (PE)	3.510	0.831

Source: (Authors)

4.3. Measurement Model (Reliability and Validity)

The results of the reflective measurement model indicated that all outer loadings were higher than 0.7, except one item was deleted as it had a low loading, the Cronbach alpha for all variables was higher than 0.7, all the composite reliability of variables was more significant than 0.6, and all the AVE of variables were higher than 0.5, as presented in Table 3.

Table 3.
Results of the Reflective Measurement Model

Items	**Outer Loading**	**Cronbach alpha**	**Composite reliability**	**AVE**
Critical value	**> 0.7**	**> 0.7**	**>0. 6**	**> 0.5**
Information Quality (IQ)		0.861	0.864	0.705
- IQ1	0.815			
- IQ2	0.872			
- IQ3	0.854			
- IQ4	0.817			
Service Quality (SQ)		0.803	0.814	0.717
- SQ1	0.810			
- SQ2	0.802			
- SQ3	0.678			
- SQ4	0.859			
- SQ5 (Deleted)	0.307			

Items	Outer Loading	Cronbach alpha	Composite reliability	AVE
Critical value	**> 0.7**	**> 0.7**	**>0. 6**	**> 0.5**
Awareness (AW)		0.708	0.704	0.634
- Aw1	0.729			
- Aw2	0.783			
- Aw3	0.694			
- Aw4	0.775			
Trust (TR)		0.804	0.807	0.717
- TR1	0.815			
- TR2	0.840			
- TR3	0.886			
Perceived Usefulness (PU)		0.836	0.837	0.753
- PU1	0.887			
- PU2	0.867			
- PU3	0.849			
Perceived Ease of use (PE)		0.806	0.819	0.633
- PE1	0.830			
- PE2	0.832			
- PE3	0.800			
- PE4	0.714			
Acceptance of Chatbots (AC)		0.894	0.895	0.758
- AC1	0.835			
- AC2	0.864			
- AC3	0.876			
- AC4	0.674			
- AC5	0.860			

Source: (Authors)

Results of the discriminant validity of the reflective measurement model include HTMT and Fornell-Larcker Criterion. Results of HTMT indicate that all correlations of indicators across variables are below 0.9, as shown in Table 4.

Table 4.
HTMT Results

	IQ	SQ	AW	TR	PU	PE	AC
IQ							
SQ	0.830						
AW	0.788	0.775					
TR	0.694	0.745	0.642				
PU	0.746	0.829	0.697	0.751			
PE	0.748	0.852	0.775	0.669	0.802		
AC	0.801	0.846	0.613	0.729	0.798	0.794	

Source: (Authors)

The results of the Fornell-Larcker criterion are reported in Table 5. It was observed that the square root of the AVE for each construct was more significant than its highest correlation with any other construct.

Table 5.
Fornell-Larcker Criterion

	IQ	SQ	AW	TR	PU	PE	AC
IQ	0.840						
SQ	0.766	0.847					
AW	0.618	0.594	0.796				
TR	0.583	0.603	0.488	0.848			
PU	0.635	0.684	0.542	0.617	0.868		
PE	0.639	0.704	0.607	0.549	0.668	0.795	
AC	0.707	0.725	0.491	0.619	0.692	0.678	0.871

Source: (Authors)

The results of the formative measurement model are presented in Table 6. All outer weights were observed to be significant, with p-value < 0.05, and all VIF values were below the critical value of 5.

Table 6.
Results of the Formative Measurement Model

Variables	**Weight**	**p-value**	**Variance inflation factor**
Critical value		**< 0.05**	**< 5**
Information Quality (IQ)	0.405	0.000	2.57
Service Quality (SQ)	0.392	0.000	2.85
Awareness (AW)	0.319	0.000	2.07
Trust (TR)	0.310	0.000	2.94
Perceived Usefulness (PU)	0.231	0.000	2.68
Perceived Ease of use	0.191	0.000	1.98
Acceptance of Chatbots	0.488	0.000	2.01

Source: (Authors)

4.4. Structural Model (Testing Hypotheses)

As shown in Table 7, structural model results indicate that the direct relationship between the AI-chatbot quality and acceptance of the AI-chatbot is significant (coefficient = 0.183, t-value 4.831, and p-value = 0.022). Therefore, H1 is supported. The results of the second hypothesis show that AI-chatbot user insignificantly affects the acceptance of the AI-chatbot (coefficient = 0.0.096, t-value = 1.162, and p-value = 0.246). Thus, H2 is unsupported. The results of the indirect relationships show that AI-chatbot quality positively impacts acceptance of AI-chatbot partially mediated by perceived usefulness (coefficient = 0.0.138, t-value = 4.863, and p-value = 0.002) and perceived ease of use (coefficient = 0.0.173, t-value = 4.004, and p-value = 0.001), so the H3 and H4 are supported. Also, the AI-chatbot user positively impacts acceptance of the AI-chatbot fully mediated by perceived usefulness (coefficient = 0.0.098, t-value = 3.373, and p-value = 0.01) and perceived ease of use (coefficient = 0.0.082, t-value = 3.337, and p-value = 0.0.01), so the H5 and H6 are supported. In addition, the global model fit results indicate that the SRMR score has an acceptable value of 0.064. Furthermore, the R2 of the endogenous constructs was a good value of 0.628 for acceptance of the AI chatbot, 0.537 for perceived usefulness, and 0.558 for perceived ease of use.

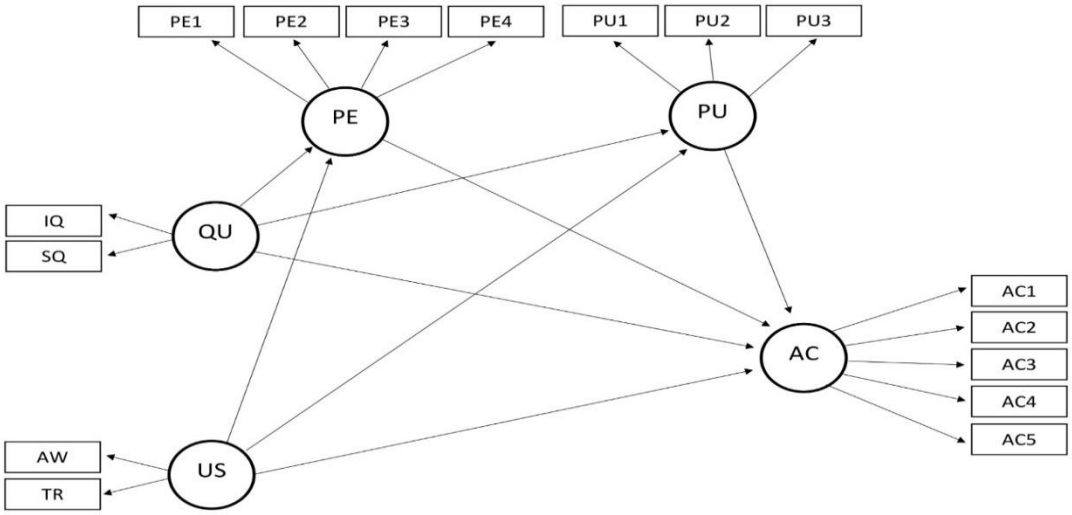

Figure 2. The Structural Model with the Moderation Variables
Source: (Authors)

Table 7.
Results of the Structural Model

					CI	
Hypotheses	**Relationship**	**Direct**	**Indirect**	**T-test**	**2.50%**	**97.50%**
H1	QU -> AC	0.183**		4.831	0.087	0.201
H2	US -> AC	0.096		1.162	- 0.096	0.258
H3	QU -> PU -> AC		0.138***	4.863	0.098	0.206
H4	QU -> PE -> AC		0.173***	4.004	0.093	0.259
H5	US -> PU -> AC		0.098 **	3.373	0.049	0.162
H6	US -> PE -> AC		0.082**	3.337	0.082	0.136

*Source: (Authors) *p > 0.05; **p > 0.01; ***p > 0.001*

5. Discussion

This study focused on the role of AI chatbot quality, AI user, and customer experience, which is mediated by the mechanism that has perceived usefulness and ease of use in the banking sector. The authors stipulate that this study is the first of its kind to the best of their knowledge.

Our results show that the validity and reliability of the formative and reflective models were significant, indicating the overall validity of the measurements.

Among the two identified direct factors, AI chatbot quality strongly affects AI chatbot acceptance, therefore, supporting H1, which is consistent with the findings of Trivedi (2019), and Nguyen et al. (2021) in the context that information quality is a critical factor that promotes customer interaction and choice of chatbots. Also, it is in line with the findings of Chen et al. (2022) that the way the information is delivered, the speed the information is provided, and its outcome are associated with customer acceptance of chatbots. Conversely, the results showed that AI chatbot users, including awareness and trust, insignificantly affect the acceptance of the AI chatbot. Thus, H2 is unsupported. This can be supported by the findings of Li (2014) that awareness can result in positive or negative usage of chatbots. Our results for the indirect relationships show that AI chatbot quality positively impacts acceptance of AI chatbot partially mediated by perceived usefulness and perceived ease of use, so the H3 and H4 are supported. This indicates that the effect of AI chatbot quality on acceptance of AI chatbots is getting stronger through perceived usefulness and ease of use, which is consistent with the findings of Wuenderlich and Paluch (2017), and Verbovetska (2019) that the change in the lifestyle and values of the banks' consumers encourage chatbots acceptance among the bank services users.

AI chatbot user, including awareness and trust, significantly impacts acceptance of the AI chatbot fully mediated through perceived usefulness and ease of use, so the H5 and H6 are supported. This demonstrates that perceived usefulness and ease of use are necessary factors to ensure that users accept AI chatbot services, which is supported by the argument of Wuenderlich and Paluch (2017) that operational factors like chatbots' capacity for problem-solving can influence how willing consumers to engage with chatbots. The global model fit results indicate that the SRMR score has an acceptable value of 0.064, which indicates that the developed model of this study was fit and suitable.

This study has a limitation. The data is collected from customers of all banks in Kuwait. However, the status of chatbots in the different banks has yet to be discovered. The study's data is cross-sectional, and with the gradual development of banking chatbots, there is a need to conduct more research to study how customer level of acceptance has changed with the development and further usage of AI chatbots in future research.

6. Conclusion

This study has clarified the phenomenon of adopting chatbots and identified gaps. This study demonstrated a significant direct relationship between AI chatbot quality and acceptance of AI chatbots in the banking sector. This relationship can be strengthened by using perceived usefulness and ease of use. At the same time, there is no direct relationship between AI-chatbot users and acceptance of AI-chatbot except through perceived usefulness and ease of use.

Competing Interests

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