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THE MEDIATING ROLE OF CHATBOT INITIAL TRUST IN ENHANCING CUSTOMER LOYALTY, ENGAGEMENT, AND USAGE INTENTION

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ABSTRACT

In the digital era, chatbots have become essential tools for companies to enhance communication efficiency with customers, particularly through popular platforms such as WhatsApp. As the adoption of this technology increases, understanding the factors that shape users initial trust becomes crucial. This study aims to analyze the influence of perceived ease of use, compatibility, performance expectancy, social influence, and perceived risk on initial trust, as well as its impact on chatbot usage intention, customer engagement, customer satisfaction, and customer loyalty. The research model was developed based on an integration of the Technology Acceptance Model (TAM), Unified Theory of Acceptance and Use of Technology (UTAUT), and Diffusion of Innovation (DOI), using a quantitative approach. A total of 223 respondents participated in a survey distributed to users of banking chatbots via WhatsApp in Indonesia. Data were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM). The results show that perceived ease of use and social influence have a significant positive effect on initial trust, while compatibility, performance expectancy, and perceived risk do not have a significant effect. However, performance expectancy was found to have a direct and significant influence on chatbot usage intention. Initial trust significantly influences usage intention, customer engagement, customer satisfaction, and customer loyalty. Furthermore, customer satisfaction also has a significant effect on customer loyalty.

Keywords: Chatbot, Customer Engagement, Customer Loyalty, Initial Trust, Perceived Risk, Usage Intention.

INTRODUCTION

The rapid advancement of artificial intelligence (AI) and natural language processing (NLP) technologies has revolutionized the way businesses interact with their customers. Among these innovations, chatbots have emerged as a transformative tool for customer service, particularly in the banking sector. Defined as software agents capable of simulating human-like conversations through text or voice interfaces (Abu Shawar & Atwell, 2007), chatbots are increasingly adopted to enhance operational efficiency, reduce service delivery costs, and improve user experience. In particular, banks across the globe have embraced chatbot technology to streamline customer support, provide real-time financial assistance, and facilitate transactions. In Indonesia, where digital banking adoption is growing rapidly, chatbots integrated into platforms such as WhatsApp have become a common channel for customer engagement. However, despite the technological advancements and increasing deployment, many users remain hesitant to fully adopt chatbot services due to concerns related to usability, trust, and perceived risk (Thusi & Maduku, 2020). Understanding the behavioral intentions behind chatbot usage is crucial for both academics and practitioners. Prior studies have explored factors influencing technology acceptance using frameworks such as the Technology Acceptance Model (TAM) (Davis, 1989), Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003), and Diffusion of Innovations (DOI) theory (Rogers, 1962). These models have been widely applied to examine user behavior toward various information systems but require further contextualization in the domain of AI-based conversational agents. This research extends existing theoretical frameworks by incorporating the concept of *initial trust* —a critical factor in early-stage interactions with unfamiliar technologies. Initial trust refers to the pre-interaction belief that a system will perform reliably and securely, even before substantial experience is gained (Corritore et al., 2003). In the context of chatbots, initial trust may mediate the relationship between key antecedents such as perceived ease of use, performance expectancy, compatibility, social influence, and perceived risk, and ultimate user behaviors such as usage intention, engagement, satisfaction, and loyalty. Moreover, while prior studies have examined trust as an outcome variable, this study positions it as a mediating construct, aligning with recent trends in

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digital service research (Jyothsna M et al., 2024; Alagarsamy & Mehrolia, 2023). This shift allows for a deeper understanding of how trust is formed during the initial interaction phase and how it influences subsequent behavioral outcomes.

LITERATURE REVIEW

Understanding user behavior toward chatbot adoption requires a solid theoretical foundation rooted in technology acceptance theories. This section reviews three major theoretical frameworks—Technology Acceptance Model (TAM), Unified Theory of Acceptance and Use of Technology (UTAUT), and Diffusion of Innovations (DOI)—that underpin this research. These models have been widely used to explain how users form intentions to adopt new technologies, especially in digital service environments such as banking.

Technology Acceptance Model (TAM)

The Technology Acceptance Model (TAM) was introduced by Davis (1989) as a simplified framework to predict user acceptance of information systems. TAM identifies two core constructs that influence behavioral intention: Perceived Usefulness (PU): The degree to which a person believes that using a particular system will enhance their job performance. Perceived Ease of Use (PEOU): The extent to which a person believes that using a system will be free of effort. In the context of chatbots, PEOU plays a critical role in shaping initial trust and usage intention. If users find chatbots difficult or confusing to interact with, they are less likely to engage with them consistently (Davis, 1989; Jyothsna et al., 2024). According to Sarkar et al. (2020), enhancing PEOU can reduce technological barriers and improve user experience. Zhou et al. (2010) further note that even minor usability issues can significantly affect user perceptions of chatbots. Davis (1989) also identified six dimensions of ease of use:

1. Easy to learn
2. Controllable
3. Clear and understandable
4. Flexible
5. Easy to become skilled
6. Easy to use

These dimensions are essential for chatbot design, particularly in customer-facing applications where simplicity and intuitiveness are key drivers of engagement.

Unified Theory of Acceptance and Use of Technology (UTAUT)

Venkatesh et al. (2003) proposed UTAUT as a comprehensive model integrating eight previous technology acceptance theories, including TAM and DOI. UTAUT posits four key constructs that determine behavioral intention and actual usage behavior: Performance Expectancy (PE): The degree to which an individual believes that using the technology will help them attain gains in job performance. Effort Expectancy (EE): The degree of ease associated with the use of the technology. Social Influence (SOS): The degree to which an individual feels that people who are important to them believe they should use the technology. Facilitating Conditions (FC): The degree to which an individual believes that organizational and technical infrastructure exists to support the use of the technology. Among these, PE and SOS are particularly relevant to chatbot adoption in banking contexts. PE reflects users' belief that chatbots can effectively assist in tasks like transaction processing, account inquiries, and customer support. SOS highlights the importance of peer recommendations or social norms in encouraging chatbot usage (Venkatesh et al., 2003; Alagarsamy & Mehrolia, 2023).

Diffusion of Innovation (DOI)

Rogers (1962) introduced the Diffusion of Innovation (DOI) theory to explain how, why, and at what rate new ideas and technologies spread within populations. DOI identifies five key attributes of innovation:

1. Relative Advantage
2. Compatibility
3. Complexity
4. Trialability
5. Observability

In this study, compatibility (COMP) is emphasized as a crucial factor influencing chatbot adoption. COMP refers to the degree to which an innovation aligns with existing values, experiences, and needs of potential adopters (Rogers, 1962). In the case of WhatsApp-based banking chatbots, COMP is high because users are already familiar with the platform, making chatbot integration more seamless and acceptable (Shahzad et al., 2024). Zhou et al. (2010) argue that compatibility reduces cognitive load and increases perceived usefulness, both of which contribute to higher user satisfaction and loyalty.

Conceptualization of Trust in Chatbot Adoption

Trust is a critical determinant of user behavior in technology-mediated interactions, especially in early-stage adoption scenarios. Corritore et al. (2003) define initial trust as the pre-interaction belief in the reliability and integrity of a system before substantial experience has been gained. In the context of chatbots, initial trust serves as a foundational element that mediates the relationship between antecedent variables and behavioral outcomes such as usage intention, engagement, satisfaction, and loyalty. Jyothsna et al. (2024) emphasize that initial trust significantly influences chatbot usage intention and mediates the effects of PEOU, PE, COMP, and SOS. Their findings suggest that initial trust acts as a psychological bridge between user perceptions and behavioral responses. Similarly, Kaabachi et al. (2019) found that trust is a central determinant in mobile banking adoption, reinforcing its relevance in chatbot contexts.

Perceived Risk and Its Impact

Perceived risk (RISK) refers to the uncertainty or potential loss associated with adopting a new technology (Thusi & Maduku, 2020). In chatbot usage, RISK encompasses several dimensions: Financial Risk: Potential monetary losses due to errors or fraud. Privacy Risk: Concerns about data security and unauthorized access. Performance Risk: Doubts regarding the accuracy and effectiveness of chatbot responses. Alagarsamy & Mehrolia (2023) highlight that RISK negatively affects chatbot trust, thereby reducing usage intention and engagement. Therefore, mitigating perceived risks through transparency, secure authentication, and clear communication is vital for fostering chatbot adoption.

Customer Engagement, Satisfaction, and Loyalty

Beyond initial trust, this study also explores downstream behavioral outcomes such as customer engagement (CE), customer satisfaction (CS), and customer loyalty (LOY). These constructs are interrelated and collectively reflect the long-term value of chatbot adoption. Customer Engagement (CE): Refers to the emotional and behavioral investment users make in interacting with chatbots (Jennerboer et al., 2022). Customer Satisfaction (CS): Reflects the overall positive evaluation of chatbot services based on user expectations and experiences (Hsu & Lin, 2023). Customer Loyalty (LOY): Denotes the likelihood of continued use and advocacy of chatbot services (Shariffuddin et al., 2023). According to Widjaja et al. (2019), CS significantly predicts LOY, suggesting that improving chatbot satisfaction can enhance retention and brand advocacy. Initial trust also directly impacts CE and CS, indicating its pivotal role in shaping post-adoption behaviors.

This research builds upon previous empirical studies that have explored chatbot adoption and user behavior. Three key studies were selected as references: Jyothsna et al. (2024) conducted a quantitative study involving 271 students from Indian Higher Education Institutes. Using Partial Least Squares Structural Equation Modeling (PLS-SEM), they examined the mediating role of initial trust in chatbot usage intention. Their results confirmed that PEOU, PE, COMP, SOS, and initial trust significantly influence CUI. Additionally, initial trust fully mediated the relationships between these antecedents and usage intention. Alagarsamy & Mehrolia (2023) focused on chatbot trust among customers of four major banks in India. They extended the UTAUT model by incorporating chatbot-specific factors such as quality, risk, and trust. Findings revealed that perceived ease of use, perceived usefulness, and image positively influenced chatbot trust, which in turn affected usage intention, engagement, and satisfaction. Kaabachi et al. (2019) investigated the determinants of mobile banking adoption, emphasizing the role of trust. They found that initial trust had a direct and significant impact on usage intention, supporting its inclusion as a central construct in chatbot adoption research.

RESEARCH METHOD

This chapter outlines the research methodology adopted to investigate the factors influencing chatbot usage intention, with a particular focus on the mediating role of initial trust. The study integrates theoretical foundations from established technology acceptance models—namely the Technology Acceptance Model (TAM), Unified Theory of Acceptance and Use of Technology (UTAUT), and Diffusion of Innovations (DOI)—to develop a comprehensive conceptual model. A quantitative approach was employed, utilizing a structured questionnaire distributed to banking customers in Indonesia who use WhatsApp-based chatbots. The methodology is designed to ensure robustness in both measurement and structural model testing, adhering to best practices in PLS-SEM as outlined by Hair et al. (2021). This chapter details the research procedures, including instrument development, data collection, sampling strategy, and analytical techniques used to test the proposed hypotheses.

Conceptual Framework and Research Model

Building upon prior studies, particularly those by Jyothsna M et al. (2024) and Alagarsamy & Mehrolia (2023), this research develops an integrated conceptual model that examines the relationships between perceived ease of use (PEOU), compatibility (COMP), performance expectancy (PE), social influence (SOS), perceived risk (RISK), initial trust (TRST), chatbot usage intention (CUI), customer engagement (CE), customer satisfaction (CS), and customer loyalty (LOY). Initial trust is introduced as a central mediating construct, bridging the relationship between antecedent variables and behavioral outcomes. The research model is presented in

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Figure 1 and serves as the foundation for hypothesis development.

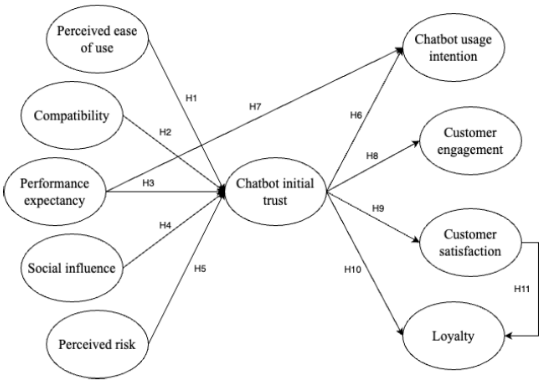

Figure 1. Conceptual Research Model

Hypothesis Development

Based on the conceptual model and supported by prior literature, the following hypotheses are formulated:

H1 : Perceived Ease of Use (PEOU) has a positive and significant effect on Initial Trust (TRST).

H2 : Compatibility (COMP) has a positive and significant effect on Initial Trust (TRST).

H3 : Performance Expectancy (PE) has a positive and significant effect on Initial Trust (TRST).

H4 : Social Influence (SOS) has a positive and significant effect on Initial Trust (TRST).

H5 : Perceived Risk (RISK) has a negative and significant effect on Initial Trust (TRST).

H6 : Initial Trust (TRST) has a positive and significant effect on Chatbot Usage Intention (CUI).

H7 : Performance Expectancy (PE) has a positive and significant effect on Chatbot Usage Intention (CUI).

H8 : Initial Trust (TRST) has a positive and significant effect on Customer Engagement (CE).

H9 : Initial Trust (TRST) has a positive and significant effect on Customer Satisfaction (CS).

H10 : Initial Trust (TRST) has a positive and significant effect on Customer Loyalty (LOY).

H11 : Customer Satisfaction (CS) has a positive and significant effect on Customer Loyalty (LOY).

These hypotheses form the basis for empirical testing using PLS-SEM.

Research Procedures

The research followed a sequential procedure comprising several stages: conceptualization and literature review, instrument design and validation, pilot testing (wording test and pre-test), main survey administration, and data analysis.

Instrument Design

The measurement items were adapted from validated scales in previous studies, ensuring content validity and reliability. Constructs such as PEOU, PE, COMP, SOS, RISK, TRST, CUI, CE, CS, and LOY were operationalized using multi-item Likert-type scales ranging from 1 (strongly disagree) to 5 (strongly agree). A wording test was conducted with five respondents to evaluate clarity and comprehensibility of the questionnaire items. Adjustments were made based on feedback to enhance item clarity and reduce ambiguity.

Pre-Testing

Following the wording test, a pre-test was administered to a small sample (n = 30) to assess the reliability and validity of the measurement instruments. Cronbach’s alpha and composite reliability values were calculated to confirm internal consistency.

Main Survey

The finalized questionnaire was distributed online via Google Forms to Indonesian banking customers who had interacted with WhatsApp-based chatbots. A total of 223 usable responses were collected, exceeding the minimum threshold required for PLS-SEM analysis.

Population and Sampling

The target population consisted of active banking customers in Indonesia who had experience using chatbots for financial inquiries or transactions. A convenience sampling method was employed due to practical constraints in accessing a broader audience. The sample size was determined based on guidelines from Hair et al. (2014), which suggest that a minimum of 10 times the largest number of structural paths pointing to a single latent variable is sufficient for PLS-SEM.

Data Collection

Data collection was conducted over a period of four weeks using an online survey platform. Participants were recruited through social media groups, university mailing lists, and bank-related forums. Informed consent was obtained from all participants, and anonymity was ensured to encourage honest responses.

Data Analysis Techniques

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Partial Least Squares Structural Equation Modeling (PLS-SEM) was selected as the primary analytical technique due to its suitability for exploratory research and its ability to handle complex models with multiple dependent variables (Hair et al., 2021). SmartPLS version 3.3.9 was used to perform the following analyses:

Measurement Model Assessment (Outer Model)

The measurement model was evaluated for Item reliability : Ensuring factor loadings above 0.7. Internal consistency reliability : Measured using Cronbach's Alpha (>0.6) and Composite Reliability (>0.7). Convergent validity : Verified through Average Variance Extracted (AVE > 0.5). Discriminant validity : Assessed using Fornell-Larcker criterion and cross-loadings.

Structural Model Assessment (Inner Model)

The structural model was tested to validate the hypothesized relationships among constructs. Bootstrapping with 5,000 resamples was performed to estimate path coefficients, t-values, and p-values. Significance levels were set at $p < 0.05$, $p < 0.01$, and $p < 0.001$ for different confidence intervals. Goodness-of-fit measures, including R^2 and Q^2, were also computed to evaluate the model's explanatory and predictive power.

RESULT AND DISCUSSION

This chapter presents a comprehensive analysis of the data collected to test the research hypotheses formulated in Chapter 3. The study employed Partial Least Squares Structural Equation Modeling (PLS-SEM) using SmartPLS version 3.3.9, which is particularly suitable for exploratory research involving complex relationships among latent constructs (Hair et al., 2021). The primary aim of this chapter is to evaluate the measurement model's reliability and validity, assess the structural model's fit and predictive relevance, and validate the hypothesized relationships between key constructs such as perceived ease of use (PEOU), compatibility (COMP), performance expectancy (PE), social influence (SOS), perceived risk (RISK), initial trust (TRST), chatbot usage intention (CUI), customer engagement (CE), customer satisfaction (CS), and customer loyalty (LOY).

The data were collected from 223 respondents who had experience using WhatsApp-based banking chatbots in Indonesia. This sample size was sufficient to meet the minimum requirements for PLS-SEM analysis, ensuring adequate statistical power for hypothesis testing. The following sections detail the analytical procedures and findings, beginning with an assessment of the measurement model, followed by an evaluation of the structural model, and concluding with the results of hypothesis testing.

Measurement Model Evaluation

Prior to conducting structural model analysis, it was essential to ensure that all measurement items adequately represented their respective constructs. The measurement model was assessed through several criteria, including item reliability, internal consistency, convergent validity, and discriminant validity.

Item Reliability

Item reliability was evaluated by examining factor loadings for each indicator. As recommended by Hair et al. (2021), indicators with factor loadings below 0.7 should be considered for removal. In this study, all indicators exceeded this threshold, confirming strong item reliability. For instance, the factor loading for TRST_6a was 0.767, while SOS_4c had a loading of 0.570, which remained above the acceptable cutoff after careful consideration of its theoretical importance.

Internal Consistency

Internal consistency was measured using Cronbach's Alpha and Composite Reliability (CR). Cronbach's Alpha values greater than 0.6 and CR values above 0.7 are generally considered acceptable (Hair et al., 2014). Table 1 confirms that all constructs met these thresholds:

Table 1. Reliabilty

Construct	Conbrach's Alpha	Composite Reability
PEOU	0.708	0.812
COMP	0.770	0.841
PE	0.884	0.911
SOS	0.703	0.789
RISK	0.812	0.864
TRST	0.790	0.876
CUI	0.911	0.931
CE	0.742	0.832
CS	0.921	0.941
LOY	0.796	0.855

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Convergent Validity

Convergent validity was established by computing the Average Variance Extracted (AVE) for each construct. An AVE value greater than 0.5 indicates that the construct explains more than half of the variance in its indicators (Hair et al., 2021). All constructs achieved AVE values above this threshold, supporting convergent validity.

Discriminant Validity

Discriminant validity was assessed using three methods: Fornell-Larcker criterion, cross-loadings, and HTMT ratio. According to the Fornell-Larcker criterion, the square root of the AVE for each construct should be higher than its correlations with other constructs. Table 4.10 confirms that this condition was satisfied for all constructs. Cross-loadings also showed that each indicator loaded more strongly on its own construct than on any other, further confirming discriminant validity. Additionally, the HTMT ratios were all below the recommended threshold of 0.90 (Henseler et al., 2015), indicating that the constructs are distinct from one another.

Structural Model Evaluation

Collinearity Assessment

Collinearity among the exogenous constructs was assessed using the Variance Inflation Factor (VIF). VIF values below 5.0 suggest that multicollinearity is not a concern (Hair et al., 2021). All VIF values in this study were within the acceptable range, indicating no significant collinearity issues.

Goodness-of-Fit Measures

The structural model was evaluated using several fit indices:

R^2 (Coefficient of Determination): Indicates the proportion of variance explained in endogenous constructs. The R^2 values were as follows: Customer Engagement (CE): 0.387. Customer Satisfaction (CS): 0.381. Chatbot Usage Intention (CUI): 0.543. Loyalty (LOY): 0.574. Initial Trust (TRST): 0.362

These values suggest moderate to high explanatory power, particularly for CUI and LOY. Q^2 (Predictive Relevance): Measured using the blindfolding procedure. Q^2 values above zero indicate predictive relevance. The Q^2 values were CE: 0.236. CS: 0.226. CUI: 0.326. LOY: 0.346. TRST: 0.174. All constructs demonstrated predictive relevance.

Hypothesis Testing

To test the proposed hypotheses, bootstrapping with 5,000 subsamples was performed to estimate path coefficients, t-values, and p-values. Hypotheses were considered statistically significant if the p-value was less than 0.05 and the t-value exceeded 1.96 at the 5% significance level.

The results of the hypothesis testing are summarized in the table at the end of this chapter. Of the eleven hypotheses tested

Specifically H1 (PEOU → TRST): Supported ($\beta = 0.419$, $p < 0.001$). H2 (COMP → TRST): Not supported ($\beta = 0.167$, $p = 0.081$). H3 (PE → TRST): Not supported ($\beta = 0.032$, $p = 0.727$). H4 (SOS → TRST): Supported ($\beta = 0.134$, $p = 0.036$). H5 (RISK → TRST): Not supported ($\beta = -0.140$, $p = 0.122$). H6 (TRST → CUI): Supported ($\beta = 0.386$, $p < 0.001$). H7 (PE → CUI): Supported ($\beta = 0.483$, $p < 0.001$). H8 (TRST → CE): Supported ($\beta = 0.622$, $p < 0.001$). H9 (TRST → CS): Supported ($\beta = 0.617$, $p < 0.001$). H10 (TRST → LOY): Supported ($\beta = 0.301$, $p < 0.001$). H11 (CS → LOY): Supported ($\beta = 0.534$, $p < 0.001$).

These findings provide empirical support for the central role of initial trust (TRST) in mediating the relationship between technology acceptance factors and behavioral outcomes such as chatbot usage intention, customer engagement, customer satisfaction, and loyalty. Initial trust was significantly influenced by perceived ease of use and social influence, but not by compatibility, performance expectancy, or perceived risk. These results suggest that users' initial perceptions of usability and social norms play a more critical role in building trust than functional benefits or risk concerns. Customer satisfaction emerged as a strong predictor of loyalty, reinforcing the importance of positive user experiences in sustaining long-term engagement with chatbots. Similarly, initial trust had a direct and substantial effect on both engagement and satisfaction, highlighting its strategic importance in chatbot design and deployment.

This chapter presented the comprehensive results of data analysis and hypothesis testing using PLS-SEM. The measurement model demonstrated strong reliability and validity, while the structural model revealed significant relationships among key constructs. Initial trust was confirmed as a critical mediator linking technology acceptance factors to behavioral outcomes.

Table 2. Hypothesis Testing

Hypothesis	Path Coefficient	T-value	p-value	Decision
H1	0.419	4.586	0.000	Accepted
H2	0.167	1.747	0.081	Rejected
H3	0.032	0.349	0.727	Rejected
H4	0.134	2.103	0.036	Accepted
H5	-0.140	1.547	0.122	Rejected
H6	0.386	7.008	0,000	Accepted
H7	0.483	7.409	0,000	Accepted
H8	0.622	11.663	0,000	Accepted
H9	0.617	12.186	0,000	Accepted
H10	0.301	4.012	0,000	Accepted
H11	0.534	7.755	0,000	Accepted

CONCLUSION

This study examined the factors influencing chatbot usage intention with a focus on the mediating role of initial trust. Drawing from TAM, UTAUT, and DOI theories, the research integrated key constructs such as perceived ease of use, performance expectancy, compatibility, social influence, perceived risk, customer engagement, customer satisfaction, and customer loyalty.

Data were collected from 223 banking customers in Indonesia who had experience using WhatsApp-based chatbots. Using PLS-SEM, eleven hypotheses were tested to determine the relationships between variables.

The findings revealed that initial trust plays a significant mediating role in shaping chatbot adoption behavior. Specifically Perceived ease of use and social influence significantly enhance initial trust. Initial trust has a strong positive effect on chatbot usage intention, customer engagement, customer satisfaction, and customer loyalty. Performance expectancy directly influences chatbot usage intention. Compatibility , performance expectancy , and perceived risk did not show statistically significant effects on initial trust in this context. Customer satisfaction was confirmed as a strong predictor of customer loyalty . These results contribute both theoretically and practically by extending existing models with initial trust as a central mediator and offering insights for improving chatbot design and user experience in digital banking.

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