

Chatbot Quality and Its Impact on User Satisfaction and Continuance Usage Intention in the Indonesian Banking Industry

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Abstract—The research aims to investigate the role of chatbot quality in influencing user satisfaction and continuance usage intention within the Indonesian banking industry. The research is among the first to apply Expectation Confirmation Theory (ECT) to chatbot usage in the Indonesian banking industry and offers a novel integration of chatbot quality dimensions within the framework. A quantitative explanatory method is adopted, and a purposive sampling method is used to collect 347 valid responses via an online structured questionnaire. Data analysis is conducted using Partial Least Squares-Structural Equation Modeling (PLS-SEM) with a focus on reflective-formative evaluation, bootstrapping for hypothesis testing, PLS-Predict for out-of-sample predictive performance, and Importance-Performance Analysis (IPMA) for managerial insights. The results show that chatbot quality significantly enhances both perceived usefulness and confirmation to subsequently reinforce user satisfaction and continuance usage intention. Satisfaction is identified as the strongest predictor of continuance usage. Meanwhile, chatbot disclosure does not have a significant impact on perceived quality, and it reflects the gap between transparency efforts and user perception. The observations underline the importance of designing chatbots that are responsive, context-aware, and linguistically adaptive specifically in the diverse communication landscape of Indonesia. The research contributes to the growing body of knowledge on AI-driven customer service technologies in emerging markets by offering practical implications for chatbot implementation in the financial sector. The identification of critical determinants of chatbot success also leads to the provision of insights for banks to enhance digital engagement, foster trust, and ensure long-term usage through optimized conversational experiences.

Index Terms—Chatbot Quality, User Satisfaction, Continuance Usage Intention, Banking, Perceived Usefulness, Indonesia, AI Customer Service

Received: March 17, 2025; received in revised form: Sep. 08, 2025; accepted: Sep. 08, 2025; available online: March 05, 2026.
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I. INTRODUCTION

THE continuous change in the banking landscape shows the critical role of AI chatbots in enhancing customer experience and optimizing operations. The concept that starts as basic rule-based systems has developed into advanced chatbots and virtual assistants capable of delivering highly personalized customer interactions. A previous study has reported that AI chatbots significantly improve satisfaction and streamlines customer interactions [1]. Several other studies have also emphasized the influence on customer loyalty [2, 3], enhancement of service quality, and assistance in fostering relationships [4]. Moreover, chatbots reduce costs significantly by automating tasks [5] through conversational ability, query understanding, and seamless integration for efficiency [6].

The implementation of chatbots with 24/7 availability capability provides several opportunities for self-service innovations. However, there is a need to understand the foundational success metrics, such as customer satisfaction and reuse intentions. It is important because the complexity of the Indonesian language which is associated with the informal nuances poses significant challenges to chatbot development [7]. The trend shows the need for effective chatbots to process natural language variations while respecting cultural sensitivity and adapting to diverse communication styles [8]. These challenges require chatbot systems to be technically sound as well as culturally and linguistically adaptive.

The quality of chatbots which depend on customer satisfaction includes perceived usefulness, responsiveness, and service quality [9]. Personalized and humanized features also enhance the user experience [10]. However, some limitations are identified in understanding queries that require human intervention [11].

The satisfaction aspect also correlates with customer loyalty with word-of-mouth reported to be a significant influential factor [4].

Previous studies have explored the characteristics of chatbots affecting customer retention and satisfaction levels such as disclosure [12, 13]. Others have also reported correlations between assurance, interactivity, reliability, responsiveness, and satisfaction [14]. Moreover, anthropocentric chatbots improve customer trust and satisfaction through human-like interactions [15].

Several contributions are associated with these studies, but the Expectation Confirmation Theory (ECT) is rarely applied in the context of chatbot use in the Indonesian banking sector. The ECT is particularly relevant due to the ability to explain post-adoption behaviors by connecting initial expectations, perceived performance, and satisfaction. The theory proposes that users form expectations before using the system. The ability of the experience to meet or exceed the expectations leads to confirmation which strengthens perceived usefulness and satisfaction and subsequently influences continuance usage intention.

Some studies show that quality factors, such as usability, warmth, and competence significantly affect satisfaction [16]. AI chatbots also outperform humans in functional quality by fostering stronger relationships and retention [16]. In Indonesia, chatbot quality positively impacts perceived usefulness, satisfaction, and loyalty [17].

A positive relationship has been established between chatbot disclosure and perceived quality in several studies [13, 16, 18–21]. The disclosure of the identity of chatbots before a conversation allows users to form clear expectations regarding the interaction to increase confidence by reducing uncertainty [19, 22]. Meanwhile, the failure to disclose can confuse user interactions [20]. The provision of information about the participation of chatbots in advance allows users to be better prepared to engage in problem-solving interactions [13, 18].

Chatbot disclosure also has an important mediating role between technology anxiety and chatbot quality [11, 20, 23]. It is because transparent disclosure during implementation reduces skepticism and assists in minimizing misperceptions about the technology [11]. The process also enhances interaction quality by fostering user understanding of how to identify accurate and high-quality responses from chatbots [19, 20]. These dynamics lead to the formulation of the following hypothesis:

H₁: Disclosure has a positive influence on chatbot quality.

The quality of chatbots is positively associated with the perceived usefulness because attributes, such as reputation, interactivity, and reliability, significantly shape users' perceptions about the information provided [4, 24–26]. The users' trust in the accuracy of the responses provided by chatbots influences the possibility of perceiving the technology as a tool for enhancing productivity [27]. Interactivity is also identified to be particularly more influential compared to the other relevant factors. It is because engaging and dynamic conversations with chatbots motivate users to complete specific tasks effectively [8, 25].

Reliability is another critical aspect of chatbot quality that drives perceived usefulness. The ability of chatbots to understand and meet users' needs develops confidence in their capacity to provide accurate information and solutions [4]. For example, the delivery of precise and contextually appropriate questions can significantly enhance the effectiveness in addressing user concerns [28]. These qualities collectively reinforce the perception of chatbots as valuable tools for solving problems and lead to the development of the following hypothesis:

H₂: Chatbot quality has a positive influence on perceived usefulness.

Previous studies have reported a positive relationship between chatbot quality, and the level of confirmation provided [6, 7, 28, 29]. High-quality chatbots meet user expectations and deliver valuable experiences [7]. Some factors such as credibility [13], interactivity [28], reliability [30], and engaging conversations [29] also validated the ability of chatbots to offer superior customer service compared to human-based support. It leads to the formulation of the following hypothesis:

H₃: Chatbot quality has a positive influence on confirmation.

A positive relationship has been consistently reported between perceived usefulness and satisfaction [4, 24, 28, 31]. A previous study has showed that positive interaction and connection to expectations influence user satisfaction [28]. Customers also report higher satisfaction when chatbots address inquiries and complaints [6]. Furthermore, customers find communication with customer service chatbots valuable and enjoyable when tasks are completed [31]. Efficient service delivery also enhances user satisfaction with chatbots through the provision of anticipated benefits and the ability to meet customer expectations [4]. It leads to the development of the following hypothesis:

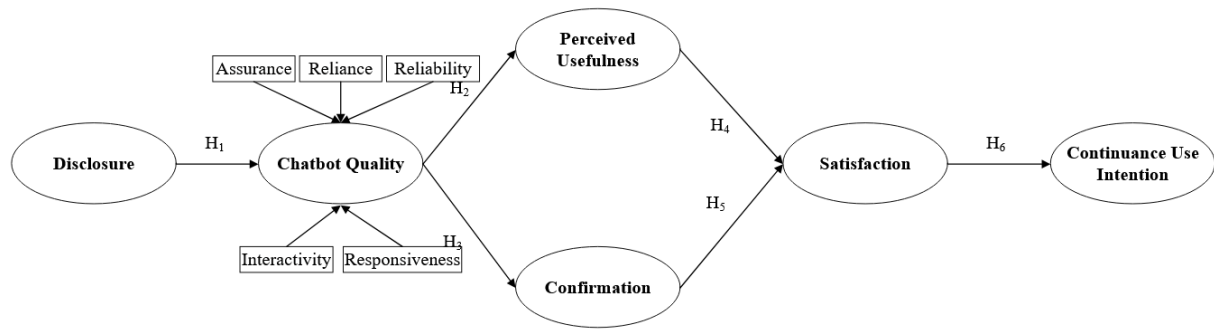


Fig. 1. Conceptual model.

H_4 : Perceived usefulness has a positive influence on satisfaction.

Previous studies have reported a positive relationship between confirmation and satisfaction [4, 7, 21, 28, 32]. The customer satisfaction increases when chatbots provide superior experiences and fulfilled expectations [32]. Communication quality is also reported to be very important in influencing customer satisfaction with electronic service agents [28]. Users are delighted when customer support chatbots address issues promptly and efficiently [4].

AI in customer support enhances the service-level agreement in resolving customer issues [1]. However, chatbots are required to provide accurate responses and appropriate solutions and interact effectively for automation to be effective [6]. The adoption of chatbots is perceived as a logical decision and a method to enhance satisfaction. These observations lead to the formulation of the following hypothesis:

H_5 : Confirmation has a positive influence on satisfaction.

A positive relationship is consistently reported between satisfaction and intention to use [4, 7, 24]. Customer satisfaction with the response and problem-solving abilities forms the basis for plans to reuse customer service chatbots across different sectors including banking [4]. The reuse of chatbots is motivated by confidence in receiving helpful and satisfying responses [24]. Furthermore, the current trend moves towards human-assisted customer support characterized by direct assistance, relevant information, problem-solving abilities, and personalized messages [7]. It leads to the formulation of the following hypothesis:

H_6 : Satisfaction has a positive influence on continuance use intention.

Some banking studies incorporating constructs, such as trust and security, are considered specifically relevant in sensitive digital finance environments. However, the research focuses on the perceived quality of chatbots and their role in shaping satisfaction and continued use. The aims are to investigate (1) how chatbot quality influences perceived usefulness and confirmation, (2) how the cognitive responses shape satisfaction, and (3) how satisfaction leads to continuance usage intention. The research also examines the contribution of chatbot disclosure to perceived quality to address transparency as a trust-enabling factor. The research aims to measure the determinants of intention to use chatbots particularly in the banking sector in Indonesia. The objectives are also to identify the quality of chatbots, the impact on user satisfaction, and the intention to continue using the technology. The objectives lead to the adoption of a quantitative design through the explanatory method known as the causal process which assesses the cause-and-effect relationships between one or more independent variables [33].

The research addresses gaps by combining the ECT with chatbot quality dimensions to examine satisfaction and continuance usage intention. The focus is on Indonesian banking with the exploration of how chatbot quality, which includes assurance, reliability, interactivity, responsiveness, and understanding, affects customer satisfaction and continuance usage intention. The aim is to provide practical insights into improving the adoption and service quality of chatbots in banking. Figure 1 presents the conceptual model of the determinant factors related to the continuance usage intention for chatbots. The suggested conceptual model also classifies quality as a reflective-formative second-order construct while the remaining factors are categorized as a first-order construct.

II. RESEARCH METHOD

The cross-sectional survey method is applied to collect data through an online questionnaire. The design allowed the capturing of user perceptions and behavioral intentions at a single point in time to enable the testing of causal relationships in the model. Then, the purposive sampling method is adopted to select respondents based on specific criteria determined in line with the study objectives and problem statement [34]. The selection of 347 respondents is based on certain inclusion criteria: (1) usage of chatbot services provided by banks in Indonesia for a minimum of one time in the last 6 months, (2) being 18 years or older, and (3) willing to complete the full questionnaire.

Primary data are used. It focuses on collecting information directly and analyzing to address the study problem [35]. The instrument is also in the form of a questionnaire designed in line with the research objectives. Moreover, a Likert scale, which ranges from 1 to 5 to reflect "strongly disagree" and "strongly agree" respectively, is adopted.

The questionnaire is developed by adapting the measurement items from previous studies. Chatbot quality is conceptualized as a second-order formative construct with five first-order reflective dimensions in the form of assurance, interactivity, reliability, responsiveness, and understandability. The other variables are perceived usefulness [28], confirmation [7], satisfaction [4], and continuance usage intention [7]. There are 32 items in the questionnaire, as shown in Table A1 in Appendix to represent all the variables.

A pre-test is conducted with 43 respondents before the hypotheses are tested. The aim is to assess the reliability and validity of the questionnaire as a study instrument. The results show that all items in the questionnaire are clear to the respondents and exhibits good reliability and validity. Hence, the questionnaire is suitable for use with the primary sample.

Next, Partial Least Squares-Structural Equation Modeling (PLS-SEM) is adopted for data analysis using SmartPLS software. The step-by-step analytical procedure follows the guidelines provided in a previous study [36]. Moreover, the reflective-formative method is used to develop the conceptual model [36]. The first step of the procedure is to assess the reflective measurement model with a focus on the reliability, internal consistency reliability, convergent validity, and discriminant validity of each indicator. The second step is to evaluate the second-order formative construct using outer weight, outer loadings, and Variance Inflation Factor (VIF) [36]. The third step is to test the structural model measurement using bootstrapping with 5,000 sub-samples. The fourth step is to assess the

predictive performance of the model using PLS-Predict analysis [37]. Finally, an Importance-Performance Map Analysis (IPMA) is performed to identify constructs that exhibit low performance but remain essential for target structures [38]. This multi-stage analysis ensures a comprehensive assessment of both measurement and structural models to enhance the transparency and rigor of the statistical procedures adopted.

III. RESULTS AND DISCUSSION

This section presents the results from the data analysis conducted. The presentation is in a structured manner. It has a descriptive summary of the respondents followed by the evaluation of the measurement model, hypothesis testing, predictive performance analysis, and importance-performance mapping.

A. Descriptive Analysis

Table I shows the descriptive analysis of the 347 respondents. The results show 55.33% female and 44.67% male with most identified being 22–30 years old (38.33%) and holding an undergraduate degree (58.21%). A higher percentage of the respondents are employees (42.36%). Then, 76.37% reside in Java, and Bank Central Asia (BCA) is the most frequently used bank (35.16%). These demographics confirm that the sample represents tech-savvy users. They are familiar with the features of chatbots and considered appropriate for the context of digital banking.

B. Reflective Measurement Model – Lower Order Construct

Table II presents the convergent validity and reliability test results for the first-order constructs. The Confirmatory Factor Analysis (CFA) is conducted using convergent and discriminant validity as well as reliability tests. Convergent validity is assessed through loading factor and Average Variance Extracted (AVE) tests. The criterion is that the instrument is valid when Loading Factor (LF) ≥ 0.70 and AVE ≥ 0.50 [39]. Meanwhile, a reliability test is conducted using Cronbach's Alpha (CA) and Composite Reliability (CR) with a threshold of ≥ 0.70 showing the instrument is reliable [39]. The results show that all items have loading factors above 0.70, AVE values over 0.50, as well as CR and Cronbach's alpha values beyond 0.70 to reflect good internal consistency and convergent validity.

Table III shows discriminant validity using the Heterotrait-Monotrait (HTMT) test. The instrument is valid when HTMT is < 0.90 [39]. All the values are lower than the 0.90 threshold. Hence, the results confirm that the constructs are empirically distinct.

TABLE I
CHARACTERISTICS OF RESPONDENTS.

	n	%
Gender		
Male	155	44.67
Female	192	55.33
Age		
18-24	10	2.88
22-30	133	38.33
31-40	110	31.70
41-50	55	15.85
51-60	31	8.93
>50	8	2.31
Domicile		
Java	265	76.37
Outside Java	82	23.63
Education Level		
High School	39	11.24
Vocational Degree	10	2.88
Undergraduate Degree	202	58.21
Master's degree	80	23.05
Doctoral Degree	11	3.17
Others	5	1.44
Profession		
Housewife	90	25.94
Academics	7	2.02
Employee	147	42.36
Student	5	1.44
Entrepreneur	36	10.37
Freelance	62	17.87
Frequently used Bank		
Bank Central Asia (BCA)	122	35.16
Bank Danamon	55	15.85
Bank Mandiri	100	28.82
Bank Negara Indonesia (BNI)	70	20.17

Note: n: number of samples (347) and %: percentage.

TABLE II
RESULTS OF CONVERGENT VALIDITY AND RELIABILITY TESTS.

Item	MEAN	LF	AVE	CA	CR
DI1	2.916	0.883			
DI2	2.859	0.865	0.817	0.891	1.056
DI3	2.957	0.960			
AS1	3.179	0.928			
AS2	3.314	0.885	0.831	0.898	0.898
AS3	3.003	0.921			
IN1	3.317	0.925			
IN2	3.277	0.941	0.881	0.932	0.934
IN3	3.458	0.949			
RL1	3.130	0.911			
RL2	3.061	0.981	0.918	0.955	0.964
RL3	3.049	0.980			
RS1	3.510	0.932			
RS2	3.360	0.967	0.908	0.949	0.952
RS3	3.444	0.960			
UN1	3.542	0.914			
UN2	3.499	0.951	0.883	0.934	0.949
UN3	3.478	0.953			
PU2	3.697	0.910			
PU4	3.409	0.737	0.732	0.813	0.807
PU5	3.718	0.909			
CO1	3.300	0.941			
CO2	3.386	0.949	0.816	0.885	0.901
CO3	3.176	0.813			
SA1	3.199	0.892			
SA2	3.242	0.898	0.810	0.883	0.883
SA3	3.556	0.910			
CI1	3.787	0.904			
CI2	3.715	0.903	0.800	0.877	0.895
CI3	3.072	0.877			

Note: CI= Continuance Usage Intention, SA= Satisfaction, CO= Confirmation, PU= Perceived Usefulness, UN= Understandability, RS= Responsiveness, RL= Reliability, IN = Interactivity, AS= Assurance, DI= Disclosure, LF= Loading Factor, AVE= Average Variance Extracted, CA= Cronbach's Alpha, and CR= Composite Reliability.

C. Measurement and Structural Model Analysis – Higher Order Construct

The assessment of the validity and reliability of lower-order constructs is followed by the calculation of the latent variable scores for assurance, interactivity, reliability, responsiveness, and understandability. It is important to examine the measurement and structural model analysis. The Variance Inflation Factor (VIF), outer weight, t-statistics, p-value, and outer loading are also determined to explain the importance of relevant dimensions of chatbot quality. The purpose of the VIF test is to assess the multicollinearity among the chatbot quality dimensions. A value of 5 or above shows the possibility of collinearity problems [39]. Table IV shows the formative measurement model analysis and the VIF value for all dimensions ranges from 1.761 to 2.331. The results reflect the absence of significant multicollinearity in the model.

D. Hypothesis Test Result

Table V shows the hypothesis test results and the coefficient of determination values. The structural model is also evaluated through a bootstrapping procedure

conducted with 5,000 subsamples, bias-corrected and accelerated (Bca bootstrap), one-tailed, and 5% significance level [39]. The significance of each relationship is assessed based on the t-statistic, p-value, and 95% confidence interval. H_1 is rejected. Meanwhile, H_2-H_5 are accepted.

Several key results are identified, including a positively significant relationship between chatbot quality and perceived usefulness ($\beta = 0.695$; t-stat = 22.142). This result shows that the chatbot quality has a substantial positive impact on perceived usefulness. Similarly, chatbot quality also significantly affects confirmation ($\beta = 0.762$, t-stat = 29.949). The trend suggests that high chatbot quality fosters better confirmation.

The positive influence of perceived usefulness on satisfaction is supported ($\beta = 0.201$; t-stat = 3.369). Customers who perceive a service as applicable have a better tendency to be satisfied. Confirmation also significantly enhances satisfaction ($\beta = 0.558$, t-stat = 8.500) which emphasizes the importance of a customer-focused method in determining satisfaction.

The results further show the significant positive effect of satisfaction on continuance usage intention (β

TABLE III
RESULT OF DISCRIMINANT VALIDITY - LOWER ORDER CONSTRUCT.

	AS	CO	CI	DI	IN	PU	RL	RS	SA	UN
AS										
CO	0.719									
CI	0.430	0.603								
DI	0.099	0.083	0.073							
IN	0.586	0.673	0.599	0.061						
PU	0.629	0.833	0.716	0.137	0.743					
RL	0.674	0.649	0.524	0.074	0.498	0.461				
RS	0.573	0.709	0.699	0.066	0.733	0.561	0.604			
SA	0.661	0.792	0.850	0.048	0.574	0.677	0.755	0.683		
UN	0.655	0.601	0.337	0.141	0.526	0.582	0.511	0.559	0.455	

Note: CI= Continuance Usage Intention, SA= Satisfaction, CO= Confirmation, PU= Perceived Usefulness, UN= Understandability, RS= Responsiveness, RL= Reliability, IN= Interactivity, AS= Assurance, and DI= Disclosure.

TABLE IV
FORMATIVE MEASUREMENT MODEL OF CHATBOT QUALITY.

Dimension	Outer Weight	T-Statistic	P-Values	Outer Loading	Variance Inflation Factor (VIF)
Assurance	0.317	5.387	0.000	0.831	2.155
Interactivity	0.430	5.732	0.000	0.863	2.081
Reliability	0.130	2.183	0.015	0.715	1.899
Responsiveness	0.144	1.818	0.035	0.794	2.331
Understandability	0.210	3.210	0.001	0.752	1.761

TABLE V
HYPOTHESIS TEST RESULTS.

Hypothesis	Original Sample	STDEV	T-Statistic	P-Value
DI → CQ	0.088	0.075	1.175	0.120
CQ → PU	0.695	0.031	22.142	0.000
CQ → CO	0.762	0.025	29.949	0.000
PU → SA	0.201	0.060	3.369	0.000
CO → SA	0.558	0.066	8.500	0.000
SA → CI	0.765	0.024	32.437	0.000

Note: STDEV= Standard Deviation, DI= Disclosure, CQ= Chatbot Quality, PU= Perceived Usefulness, CO= Confirmation, SA= Satisfaction, and CI= Continuance Usage Intention.
R² of CI= 0.585, SA= 0.509, CO= 0.580, PU= 0.484, and CQ= 0.008.

TABLE VI
PARTIAL LEAST SQUARES (PLS) PREDICTION RESULTS.

	Q ² Predict	PLS-SEM_RMSE	LM_RMSE	ΔPLS-LM
CI1	0.003	0.978	0.964	0.014
CI2	0.000	0.983	0.978	0.004
CI3	-0.005	1.174	1.181	-0.007

Note: PLS-SEM= Partial Least Squares Structural Equation Modeling, RMSE= Root Mean Square Error, LM= Linear Model, and CI= Continuance Usage Intention.

= 0.765, t-stat = 32.437). This result is a sign that satisfied customers have more possibilities of possessing a higher intention to continue using chatbots. However, the relationship between disclosure and chatbot quality is not significant ($\beta = 0.088$, t-stat = 1.175). This result suggests that disclosure does not significantly affect chatbot quality. The results emphasize the importance of chatbot quality, perceived usefulness, confirmation, and satisfaction in influencing continuance usage in-

tention while disclosure is found to be less impactful in the model.

Next, the coefficient of determination (R²) values shows that the quality of exogenous variables determine the endogenous variable by being between 0 and 1. The satisfaction is able to explain 58.5% of continuance usage intention. Moreover, perceived usefulness and confirmation explain 50.9% of satisfaction. Chatbot quality also explains 58% of confirmation and 48.4% of perceived usefulness.

E. Partial Least Squares (PLS) Prediction Test

PLS prediction test is conducted to assess the out-of-sample prediction strength of the model [40]. It is also used to evaluate predictive performance and compare alternative models [41]. The analysis includes the comparison of the PLS and Linear Model (LM) values. The model is considered to have high predictive power when all the indicators for Δ PLS-LM are negative [39]. The results in Table VI show that only one indicator had a negative value. The result leads to the inference that the model has weak predictive performance but acceptable out-of-sample predictive power.

F. Importance-Performance Map Analysis (IPMA)

The IPMA is a tool to analyze and visualize the importance and performance of indicators within a PLS-SEM model. It assists in identifying areas requiring improvement. Figure 2 shows the relative significance and

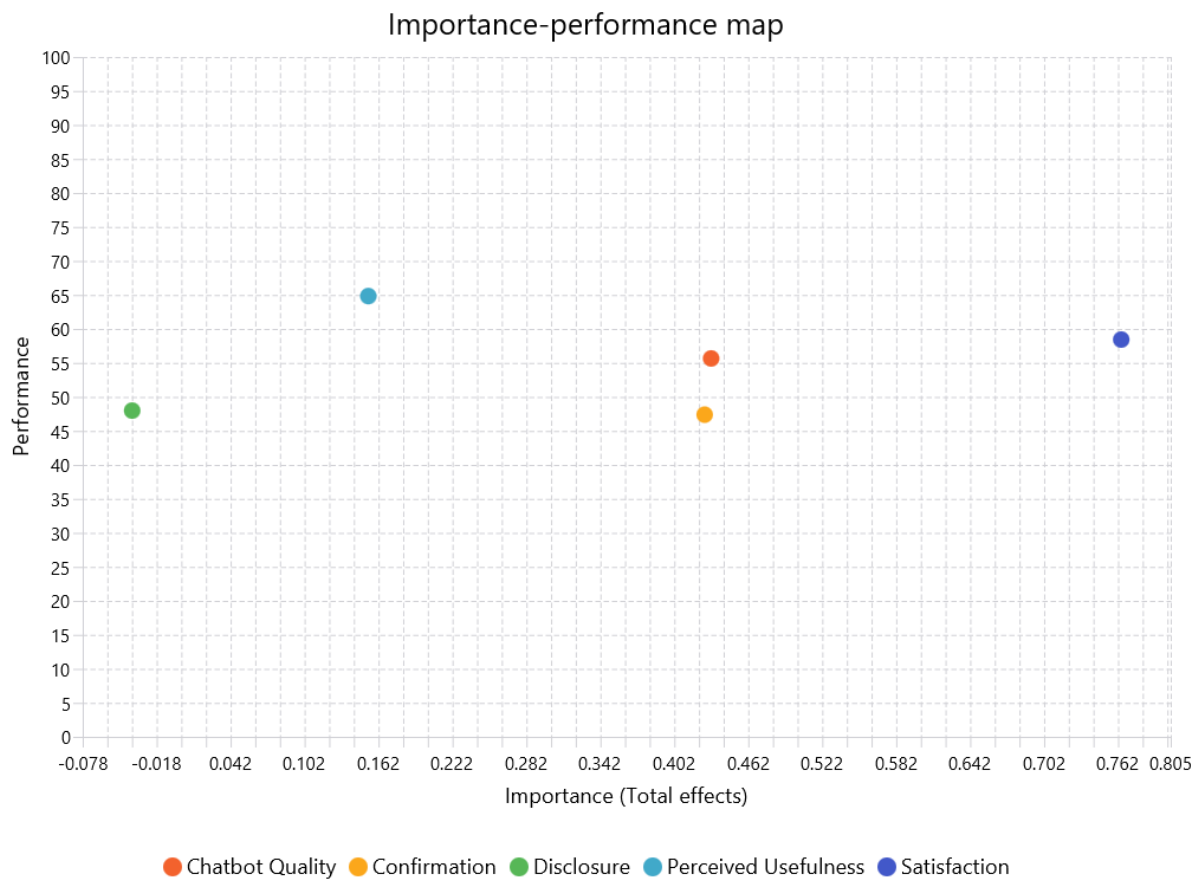


Fig. 2. Importance-Performance Map Analysis (IPMA) of Continuance Usage Intention results.

performance levels of several factors including chatbot quality, confirmation, disclosure, perceived usefulness, and satisfaction. However, the performance is not in line with the level of importance. This discrepancy suggests that chatbot quality is very important in the overall system or service, but the performance requires enhancement to meet the desired benchmarks. The improvement can significantly enhance user satisfaction and the overall efficacy of the service.

The results show that disclosure does not affect chatbot quality significantly and lead to the rejection of the related hypothesis. This result is in contrast to the previous studies [13, 16, 18–20]. They have emphasized the role of disclosure in enhancing user trust and perceived transparency. The discrepancy can be explained by the utilitarian nature of chatbot usage in the Indonesian banking context where users prioritize task completion, speed, and relevance of responses over system transparency. The users in high-efficiency service environments, such as banking, often exhibit a “function-first” mind which leads to less sensitivity to the disclosure of the identity of chatbots. This insight

emphasizes a contextual nuance that differs from e-commerce of customer service chatbots in less formal settings where social presence and human-likeness are more valued.

Chatbot quality has a significant positive effect on perceived usefulness. It is a reflection that higher chatbot quality enhances perceived usefulness in line with the observations of previous studies [4, 24–26]. The trend also supports the theoretical proposition of ECT that system attributes to the cognitive evaluations and perceived task efficiency of users. The key dimensions, such as interactivity, responsiveness, and understandability, are very important in shaping the perception of usefulness by users. The observation shows that the technical robustness of chatbot services becomes a core determinant of perceived value in banking contexts where information accuracy is very important.

Chatbot quality significantly and positively influences confirmation. The trend shows that better chatbot quality increases user confirmation levels in line with the previous research [6, 7, 28, 29, 42–44]. This result affirms the ECT mechanism where confirmation is as-

sociated with the connection between user expectations and actual system performance. Chatbot quality in the model developed includes the assurance and reliability that assist in fulfilling expectations and lead to stronger confirmation responses. The phenomenon reinforces the idea that delivering a consistent and trustworthy chatbot experience is critical for retaining users in high-trust digital environments such as banking.

The results further show that perceived usefulness has a significant positive effect on satisfaction. It is a sign that greater perceived usefulness leads to the increased satisfaction in line with the previous study [4, 24, 28, 45]. The trend reinforces the theoretical foundation of ECT that users have a higher tendency to experience satisfaction when the system is considered helpful particularly in terms of enhancing productivity or efficiency. The focus on banking, where speed and reliability are essential, reflects the possibility of chatbots to fulfill task-oriented needs effectively. Therefore, the relationship between functional utility and user expectations is identified as a critical driver of satisfaction. This result directly supports the objective of understanding how system evaluation contributes to continued use.

Confirmation is another factor with a significant effect on satisfaction. It shows that a higher level of confirmation enhances user confirmation as supported through the studies [4, 7, 28, 32]. The result is also in line with the emphasis of ECT that users derive satisfaction when the initial expectations are met or exceeded. The users perceive the banking chatbots to perform as expected in terms of responsiveness, accuracy, and interaction quality. This result suggests that consistent and expectation-connected service delivery is essential for building satisfaction. The confirmation of expectations through high-quality chatbot performance can allow financial institutions to foster a more favorable user experience.

Satisfaction significantly influences continuance usage intention. Higher satisfaction levels lead to a stronger intention to continue using chatbot services in line with the previous research [4, 7, 24]. The result further validates the post-adoption path of ECT where satisfaction acts as a key mediator between prior evaluations and future behavioral intentions. The trend shows that users have a higher tendency to perceive long-term value and sustain the usage of chatbots in the Indonesian banking context when reliable and practical support is delivered by the technology.

The observations collectively show the robustness of ECT in explaining continuance usage intention in the context of AI-based chatbots. Theoretically, this research advances ECT by integrating reflective-formative constructs of chatbot quality and contributes

to the growing literature on post-adoption technology behavior. The rejected hypothesis of disclosure and chatbot quality suggests that trust-related constructs possibly do not operate continuously and uniformly across service domains.

The results provide practical, actionable insights for banks. For example, the adoption and long-term engagements with chatbots can be improved by ensuring banks prioritize performance-related dimensions, such as responsiveness, interactivity, and understandability, over non-functional features in the form of disclosure. It shows the need to allocate development resources toward enhancing conversation accuracy, contextual comprehension, and issue resolution speed.

IV. CONCLUSION

In conclusion, the research examined the effect of chatbot quality on user satisfaction and the intention to continue using chatbot services in the context of the Indonesian banking industry. The ECT is used as the guide to assess the five core dimensions of chatbot quality (assurance, interactivity, reliability, responsiveness, and understandability) and their relationship to perceived usefulness, confirmation, and overall user satisfaction. The results show that chatbot quality significantly improves both perceived usefulness and confirmation which subsequently and positively influence satisfaction and continuance usage intention. User satisfaction is identified as the most influential factor driving continuance usage intention compared to the other paths analyzed. It emphasizes the importance of delivering chatbot experiences that function effectively and meet or exceed user expectations. Confirmation also shows a strong positive relationship with satisfaction. The trend suggests that chatbots have a better tendency for continuous usage when the interactions are in line with the expectations of users. Interestingly, chatbot disclosure is often perceived to increase user trust by showing that the interaction is with an AI, but it does not have a significant impact on perceived quality. It is a sign that users can value performance and efficiency over transparency in a goal-oriented context such as banking. The phenomenon reflects that functionality remains supreme in shaping perceptions of quality.

The results emphasize the central importance of chatbot quality in determining user experience and technology adoption. The analysis shows that key quality attributes, such as interactivity, reliability, and responsiveness, influence perceived usefulness and satisfaction and serve as foundational drivers of continuance usage intention. Satisfaction is identified as the most potent mediator reflecting that positive user

experiences require technical capabilities. The consistency of these effects suggests that users evaluate the performance of chatbots through both functional outcomes and affective impressions. Quality is considered very important in fostering sustained engagement of users with chatbots specifically in high-trust service environments such as banking.

The research contributes to the growing literature on AI-mediated service interactions. It also provides actionable insights for banks aiming to enhance digital service strategies. Practitioners are motivated to focus on refining interaction design, improving natural language comprehension, and ensuring consistency in service delivery.

Several limitations are identified despite the contributions. However, these limitations ensure opportunities for future studies. First, data are collected through a cross-sectional survey in the Indonesian banking sector which limits the generalizability of results across other industries or cultural contexts. Second, the study does not assess awareness of users about disclosure timing, and it can influence perceptions differently. Lastly, the use of self-reported data is capable of introducing response bias.

Future studies should integrate trust, perceived security, and social presence as potential moderators to explore the conditions for disclosure to become salient. Furthermore, longitudinal or cross-industry comparative studies can further validate the boundary conditions of chatbot quality perception. Future studies should incorporate behavioral or usage data to validate the results.

AUTHOR CONTRIBUTION

Conceived and designed the analysis, A. I., S. T., T. B. A., and A. M. S.; Collected the data, A. I., S. T., and T. B. A.; Contributed data or analysis tools, A. I., S. T., T. B. A., and A. M. S.; Performed the analysis, A. I., S. T., and A. M. S.; and Wrote the paper, A. I., S. T., T. B. A., and A. M. S.

DATA AVAILABILITY

The data that support the findings of the research are openly available in Zenodo at <https://zenodo.org/records/15541374>.

REFERENCES

- [1] V. Kaushal and R. Yadav, "Learning successful implementation of chatbots in businesses from B2B customer experience perspective," *Concurrency and Computation: Practice and Experience*, vol. 35, no. 1, 2023.
- [2] R. M. Qadiri, N. Shabir, and M. Qadri, "Conceptualizing possibilities of artificial intelligence in furtherance of the banking sector: An effective tool for improving customer relationship, customer service and public relations," *International Journal of Finance, Insurance and Risk Management*, vol. 10, no. 2, pp. 44–65, 2020.
- [3] D. Doherty and K. Curran, "Chatbots for online banking services," *Web Intelligence*, vol. 17, no. 4, pp. 327–342, 2019.
- [4] D. M. Nguyen, Y. T. H. Chiu, and H. D. Le, "Determinants of continuance intention towards banks' chatbot services in Vietnam: A necessity for sustainable development," *Sustainability*, vol. 13, no. 14, pp. 1–24, 2021.
- [5] A. Kwangsawad and A. Jattamart, "Overcoming customer innovation resistance to the sustainable adoption of chatbot services: A community-enterprise perspective in Thailand," *Journal of Innovation & Knowledge*, vol. 7, no. 3, pp. 1–13, 2022.
- [6] J. S. Chen, T. T. Y. Le, and D. Florence, "Usability and responsiveness of artificial intelligence chatbot on online customer experience in e-retailing," *International Journal of Retail & Distribution Management*, vol. 49, no. 11, pp. 1512–1531, 2021.
- [7] M. Li and R. Wang, "Chatbots in e-commerce: The effect of chatbot language style on customers' continuance usage intention and attitude toward brand," *Journal of Retailing and Consumer Services*, vol. 71, 2023.
- [8] M. Adam, M. Wessel, and A. Benlian, "AI-based chatbots in customer service and their effects on user compliance," *Electronic Markets*, vol. 31, no. 2, pp. 427–445, 2021.
- [9] E. M. Safitri, A. Pratama, M. A. Furqon, I. R. Mukhlis, Agussalim, and A. Faroqi, "Interaction effect of system, information and service quality on intention to use and user satisfaction," in *2020 6th Information Technology International Seminar (ITIS)*. Surabaya, Indonesia: IEEE, Oct. 14–16, 2020, pp. 92–97.
- [10] Y. Ruan and J. Mezei, "When do AI chatbots lead to higher customer satisfaction than human front-line employees in online shopping assistance? Considering product attribute type," *Journal of Retailing and Consumer Services*, vol. 68, pp. 1–16, 2022.
- [11] L. Rajaobelina, S. Prom Tep, M. Arcand, and L. Ricard, "Creepiness: Its antecedents and impact on loyalty when interacting with a chatbot," *Psychology & Marketing*, vol. 38, no. 12, pp.

- 2339–2356, 2021.
- [12] X. Cheng, Y. Bao, A. Zarifis, W. Gong, and J. Mou, "Exploring consumers' response to text-based chatbots in e-commerce: The moderating role of task complexity and chatbot disclosure," *Internet Research*, vol. 32, no. 2, pp. 496–517, 2022.
- [13] N. Mozafari, W. H. Weiger, and M. Hamerschmidt, "Trust me, i'm a bot—Repercussions of chatbot disclosure in different service front-line settings," *Journal of Service Management*, vol. 33, no. 2, pp. 221–245, 2022.
- [14] L. Li, K. Y. Lee, E. Emokpae, and S. B. Yang, "What makes you continuously use chatbot services? Evidence from Chinese online travel agencies," *Electronic Markets*, vol. 31, no. 3, pp. 575–599, 2021.
- [15] K. Klein and L. F. Martinez, "The impact of anthropomorphism on customer satisfaction in chatbot commerce: An experimental study in the food sector," *Electronic Commerce Research*, vol. 23, no. 4, pp. 2789–2825, 2023.
- [16] W. B. Kim and H. J. Hur, "What makes people feel empathy for AI chatbots? Assessing the role of competence and warmth," *International Journal of Human–Computer Interaction*, vol. 40, no. 17, pp. 4674–4687, 2024.
- [17] D. El-Shihy, M. Abdelraouf, M. Hegazy, and N. Hassan, "The influence of AI chatbots in fintech services on customer loyalty within the banking industry," *Future of Business Administration*, vol. 3, no. 1, pp. 16–28, 2024.
- [18] F. Y. Lee and T. J. Chan, "Establishing credibility in AI chatbots: The importance of customization, communication competency and user satisfaction," in *4th International Conference on Communication, Language, Education and Social Sciences (CLESS 2023)*. Melaka, Malaysia (Online): Atlantis Press, 2024, pp. 88–106.
- [19] J. Rhim, M. Kwak, Y. Gong, and G. Gweon, "Application of humanization to survey chatbots: Change in chatbot perception, interaction experience, and survey data quality," *Computers in Human Behavior*, vol. 126, 2022.
- [20] S. C. Silva, R. De Cicco, B. Vlačić, and M. G. Elmashhara, "Using chatbots in e-retailing—How to mitigate perceived risk and enhance the flow experience," *International Journal of Retail & Distribution Management*, vol. 51, no. 3, pp. 285–305, 2023.
- [21] A. M. Sundjaja, P. Utomo, and F. Colline, "The determinant factors of continuance use of customer service chatbot in indonesia e-commerce: Extended expectation confirmation theory," *Journal of Science and Technology Policy Management*, vol. 16, no. 1, pp. 182–203, 2025.
- [22] Y. Jiang, X. Yang, and T. Zheng, "Make chatbots more adaptive: Dual pathways linking human-like cues and tailored response to trust in interactions with chatbots," *Computers in Human Behavior*, vol. 138, 2023.
- [23] G. Park, M. C. Yim, J. Chung, and S. Lee, "Effect of AI chatbot empathy and identity disclosure on willingness to donate: The mediation of humanness and social presence," *Behaviour & Information Technology*, vol. 42, no. 12, pp. 1998–2010, 2023.
- [24] M. Ashfaq, J. Yun, S. Yu, and S. M. C. Loureiro, "I, chatbot: Modeling the determinants of users' satisfaction and continuance intention of AI-powered service agents," *Telematics and Informatics*, vol. 54, 2020.
- [25] I. Lubbe and N. Ngoma, "Useful chatbot experience provides technological satisfaction: An emerging market perspective," *South African Journal of Information Management*, vol. 23, no. 1, pp. 1–8, 2021.
- [26] F. A. Silva, A. S. Shojaei, and B. Barbosa, "Chatbot-based services: A study on customers' reuse intention," *Journal of Theoretical and Applied Electronic Commerce Research*, vol. 18, no. 1, pp. 457–474, 2023.
- [27] Y. Zhu, J. Zhang, J. Wu, and Y. Liu, "AI is better when I'm sure: The influence of certainty of needs on consumers' acceptance of AI chatbots," *Journal of Business Research*, vol. 150, pp. 642–652, 2022.
- [28] M. Chung, E. Ko, H. Joung, and S. J. Kim, "Chatbot e-service and customer satisfaction regarding luxury brands," *Journal of Business Research*, vol. 117, pp. 587–595, 2020.
- [29] C. L. Hsu and J. C. C. Lin, "Understanding the user satisfaction and loyalty of customer service chatbots," *Journal of Retailing and Consumer Services*, vol. 71, 2023.
- [30] R. Pillai, Y. Ghanghorkar, B. Sivathanu, R. Algharabat, and N. P. Rana, "Adoption of Artificial Intelligence (AI) based Employee Experience (EEX) chatbots," *Information Technology & People*, vol. 37, no. 1, pp. 449–478, 2024.
- [31] P. K. Tan and C. M. Lim, "Factors that affect user satisfaction of using e-commerce chatbot: A study on Generation Z," *International Journal of Business and Technology Management*, vol. 5, no. 1, pp. 292–303, 2023.
- [32] P. Singh and V. Singh, "The power of AI: Enhanc-

- ing customer loyalty through satisfaction and efficiency," *Cogent Business & Management*, vol. 11, no. 1, pp. 1–14, 2024.
- [33] H. Oppewal, "Causal research," in *Wiley International Encyclopedia of Marketing*. Wiley, 2010.
- [34] N. Rai and B. Thapa, *A study on purposive sampling method in research*. Kathmandu School of Law, 2015.
- [35] U. Sekaran and R. Bougie, *Research methods for business: A skill building approach*. John Wiley & Sons, 2016.
- [36] M. Sarstedt, J. F. Hair Jr, J. H. Cheah, J. M. Becker, and C. M. Ringle, "How to specify, estimate, and validate higher-order constructs in PLS-SEM," *Australasian Marketing Journal*, vol. 27, no. 3, pp. 197–211, 2019.
- [37] G. Shmueli, M. Sarstedt, J. F. Hair, J. H. Cheah, H. Ting, S. Vaithilingam, and C. M. Ringle, "Predictive model assessment in PLS-SEM: Guidelines for using PLSpredict," *European Journal of Marketing*, vol. 53, no. 11, pp. 2322–2347, 2019.
- [38] A. F. Hariansyah, S. Audre, J. Owen, and A. M. Sundjaja, "Unveiling the determinants of marketplace customer service chatbot continuous intention to use in Indonesia: A descriptive analysis," in *2023 International Conference on Informatics, Multimedia, Cyber and Informations System (ICIMCIS)*. Jakarta Selatan, Indonesia: IEEE, Nov. 7–8, 2023, pp. 452–457.
- [39] J. F. Hair, G. T. M. Hult, C. Ringle, and M. Sarstedt, *A primer on Partial Least Squares Structural Equation Modeling (PLS-SEM)*. SAGE Publications, 2016.
- [40] J. F. Hair, J. J. Risher, M. Sarstedt, and C. M. Ringle, "When to use and how to report the results of PLS-SEM," *European Business Review*, vol. 31, no. 1, pp. 2–24, 2019.
- [41] G. Shmueli, S. Ray, J. M. V. Estrada, and S. B. Chatla, "The elephant in the room: Predictive performance of PLS models," *Journal of business Research*, vol. 69, no. 10, pp. 4552–4564, 2016.
- [42] F. N. Shabrina, A. Anggraeni, A. S. Ramadhan, and S. Putra, "Negative emotions on a digital bank brand: How do scandals impact brand love?" in *2023 International Conference on Informatics, Multimedia, Cyber and Informations System (ICIMCIS)*. Jakarta Selatan, Indonesia: IEEE, Nov. 7–8, 2023, pp. 467–472.
- [43] D. Darmayanti and H. Cahyono, "The influence of perceived service quality, attitudinal loyalty and corporate social responsibility on repeat patronage intention in retail banking in indonesia," *Journal of Business and Retail Management Research*, vol. 8, no. 2, pp. 16–23, 2014.
- [44] A. F. Utami, I. A. Ekaputra, and A. Japutra, "Adoption of FinTech products: A systematic literature review," *Journal of Creative Communications*, vol. 16, no. 3, pp. 233–248, 2021.
- [45] V. Tohang, E. Lo, and A. Anggraeni, "Financial Technology 3.0 adoption in financial and non-financial institutions from modified UTAUT perspective," in *Conference on International Issues in Business and Economics Research (CIIBER 2019)*. Malang, Indonesia: Atlantis Press, 2021, pp. 1–6.

APPENDIX

The Appendix can be seen in the next page.

TABLE A1
QUESTIONNAIRE LIST.

Variable and Indicator	Statement
Disclosure	
DI1	It is important to me that the identity of the chatbot service is shown before the conversation begins.
DI2	The banking chatbot service I use hides the chatbot's identity.
DI3	I know the identity of the chatbot even before the conversation starts.
Assurance	
AS1	I trust the chatbot service.
AS2	I feel safe when using the chatbot service.
AS3	The chatbot service resolves my issue.
Interactivity	
IN1	My banking service needs can be met through chatbot services.
IN2	Chatbot services understand what I need during interactions.
IN3	The services enable feedback.
Reliability	
RL1	Chatbot services are reliable.
RL2	When faced with a problem, the service seems convincing.
RL3	I can rely on chatbot services to solve banking needs.
Responsiveness	
RS1	The chatbot system provides services that meet my expectations.
RS2	The chatbot service responds quickly to my request.
RS3	Chatbot provides service when needed.
Understandability	
UN1	I feel that the chatbot service understands my question.
UN2	I feel that the chatbot service understands my sentences.
UN3	I feel that the chatbot service understands my intentions.
Perceived Usefulness	
PU1	Using a chatbot increases productivity.
PU2	Using chatbots increases the effectiveness of activities.
PU3	I find chatbots useful in daily activities.
PU4	Using chatbots helps to get work done faster.
PU5	Using chatbots increases efficiency in problem resolution.
Confirmation	
CO1	My experience of using chatbot services is better than I have anticipated.
CO2	The chatbot service level agreement is better than I expect.
CO3	Most expectations when using chatbot services are anticipated.
Satisfaction	
SA1	I feel satisfied because the chatbot can answer to personal needs.
SA2	I am satisfied with the solution provided by the chatbot.
SA3	I am satisfied with the implementation of the chatbot system.
Continuance Usage Intention	
CI1	I prefer chatbot services over traditional services.
CI2	I hope to continue using this service in the future.
CI3	I will use chatbots more often if possible.