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Chatbot Adoption in Indonesian Banking: Exploring the Roles of Trust and Corporate Reputation

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Abstract

The advancement of artificial intelligence (AI) has significantly transformed the financial services sector, particularly in banking. One of the most widely adopted applications is the chatbot, which enables banks to deliver faster, more efficient, and responsive customer service through automated interactions. Despite its growing implementation, public acceptance of chatbot technology remains varied. Users tend to evaluate these systems not only based on how useful or easy they are to use, but also on how much they trust the system and the organization behind it. This study explores the factors that drive users' behavioral intention to use banking chatbots by modifying the Technology Acceptance Model (TAM) to incorporate trust in the chatbot system and corporate reputation. The model incorporates perceived ease of use, perceived usefulness, trust in chatbot, and corporate reputation. Data were gathered through an online survey involving 111 respondents who had prior experience using banking chatbot services. Using Partial Least Squares Structural Equation Modeling (PLS-SEM), reveal that perceived ease of use significantly predicts perceived usefulness, while corporate reputation strongly influences trust. Furthermore, both perceived usefulness and trust are found to be significant predictors of behavioral intention to use banking chatbots. Trust also exerts a notable effect on perceived usefulness. These findings suggest that fostering user trust and managing institutional reputation are critical in promoting the sustainable adoption of AI-driven financial technologies. Banks are encouraged to focus not only on improving the technical features of chatbot systems but also on strengthening their credibility and transparency to enhance user confidence and perceived utility.

Keywords: chatbot, digital banking, artificial intelligence (AI), technology acceptance model (TAM), trust, corporate reputation

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1. Introduction

The development of artificial intelligence (AI) technology has driven digital transformation across various sectors, including the banking and financial services industry. Globally, spending on AI-based systems reached \$154 billion in 2023, with the banking sector accounting for the largest portion of this investment, totaling \$20.6 billion (Thormundsson, 2024). In the financial domain, AI has been integrated into various services, including chatbots, robo-advisors, automated credit scoring systems, fraud detection mechanisms, and investment recommendation platforms.

Among these applications, chatbots stand out as a prominent implementation of AI, functioning as virtual assistants with text- and voice-based interfaces to support fast, efficient, and 24/7 customer service (Anaya et al., 2024; Doherty & Curran, 2019; Oyeniyi et al., 2024).

In Indonesia, numerous banks such as BRI, BNI, Mandiri, and BCA have adopted chatbots (e.g., Sabrina, Cinta, Mita, and Vira) to enhance service quality and meet the digital needs of customers (Aji et al., 2023). A 2023 survey found that 59% of Indonesian respondents expressed a willingness to use chatbots for customer service, highlighting the potential of AI technology in the country's financial sector (Siahaan, 2024). The presence of chatbots offers numerous benefits, including enhanced customer satisfaction (Eren, 2021; Wiliam et al., 2019), operational efficiency (Doherty & Curran, 2019), and personalized services (Aji et al., 2023). However, chatbot adoption also presents serious challenges, particularly concerning data privacy, user trust, and technological fit (Abdallah et al., 2023; Gemihartono, 2024; Mahury & Arief, 2024).

Banking remains the most widely utilized financial service among Indonesians. According to the 2022 National Survey on Financial Literacy and Inclusion, banking inclusion reached 74.03%, significantly surpassing insurance (16.63%) and financing institutions (16.13%) (antaranews, 2024; OJK, 2022). In the Indonesian context, users' hesitation to adopt chatbots is often tied to perceived risks, especially data privacy and security issues (Gemihartono, 2024). Meanwhile, trust emerges as a crucial enabler, shaped not only by the chatbot's technical performance but also by users' perception of whether the system acts in their best interests and upholds information integrity (Aji et al., 2023; Sanny et al., 2020). An equally influential factor is the corporate reputation of the institution behind the chatbot. Research indicates that institutions with a credible image, transparency, and a proven track record in data protection are more likely to earn user trust in AI-based applications like chatbots (Abdallah et al., 2023; Gemihartono, 2024).

Although prior studies have explored several predictors of chatbot adoption—including perceived usefulness, perceived ease of use, and trust—only a limited number have examined how institutional-level factors, particularly corporate reputation, interact with user trust to shape adoption in Indonesia's banking sector. Moreover, existing literature has not sufficiently addressed the dual role of trust as both a direct determinant of behavioral intention and an antecedent of perceived usefulness. This study addresses these gaps by extending the Technology Acceptance Model (TAM) to incorporate trust in chatbot systems and corporate reputation, offering a more comprehensive understanding of factors driving chatbot adoption in Indonesian banking services.

The Technology Acceptance Model (TAM) serves as the theoretical foundation of this research and is extended to examine consumer intention in chatbot usage. Past research has compared different behavioral models for technology adoption and found TAM to remain relevant, with predictive accuracy for intention to use exceeding 50% in several cases (Ahmed & Ward, 2016; Cheng, 2019; M. M. Rahman et al., 2017; Rejali et al., 2023; Rondan-Cataluña et al., 2015). Although UTAUT and UTAUT2 may show stronger predictive capabilities in some contexts, studies by Ahmed & Ward (2016), Rahman et al. (2017), Rondan-Cataluña et al. (2015), and Rejali et al. (2023) show that the Technology Acceptance Model (TAM) still maintains a predictive strength exceeding 50% for behavioral intention to use. The findings of this study are expected to

provide insights for banks and chatbot developers to optimize chatbot adoption in enhancing digital service delivery, particularly within the banking sector.

The literature on banking chatbot adoption reveals that most previous studies have primarily concentrated on technical and individual-level factors of user behavior, such as perceived ease of use, perceived usefulness, and trust in the system. However, as illustrated in the literature matrix (see Table 1), a growing body of research highlights the importance of incorporating institutional and social dimensions when analyzing users’ intentions to adopt AI-based technologies. This is particularly relevant in the context of emerging economies, where institutional reputation continues to serve as a key determinant in fostering public trust in digital technologies (Li et al., 2022; Nguyen et al., 2022; Sundjaja et al., 2024).

Tabel 1. Literature Review

Authors	Focus	Key Findings	Variables
Flavián et al. (2005)	Role of corporate reputation in online behavior	Reputation influences loyalty through trust	Corporate Reputation, Trust, Loyalty
Doherty & Curran (2019)	Banking chatbots and customer satisfaction	Chatbots improve user efficiency and satisfaction	Perceived Usefulness, Behavioral Intention
Silitonga & Isbah (2023)	Chatbot adoption in Indonesian banks	Younger generations are more inclined to use chatbots	PEOU, Trust, Behavioral Intention
Gemihartono (2024)	Factors influencing chatbot adoption in banking	Trust and perceived data risk affect usage intention	Trust, Perceived Risk, Intention
Nguyen et al. (2022)	Corporate reputation and trust in AI	Corporate reputation affects trust in digital services	Corporate Reputation, Trust
Sheth et al. (2022)	AI in banking	Experience and ease of use influence usage intention	Perceived Ease of Use, Perceived Usefulness, Behavioral Intention
Li et al. (2022)	AI in service encounters	Misalignment between service schemes and AI use may reduce trust and satisfaction, but high corporate reputation can mitigate this effect	Trust, Service Satisfaction, Corporate Reputation
Mei et al. (2024)	AI-based services in financial contexts	Perceived usefulness and ease of use drive usage intention, especially when AI systems demonstrate social presence	Perceived Usefulness, Perceived Ease of Use, Perceived Social Presence, Usage Intention
Yanti et al. (n.d.)	Chatbots in digital banking services	User trust is the most dominant factor in repeated use of banking chatbots	Perceived Ease of Use, Perceived Security, Trust, Behavioral Intention
Rahman et al. (2023)	AI technology adoption in Malaysian banking	Trust and perceived risk are the key predictors of AI adoption	Perceived Risk, Perceived Trust, Perceived Usefulness, Perceived Ease of Use, Awareness, Subjective Norms, Knowledge in Technology, Attitude toward AI, Intention to Use AI

Gemihartono (2024) and Mahury & Arief (2024) highlight that customers remain hesitant to entrust their personal data to chatbots, particularly when a bank’s reputation is weak, or its systems lack transparency. Yanti et al. (2024) further found that trust is more strongly influenced by perceptions of institutional reputation than by the chatbot’s technical features alone. Meanwhile, Sheth et al. (2022) and Mei et al. (2024) emphasize the critical role of user experience in driving chatbot adoption, underscoring that a positive experience serves as the essential bridge between initial

perceptions of the technology and the decision to continue using it. Notably, Rahman et al. (2023) and Flavián et al. (2005) demonstrate that corporate reputation not only shapes trust but also strengthens user loyalty—especially in sensitive service contexts such as finance and healthcare. These findings collectively provide a solid rationale for including corporate reputation as a key variable in studying chatbot adoption within Indonesian banking. By modifying the original Technology Acceptance Model (TAM), the proposed research model is illustrated in Figure 1.

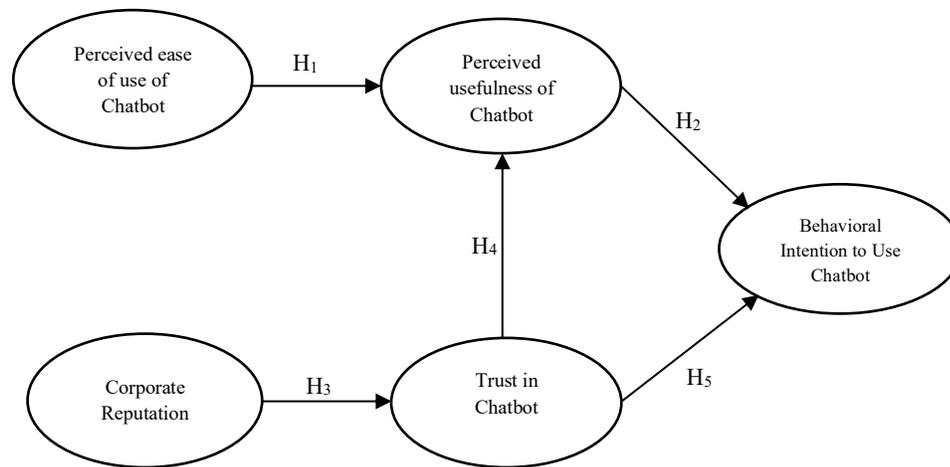


Figure 1. Purposed research framework

1.1 Perceived Ease of Use of Chatbot

Perceived ease of use (PEOU) refers to the degree to which an individual believes that utilizing a particular system will require minimal effort (Davis, 1989). In the context of banking chatbots, this perception encompasses features such as an intuitive user interface, comprehensible language, and prompt system responses. A study by Sanny et al. (2020) demonstrated that ease of use significantly influences users' perceptions regarding the usefulness of chatbots in performing banking-related tasks. This is further supported by research conducted by Richad et al. (2019), which highlights that younger generations are more inclined to adopt new technologies when they find them easy to access and operate without experiencing discomfort or technical barriers. These findings reinforce the importance of ease of use as a precursor to perceived usefulness. Accordingly, it is hypothesized that perceived ease of use has a positive influence on the perceived usefulness of banking chatbots (H1).

1.2 Perceived Usefulness of Chatbot

Perceived usefulness (PU) refers to the belief that using a particular system will enhance an individual's performance or outcomes (Davis, 1989). In the context of banking chatbots, PU is associated with the extent to which the technology assists users in completing transactions or accessing information in a timely and accurate manner. A study by Doherty & Curran (2019) revealed that higher levels of perceived usefulness are positively linked to users' intentions to continue utilizing chatbot services in banking. Similar findings are reported by Sheth et al. (2022) and Sundjaja et al. (2024), both of whom identify PU as a key predictor of behavioral intention.

Based on these insights, it is hypothesized that perceived usefulness positively influences users' behavioral intention to use banking chatbots (H2).

1.3 Corporate Reputation

Corporate reputation refers to the public's collective perception of a company's credibility, reliability, and core values. In the context of digital services such as chatbots—particularly in the highly security-sensitive financial sector—corporate reputation plays a pivotal role in shaping users' trust. Previous studies by Nguyen et al. (2022) and Flavián et al. (2005) emphasized that corporate reputation not only has a direct effect on trust but also indirectly influences behavioral intention and customer loyalty. Adding to this perspective, Li et al. (2022) explored how corporate reputation mediates the relationship between digital service quality and consumers' behavioral intentions. Their findings suggest that a strong and positive reputation can mitigate users' perceived risks associated with technology, thereby enhancing trust and willingness to adopt AI-based systems. Within the Indonesian banking landscape, corporate reputation carries significant symbolic weight. Research by Sundjaja et al. (2024) and Gemihartono (2024) confirms that customers are more inclined to trust and interact with chatbots offered by banks with a proven track record in digital security, service transparency, and social responsibility. Accordingly, it is hypothesized that corporate reputation positively influences users' trust in banking chatbots (H3).

1.4 Trust in Chatbot

Trust, in the context of chatbot usage, refers to the extent to which users believe that the system will function reliably, safeguard personal data, and act in their best interest. Gemihartono (2024) found that trust directly contributes to users' perceptions of usefulness; when individuals place trust in a chatbot system, they are more likely to view it as a genuinely helpful tool. Similarly, Eren (2021) research in the Turkish banking sector confirmed that trust in chatbot systems enhances perceived usefulness, as users feel more secure conducting financial activities through automated assistance. Trust also plays a critical role in shaping users' behavioral intentions to use chatbots. Studies by Nguyen et al. (2022) and Patil et al. (2024) emphasize that in AI-driven services, trust serves as a foundational element in human-machine interaction—particularly when sensitive data such as financial information is involved. Supporting this view, Silitonga & Isbah (2023) found that low levels of trust in system security remain a major barrier to chatbot adoption in Indonesia, even among users who acknowledge the potential benefits of such technology. Therefore, we hypothesize that trust in chatbots positively influences both perceived usefulness (H4) and behavioral intention to use chatbots (H5).

2. Method

This study is quantitative research that aims to examine a conceptual model of chatbot adoption in Indonesian banking services (see Figure 1). The primary focus of this research is to analyze the influence of perceived ease of use and perceived usefulness on behavioral intention to use chatbots, as well as to explore the roles of trust and corporate reputation as determinants in shaping such intention. Sample size determination refers to the guidelines of Hair et al. (2017), which recommend a minimum of 100–200 respondents for Structural Equation Modeling (SEM). The unit of analysis in this study is individual users of banking chatbots in Indonesia. The sample consisted of 111 respondents who had prior experience using customer service chatbots from Indonesian banks. A non-probability sampling technique, specifically purposive sampling, was employed to ensure that only individuals who had interacted with banking chatbots were included

in the analysis. This approach aligns with the study’s objective of examining user perceptions based on actual usage experience. The research instrument is a questionnaire consisting of two sections. The first section collects demographic information of respondents, while the second section measures their perceptions of the studied variables. The questionnaire items were developed based on previous studies and translated into Indonesian. All items were measured using a 7-point Likert scale, ranging from "1 = strongly disagree" to "7 = strongly agree". The research procedure began by identifying and defining the problem, followed systematically by stages that led to drawing conclusions and providing recommendations. Figure 2 visually illustrates the procedural steps followed in this study.

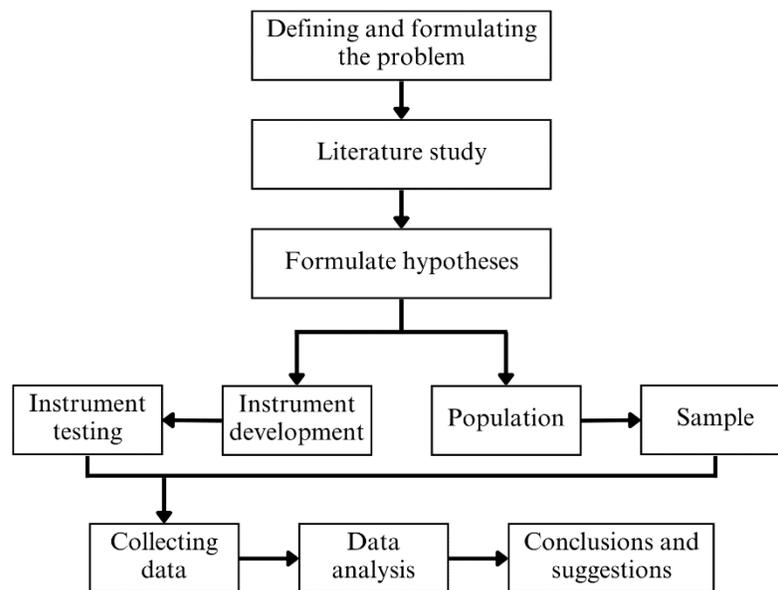


Figure 2. Stages of the Research Process

As shown in Table 1, the majority of participants were male (60.36%). Most respondents had completed senior high school as their highest level of education (54.95%), and the student group represented the largest proportion of occupations (54.05%).

Tabel 1. Demographic Profile of Respondents

Demographic Variable	Category	Frequency	Percentage (%)
Gender	Male	67	60.36%
	Female	44	39.63%
Age	17–22	63	56.76%
	23–28	10	9.01%
	>29	38	34.23%
Education	Doctoral Degree	3	2.70%
	Master’s Degree	2	1.80%
	Bachelor’s Degree	35	31.53%
	Diploma or equivalent	6	5.41%
	Senior High School or equivalent	61	54.95%
	Junior High School or equivalent	2	1.80%
	Elementary School or equivalent	2	1.80%

Demographic Variable	Category	Frequency	Percentage (%)
Occupation	Student	60	54.05%
	Housewife	14	12.61%
	Entrepreneur	14	12.61%
	Other Occupations	23	20.73%

3. Result and Discussion

The proposed model was tested using the Partial Least Squares Structural Equation Modeling (PLS-SEM) approach, implemented with the SmartPLS 4 software. PLS-SEM comprises two key components: the measurement model, which describes how the observed variables represent their respective constructs, and the structural model, which illustrates the relationships among the constructs (Hair et al., 2017).

The measurement model was assessed by evaluating internal reliability, convergent validity, and discriminant validity. The results of the measurement model analysis are presented in Table 2 and Table 2. Following the guidelines of Hair et al. (2017), all outer loading values ranged from 0.688 to 0.933. Furthermore, convergent validity at the construct level is typically determined through the Average Variance Extracted (AVE). As shown in Table 2, the AVE values for all constructs ranged from 0.682 to 0.826, well above the recommended threshold of 0.50. Therefore, the criterion for convergent validity was met in this study. In addition, Cronbach’s Alpha (CA) values ranged from 0.840 to 0.929, while Composite Reliability (CR) values ranged from 0.895 to 0.950. Both exceeded the commonly accepted minimum threshold of 0.70 (Hair et al., 2017). Collectively, these results demonstrate strong internal reliability for all constructs.

Table 2. Measurement Model Result

Construct	Adapted from	Loading	CR	Cronbach’s Alpha	AVE
Behavioral Intention to Use			0.948	0.926	0.819
IU1: I intend to use the chatbot for future banking transactions.	Silva et al. (2023)	0.880			
IU2: I will continue using the chatbot as part of my banking services.		0.933			
IU3: I will recommend this banking chatbot to others.		0.933			
IU4: The chatbot is my primary choice for accessing banking services.		0.872			
Perceived Ease of Use			0.895	0.840	0.682
PEOU1: The banking chatbot is easy to use for accessing services.	Wu et al. (2025)	0.901			
PEOU2: I can quickly understand how this chatbot works.		0.904			
PEOU3: Using the banking chatbot is not confusing.		0.792			
PEOU4: I do not need additional help to use the banking chatbot.		0.688			
Perceived Usefulness			0.944	0.920	0.809
PU1: The chatbot helps me complete banking transactions efficiently.	Wu et al. (2025)	0.871			
PU2: I feel that the chatbot makes it easier to access my account information.		0.932			
PU3: The chatbot makes banking services faster and more practical.		0.943			
PU4: The chatbot makes it easier for me to handle my banking needs whenever needed.		0.847			
Trust			0.941	0.916	0.799
TR1: I believe the chatbot can provide reliable banking services.	Silva et al. (2023)	0.868			

Construct	Adapted from	Loading	CR	Cronbach's Alpha	AVE
TR2: I am confident that the chatbot keeps my data confidential.		0.850			
TR3: I believe the chatbot provides accurate banking information.		0.926			
TR4: I feel comfortable interacting with the chatbot for my banking needs.		0.930			
Corporate Reputation			0.950	0.929	0.826
CR1: I believe this Bank has a better reputation compared to its competitors.	Özkan et al. (2020)	0.854			
CR2: I perceive this Bank as modern and technologically advanced.		0.939			
CR3: I am confident that this Bank continuously makes improvements.		0.931			
CR4: This Bank is superior and a pioneer among its competitors.		0.908			

Discriminant validity was assessed using the Heterotrait-Monotrait (HTMT) ratio, as presented in Table 3. All HTMT values between constructs were well below the conservative threshold of 0.90 and also fell beneath the more stringent threshold of 0.85 (Hair et al., 2017). Specifically, the HTMT value between Behavioral Intention to Use and Corporate Reputation was 0.623; between Perceived Usefulness and Perceived Ease of Use was 0.815; and between Trust and Behavioral Intention to Use was 0.838. These values collectively demonstrate strong discriminant validity for each construct within the model. Therefore, it can be concluded that the constructs are empirically distinct and sufficiently differentiated from one another, indicating the absence of measurement overlap.

Table 3. Heterotrait-Monotrait Ratio (HTMT)

Variable	Behavioral Intention to Use	Corporate Reputation	Perceived Ease of Use	Perceived Usefulness
Behavioral Intention to Use				
Corporate Reputation	0.623			
Perceived Ease of Use	0.719	0.699		
Perceived Usefulness	0.810	0.612	0.815	
Trust	0.838	0.739	0.667	0.783

The structural model evaluation is presented in Figure 3, Table 4, and Table 5. The R² (coefficient of determination) and Q² (predictive relevance) values summarized in Table 4 provide insight into the model's explanatory and predictive power. Specifically, the R² value for Behavioral Intention to Use is 0.677, indicating that Perceived Usefulness and Trust in chatbot collectively explain 67.7% of the variance in Behavioral Intention to Use. The R² value for Perceived Usefulness is 0.654, suggesting that Perceived Ease of Use and Trust account for 65.4% of its variance. Lastly, Trust in Chatbot shows an R² value of 0.479, indicating that Corporate Reputation explains 47.9% of its variance. Furthermore, the Q² values, which assess the model's predictive relevance for out-of-sample observations, are all greater than zero. The Q² for Behavioral Intention to Use is 0.397, for Perceived Usefulness is 0.512, and for Trust in Chatbot is 0.457. These positive Q² values confirm that the model exhibits adequate predictive relevance for the endogenous constructs, demonstrating its strong capability to explain the observed data.

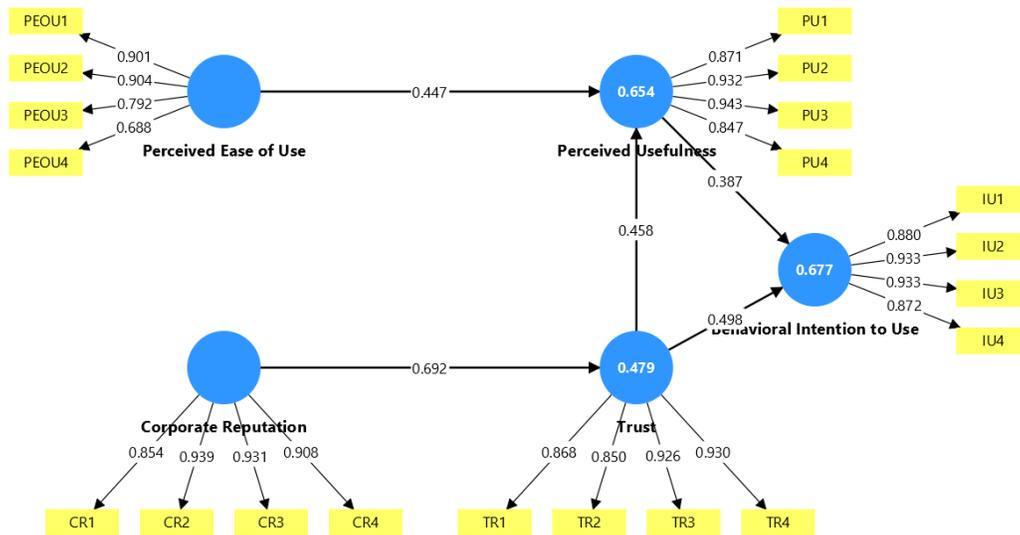


Figure 3. Structural Analysis Result

Tabel 4. Saturated model results

Construct	R-square	R-square adjusted	Q ²
Behavioral Intention to Use	0.677	0.671	0.397
Perceived Usefulness	0.654	0.648	0.512
Trust	0.479	0.474	0.457

Tabel 5. Path Coefficients

Hypotesis	Path	Beta	T-Statistics	P values	Decision
H ₁	Perceived Ease of Use → Perceived Usefulness	0.447	4.779	0.000	Supported
H ₂	Perceived Usefulness → Behavioral Intention to Use	0.387	3.790	0.000	Supported
H ₃	Corporate Reputation → Trust	0.692	10.772	0.000	Supported
H ₄	Trust → Perceived Usefulness	0.458	5.084	0.000	Supported
H ₅	Trust → Behavioral Intention to Use	0.498	4.548	0.000	Supported

The direct path analysis results, summarized in Table 5, indicate that all hypothesized relationships between the constructs are both positive and statistically significant. Perceived Ease of Use (PEOU) exerts a strong and positive effect on Perceived Usefulness (PU) ($\beta = 0.447$, $p < 0.001$), supporting the notion that user-friendly chatbots are more likely to be perceived as beneficial (H1 Supported). This finding reinforces the core tenet of the Technology Acceptance

Model (TAM), which posits that ease of use often precedes the perception of usefulness. The easier a system is to operate, the more likely users are to consider it valuable. In the Indonesian context, Sanny et al. (2020) further emphasize that seamless real-time interactions through natural language processing (NLP)-based interfaces have become a key driver in fostering chatbot acceptance.

Corporate Reputation significantly and positively influences Trust ($\beta = 0.692, p < 0.001$), indicating that a reputable corporate image enhances consumers' trust in chatbot services (H3 Supported). This is in line with broader literature asserting that reputation serves as a foundational element in developing trust in digital platforms. Eren (2021) and Škerháková et al. (2022) assert that a strong corporate image fosters user trust and satisfaction in chatbot usage. Within the banking sector, Eren (2021) found that users' trust in institutions is strongly shaped by perceptions of the institution's reputation and the performance of its digital services.

Both Perceived Usefulness ($\beta = 0.387, p < 0.001$) and Trust ($\beta = 0.498, p < 0.001$) exhibit significant positive effects on Behavioral Intention to Use, underscoring their central roles in influencing chatbot adoption (H2 and H5 Supported). These results corroborate prior research suggesting that users are more inclined to adopt technologies they perceive as both useful and trustworthy. This aligns with the findings of Sanny et al. (2020), who identified innovation, usefulness, and trust as critical predictors of user satisfaction and usage intention, particularly among younger generations. Similarly, Ramadhani et al. (2024), studying Shopee's chatbot, revealed that information quality, user experience, and response time significantly shape users' perceptions of usefulness and trust in the system.

Trust also has a significant positive influence on Perceived Usefulness ($\beta = 0.458, p < 0.001$) (H4 Supported), indicating that when users trust a chatbot, they are more likely to perceive it as useful. When users feel secure and confident in the chatbot's reliability, their evaluation of the system's utility tends to improve. This finding echoes Mahury & Arief (2024), who highlight the importance of emotional safety and data privacy when using chatbots—particularly in contexts involving personal or financial information. In line with this, Gemihartono (2024) underscores that transparent data governance and ethical approaches to AI are vital for building user trust, especially in the financial and legal service sectors in Indonesia.

4. Conclusion

This study provides a comprehensive analysis of the adoption of Artificial Intelligence (AI) in Indonesia's banking sector, with a particular emphasis on understanding consumer acceptance of chatbot services. By modifying the original Technology Acceptance Model (TAM), the research identifies key variables that significantly influence consumers' behavioral intention to use AI-based systems. The findings highlight the pivotal role of Corporate Reputation in fostering Trust in banking chatbots, suggesting that the institution's image plays a crucial role in encouraging digital adoption. Furthermore, Perceived Ease of Use was found to significantly influence Perceived Usefulness, consistent with TAM's core assumption that user-friendly systems enhance perceived benefits. Most importantly, Perceived Usefulness and Trust emerged as strong predictors of Behavioral Intention to Use, indicating that users are more likely to adopt chatbot services that are both functional and trustworthy. The positive effect of Trust on Perceived Usefulness further illustrates how confidence in the system enhances the perceived value of the service.

Overall, the study demonstrates that successful chatbot adoption is not solely dependent on technological utility but is shaped by the interaction between ease of use, organizational reputation, and user trust. As such, digital service providers should integrate these dimensions into the design of AI-driven services and their communication strategies to foster sustainable user engagement. These findings offer actionable insights for financial institutions and AI developers in Indonesia.

Understanding the interplay between ease of use, perceived usefulness, trust, corporate image, and generational characteristics is vital to developing effective chatbot strategies. By emphasizing usability, demonstrating tangible benefits, building trust through a reputable brand image, and tailoring approaches to meet generational preferences, banks can significantly enhance the acceptance and usage of AI-powered customer service solutions—ultimately improving operational efficiency and customer satisfaction in the digital banking era.

This study is limited to incorporating two additional variables—trust and corporate reputation—as modifications to the original Technology Acceptance Model (TAM). While the findings provide important insights, incorporating other relevant constructs in future research may enrich the understanding of factors influencing the acceptance of banking chatbots in a more comprehensive manner. Furthermore, this study does not segment respondents based on generational cohorts. This presents an opportunity and a challenge for subsequent research to explore whether the adoption of chatbot services differs across age groups. Considering that banking services are intended for users of all ages, future studies may benefit from analyzing generational differences in technology adoption behavior, especially since younger and older users may exhibit distinct attitudes and levels of digital readiness.

References

- Abdallah, W., Harraf, A., Mosusa, O., & Sartawi, A. (2023). Investigating Factors Impacting Customer Acceptance of Artificial Intelligence Chatbot: Banking Sector of Kuwait. *International Journal of Applied Research in Management and Economics*, 5(4), 45–58. <https://doi.org/10.33422/ijarme.v5i4.961>
- Ahmed, E., & Ward, R. (2016). A comparison of competing technology acceptance models to explore personal, academic and professional portfolio acceptance behaviour. *Journal of Computers in Education*, 3(2), 169–191. <https://doi.org/10.1007/s40692-016-0058-1>
- Aji, B. J. P. S., Masnita, Y., & Kurniawati. (2023). The Influence of Chatbot Anthropomorphism on Trust, Intention, and Engagement of Indonesian State-Owned Bank Customers: Investigation Using the DOI Theory. *INTERNATIONAL JOURNAL OF APPLIED BUSINESS RESEARCH*, 2023(2), 152–166. <https://doi.org/10.35313/ijabr.v5i02.293>
- Anaya, L., Braizat, A., & Al-Ani, R. (2024). Implementing AI-based Chatbot: Benefits and Challenges. In: *Procedia Computer Science. Elsevier B.V.*
- antaranews. (2024). *OJK catat indeks literasi keuangan di perbankan capai 64,05 persen*. <https://www.antaranews.com/berita/4240703/ojk-catat-indeks-literasi-keuangan-di-perbankan-capai-6405-persen>
- Cheng, E. W. L. (2019). Choosing between the theory of planned behavior (TPB) and the technology acceptance model (TAM). *Educational Technology Research and Development*, 67(1), 21–37. <https://doi.org/10.1007/s11423-018-9598-6>
- Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly: Management Information Systems*, 13(3), 319–339. <https://doi.org/10.2307/249008>
- Doherty, D., & Curran, K. (2019). Chatbots for online banking services. *Web Intelligence*, 17(4), 327–342. <https://doi.org/10.3233/WEB-190422>
- Eren, B. A. (2021). Determinants of customer satisfaction in chatbot use: evidence from a banking application in Turkey. *International Journal of Bank Marketing*, 39(2), 294–311. <https://doi.org/10.1108/IJBM-02-2020-0056>

- Flavián, C., Guinaliú, M., & Torres, E. (2005). The influence of corporate image on consumer trust: A comparative analysis in traditional versus internet banking. In *Internet Research* (Vol. 15, Issue 4, pp. 447–470). <https://doi.org/10.1108/10662240510615191>
- Gemihartono, I. (2024). Analysis of Personal Data Preservation Policy in Utilizing AI-Based Chatbot Applications in Indonesia. *Medium: Jurnal Ilmiah Fakultas Ilmu Komunikasi Universitas Islam Riau*, 12, 63–78.
- Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2017). A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM). Thousand Oaks. In *Sage*.
- Li, D., Liu, C., & Xie, L. (2022). How do consumers engage with proactive service robots? The roles of interaction orientation and corporate reputation. *International Journal of Contemporary Hospitality Management*, 34(11), 3962–3981. <https://doi.org/10.1108/IJCHM-10-2021-1284>
- Mahury, R. A., & Arief, N. N. (2024). The Factors Affecting Continuance Intention of ChatGPT as An AI Chatbot in Indonesia. *Social Science Studies*, 4(2), 103–116. <https://doi.org/10.47153/sss42.8472024>
- Mei, H., Bodog, S. A., & Badulescu, D. (2024). Artificial Intelligence Adoption in Sustainable Banking Services: The Critical Role of Technological Literacy. *Sustainability (Switzerland)*, 16(20). <https://doi.org/10.3390/su16208934>
- Nguyen, Y. T. H., Tapanainen, T., & Nguyen, H. T. T. (2022). Reputation and its consequences in Fintech services: the case of mobile banking. *International Journal of Bank Marketing*, 40(7), 1364–1397. <https://doi.org/10.1108/IJBM-08-2021-0371>
- OJK. (2022). *Survei Nasional Literasi dan Inklusi Keuangan (SNLIK)*.
- Oyeniyyi, L. D., Ugochukwu, C. E., & Mhlongo, N. Z. (2024). Implementing AI in banking customer service: A review of current trends and future applications. *International Journal of Science and Research Archive*, 11(2), 1492–1509. <https://doi.org/10.30574/ijSra.2024.11.2.0639>
- Özkan, P., Süer, S., Keser, İ. K., & Kocakoç, İ. D. (2020). The effect of service quality and customer satisfaction on customer loyalty: The mediation of perceived value of services, corporate image, and corporate reputation. *International Journal of Bank Marketing*, 38(2), 384–405. <https://doi.org/10.1108/IJBM-03-2019-0096>
- Patil, K. P., Kulkarni, M. S., & Hudnurkar, M. (2024). Enhancing service quality in the insurance industry with AI-powered humanoid chatbots. *TQM Journal*. <https://doi.org/10.1108/TQM-11-2023-0354>
- Rahman, M. M., Lesch, M. F., Horrey, W. J., & Strawderman, L. (2017). Assessing the utility of TAM, TPB, and UTAUT for advanced driver assistance systems. *Accident Analysis and Prevention*, 108(June), 361–373. <https://doi.org/10.1016/j.aap.2017.09.011>
- Rahman, M., Ming, T. H., Baigh, T. A., & Sarker, M. (2023). Adoption of artificial intelligence in banking services: an empirical analysis. *International Journal of Emerging Markets*, 18(10), 4270–4300. <https://doi.org/10.1108/IJOEM-06-2020-0724>
- Ramadhani, D. R., Birawa, M. S., Sholikah, D. S., & Prabandanu, R. M. A. A. H. (2024). Analisis Pengaruh Kualitas Pelayanan Berbasis Chatbot Terhadap Kepuasan Pelanggan Dalam Transaksi Online Dengan Objek Aplikasi Shopee. *Journal of Exploratory Dynamic Problems*, 1(3), 104–115.
- Rejali, S., Aghabayk, K., Esmaeli, S., & Shiwakoti, N. (2023). Comparison of technology acceptance model, theory of planned behavior, and unified theory of acceptance and use of technology to assess a priori acceptance of fully automated vehicles. *Transportation Research*

- Part A: Policy and Practice*, 168(January 2021), 103565.
<https://doi.org/10.1016/j.tra.2022.103565>
- Richad, R., Vivensius, V., Sfenrianto, S., & Kaburuan, E. R. (2019). Analysis Of Factors Influencing Millennial's Technology Acceptance Of Chatbot In The Banking Industry In Indonesia. *International Journal of Management (IJM)*, 10(3), 107–118. <http://www.iaeme.com/IJM/index.asp107http://www.iaeme.com/ijm/issues.asp?JType=IJM&VType=10&IType=3JournalImpactFactor>
- Rondan-Cataluña, F. J., Arenas-Gaitán, J., & Ramírez-Correa, P. E. (2015). A comparison of the different versions of popular technology acceptance models a non-linear perspective. *Kybernetes*, 44(5), 788–805. <https://doi.org/10.1108/K-09-2014-0184>
- Sanny, L., Susastra, A. C., Roberts, C., & Yusramdaleni, R. (2020). The analysis of customer satisfaction factors which influence chatbot acceptance in Indonesia. *Management Science Letters*, 10(6), 1225–1232. <https://doi.org/10.5267/j.msl.2019.11.036>
- Sheth, J. N., Jain, V., Roy, G., & Chakraborty, A. (2022). AI-driven banking services: the next frontier for a personalised experience in the emerging market. *International Journal of Bank Marketing*, 40(6), 1248–1271. <https://doi.org/10.1108/IJBM-09-2021-0449>
- Siahaan, M. (2024). *Willingness to use chatbots Indonesia 2023, by type of activity*. <https://www.statista.com/statistics/1493374/indonesia-willingness-to-use-chatbots-by-activity-type/>
- Silitonga, F., & Isbah, M. F. (2023). Artificial Intelligence and the Future of Work in the Indonesian Public Sector. *Jurnal Ilmu Sosial Dan Humaniora*, 12(2), 296–308. <https://doi.org/10.23887/jish.v12i2.62297>
- Silva, S. C., De Cicco, R., Vlačić, B., & Elmashhara, M. G. (2023). Using chatbots in e-retailing – how to mitigate perceived risk and enhance the flow experience. *International Journal of Retail and Distribution Management*, 51(3), 285–305. <https://doi.org/10.1108/IJRDM-05-2022-0163>
- Škerháková, V., Ali Taha, V., Tirpák, D., & Král, Š. (2022). Perception of Corporate Reputation in the Era of Digitization: Case Study of Online Shopping Behavior on Young Consumers. *Sustainability (Switzerland)*, 14(21). <https://doi.org/10.3390/su142114302>
- Sundjaja, A. M., Utomo, P., & Colline, F. (2024). 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*. <https://doi.org/10.1108/JSTPM-04-2024-0137>
- Thormundsson, B. (2024). *Global spending on AI 2023, by industry*. <https://www.statista.com/statistics/1446052/worldwide-spending-on-ai-by-industry/>
- Wiliam, A., Sasmoko, Prabowo, H., Hamsal, M., Indrianti, Y., & Princes, E. (2019). Analysis of E-Service Chatbot and Satisfaction of Banking Customers in Indonesia. *Asia Proceedings of Social Sciences*, 4 (3)(2), 72–75. <https://doi.org/10.1177/109467050032001>
- Wu, C. C., Chen, C. T., Huang, K. C., & Chou, Y. Y. (2025). Determinants of Chatbot adoption among older adults: An extended TAM approach using PLS-SEM. *Information Development*, 41(3 Special Issue: “Artificial Intelligence initiatives”), 656–674. <https://doi.org/10.1177/02666669251315839>
- Yanti, E., Mardhiah, A., Tia Novita, P., Ardilla, A., & Hijri Khana, F. (2024). *Medical Research, Nursing, Health and Midwife Participation THE IMPLEMENTATION OF AI CHATBOTS IN INDONESIAN PUBLIC HOSPITALS: OPPORTUNITIES AND CHALLENGES*. <https://medalionjournal.com/>