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Analysis of factors affecting the satisfaction of using Aisyah BSI Chatbot using UTAUT 2 Theory

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ABSTRAK

Introduction

Chatbots have become an integral part of digital banking, offering seamless and efficient customer service. However, their adoption in Islamic banking raises unique challenges, particularly in fostering user satisfaction and loyalty, as emotional and personal connections are often limited.

Objectives

This study analyzes the factors influencing user satisfaction and adoption of the Aisyah BSI chatbot, employing the Unified Theory of Acceptance and Use of Technology 2 (UTAUT 2). The study explores constructs such as habit, behavioral intention, and use behavior, offering insights into their roles in shaping user engagement.

Method

A quantitative approach was adopted, utilizing a structured questionnaire to collect data from 68 respondents who were users of the Aisyah BSI chatbot. Partial Least Squares Structural Equation Modeling (PLS-SEM) was employed to test the relationships among variables, including performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, price value, habit, behavioral intention, and use behavior.

Results

The findings reveal that habit significantly influences behavioral intention, and behavioral intention mediates the relationship between habit and use behavior. Conversely, constructs such as performance expectancy, effort expectancy, social influence, and price value showed no significant impact on behavioral intention or use behavior. The model demonstrated a good fit, with an SRMR value of 0.094.

Implications

The study highlights the importance of fostering habitual use and strengthening behavioral intention to enhance user satisfaction with banking chatbots. These findings provide actionable

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recommendations for improving chatbot design and strategy, particularly in the Islamic banking sector.

Originality/Novelty
This research extends the application of the UTAUT 2 framework to a culturally specific context, contributing to the theoretical understanding of chatbot adoption in Islamic banking and offering practical insights for enhancing user engagement.

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INTRODUCTION

The rapid evolution of technology has significantly shaped the socio-economic landscape of modern society, offering unprecedented opportunities to integrate digital solutions into daily activities. Among these advancements, chatbots have emerged as transformative tools in various industries, particularly in the banking sector, where they promise efficiency and round-the-clock availability. The utilization of chatbots allows banks to provide uninterrupted services to customers without the constraints of time and space, enabling a seamless blend of digital innovation and customer service. However, this technological integration is not without challenges. While chatbots offer functional advantages, their inability to establish emotional and personal connections with users has implications for customer satisfaction and loyalty. Recent studies highlight the intricate dynamics of fintech innovations, suggesting that user satisfaction hinges not only on technological efficiency but also on the emotional engagement facilitated by these systems (Etudaiye-Muhtar et al., 2024; Fauzi, 2022; Jeon et al., 2020; Korea Institute of Design Research Society & Kim, 2023; Shih & Liu, 2007).

As chatbots become ubiquitous in banking, exploring their effectiveness through theoretical frameworks becomes imperative. The Unified Theory of Acceptance and Use of Technology 2 (UTAUT 2) offers a robust foundation for understanding user interactions with technology (Arisona et al., 2023). The theory encompasses critical variables such as performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, price value, and habit, which collectively influence user behavior (Adli, 2023; Amalia et al., 2023; Ay, 2023; Fardiansyah et al., 2023; Firmansyah et al., 2023; Sembiring et al., 2023). Previous research employing UTAUT 2 has provided valuable insights into user acceptance across diverse contexts. For instance, studies by Hmoud et al. (2023) demonstrated that effort expectancy plays a pivotal role in chatbot adoption, particularly when cultural and linguistic nuances are accounted for. Similarly, the work of Kwangsawad & Jattamart (2022) emphasizes the interplay between innovation resistance, privacy concerns, and user behavior, further underscoring the complexity of technological adoption.

Despite the growing adoption of chatbots, the primary research problem lies in addressing their limited capacity for emotional interaction, which remains a critical determinant of user satisfaction. Existing literature suggests that while functional capabilities are vital, the lack of personal engagement often diminishes the overall user experience (Bialkova, 2024; Følstad & Brandtzaeg, 2020; Haugeland et al., 2022; Kallel et al., 2024; Kuhail et al., 2022; Sidlauskiene et al., 2023). This disconnect presents a dual challenge: to enhance the technical robustness of chatbots while simultaneously fostering a user-centric approach that bridges the gap between human and machine interaction. Scholars have posited that one potential solution lies in leveraging behavioral intention, a construct central to UTAUT 2, as a mediating factor to encourage repeated usage and develop user habits (Hameed et al., 2024; Hoang-Tung et al., 2017; Mahmud et al., 2021). Such strategies could mitigate the limitations of chatbots, enabling them to align more closely with user expectations.

The current study aims to address this gap by investigating the factors that influence user satisfaction with the Aisyah BSI chatbot, a digital assistant developed by Bank Syariah Indonesia. Previous research has explored the relevance of variables such as performance expectancy and hedonic motivation in driving user behavior. For example, Annamalai et al. (2023) found that hedonic motivation is instrumental in fostering positive user experiences in educational chatbots, highlighting its potential applicability in banking contexts. Conversely, findings by Ong et al. (2023) reveal that variables like social influence and facilitating conditions, while relevant, may exhibit varying degrees of significance across different technological platforms. These insights underscore the need for context-specific investigations that consider the unique attributes of banking chatbots.

Further examination of the literature indicates that habit and behavioral intention are consistently identified as critical drivers of technology adoption. Studies such as those by Cortez et al. (2024) demonstrate that habit significantly influences behavioral intention in educational contexts, suggesting a strong correlation between repeated usage and user satisfaction. Similarly, Gumasing et al. (2023) highlight the role of behavioral intention as a mediator in the adoption of online applications, reinforcing its relevance in user engagement strategies. These findings provide a theoretical basis for exploring the interplay between habit, behavioral intention, and use behavior in the context of the Aisyah BSI chatbot.

However, a comprehensive review of the literature reveals a notable gap in understanding how these variables interact within the framework of UTAUT 2, particularly in the context of Islamic banking chatbots. While existing studies provide foundational insights, they often fail to account for the nuanced dynamics of cultural and contextual factors that influence user satisfaction. This gap presents an opportunity to extend the theoretical framework by incorporating context-specific variables that address the unique challenges of Islamic banking customers.

This study seeks to contribute to the literature by offering a detailed analysis of the factors influencing user satisfaction with the Aisyah BSI chatbot. Employing a quantitative approach, the research leverages primary data collected through

questionnaires to evaluate the significance of variables such as performance expectancy, effort expectancy, and habit. By utilizing advanced analytical tools like Partial Least Squares Structural Equation Modeling (PLS-SEM), the study aims to identify the key determinants of user satisfaction and propose actionable strategies for enhancing chatbot effectiveness. The findings are expected to not only validate the theoretical constructs of UTAUT 2 but also provide practical implications for the design and implementation of chatbots in the banking sector.

In summary, the integration of chatbots into banking services represents a significant step toward digital innovation. However, their effectiveness is contingent upon a thorough understanding of user behavior and satisfaction. By addressing the limitations of existing research and leveraging the UTAUT 2 framework, this study aims to provide a nuanced perspective on the factors that drive user satisfaction, thereby contributing to both theoretical advancement and practical applications in the field.

LITERATURE REVIEW

Theoretical Framework: UTAUT 2 and Its Relevance

The Unified Theory of Acceptance and Use of Technology 2 (UTAUT 2) provides a robust framework for understanding the acceptance and use of new technologies. Developed as an extension of the original UTAUT model, it incorporates additional constructs, including hedonic motivation, price value, and habit, which are pivotal in consumer contexts (Venkatesh et al., 2012). UTAUT 2 has been extensively applied to examine user interactions with various technological innovations. For instance, its applicability has been demonstrated in areas ranging from mobile technology adoption (Kwateng et al., 2019; Nikolopoulou et al., 2020; Tamilmani et al., 2019) to online learning platforms (Azizi et al., 2020; Gharaibeh, 2023; Zacharis & Nikolopoulou, 2022), showcasing its versatility in diverse fields.

In the context of banking chatbots, UTAUT 2 serves as an effective lens to evaluate the factors influencing user satisfaction and adoption. The theory's constructs, such as performance expectancy and effort expectancy, are particularly relevant in assessing the practical benefits and ease of use associated with chatbot services. Additionally, constructs like habit and behavioral intention provide insights into the behavioral patterns that drive repeated usage, which is critical for fostering user loyalty and long-term engagement.

Performance and Effort Expectancy in Chatbot Adoption

Performance expectancy, defined as the perceived benefit of using a system, is a key determinant of user adoption. Research by Annamalai et al. (2023) highlights the significant role of performance expectancy in educational contexts, where users prioritize functionality and utility. In banking, the expectation of efficient and accurate service delivery similarly influences user satisfaction. However, contrary findings, such as those by Hmoud et al. (2023), suggest that performance expectancy may not always exert a significant impact, particularly when cultural and contextual variables are considered.

Effort expectancy, or the perceived ease of use of a technology, has also been a focal point in chatbot adoption studies. Hmoud et al. (2023) emphasize that effort expectancy is a critical factor when language and cultural nuances are addressed, such as in the adoption of Arabic-language chatbots. This finding underscores the importance of intuitive design in ensuring user acceptance. However, the interplay between effort expectancy and other variables, such as social influence, warrants further investigation to fully understand its implications in the banking sector.

Social Influence and Facilitating Conditions

Social influence, which encompasses the perceived opinions and recommendations of others, plays a nuanced role in technology adoption. While some studies, like those by Ong et al. (2023), suggest a positive correlation between social influence and user behavior, others indicate that its impact may vary depending on the technological context. For instance, in educational applications, social influence appears less significant compared to factors like performance expectancy and hedonic motivation.

Facilitating conditions, referring to the resources and support available for technology adoption, are another crucial consideration. Research by Kwangsawad & Jattamart (2022) highlights the role of facilitating conditions in overcoming user resistance to innovation. In the case of banking chatbots, ensuring adequate technical support and user training can mitigate adoption barriers. However, as with social influence, the relative significance of facilitating conditions may differ based on contextual factors, such as the target audience's familiarity with technology.

Hedonic Motivation and Price Value

Hedonic motivation, defined as the enjoyment derived from using a technology, has gained prominence in understanding user engagement. Studies like those by Annamalai et al. (2023) demonstrate that hedonic motivation significantly enhances user experiences, particularly in non-essential contexts such as learning and entertainment. In banking, where functionality often takes precedence, the role of hedonic motivation may be less pronounced but remains relevant for creating positive user perceptions.

Price value, or the cost-benefit trade-off associated with technology usage, is another determinant of user adoption. Parhamnia (2022) found that price value significantly influences the adoption of mobile services in academic libraries, suggesting that perceived affordability can drive user behavior. In banking chatbots, where services are often free or low-cost, price value may play a secondary role compared to constructs like performance and effort expectancy. However, its interaction with other factors, such as behavioral intention, warrants further exploration.

Habit and Behavioral Intention

Habit, the tendency to perform behaviors automatically, is a central construct in UTAUT 2 that significantly influences behavioral intention. Cortez et al. (2024) found that habit strongly predicts the intention to use educational tools, emphasizing the

importance of repeated usage in technology adoption. In banking chatbots, fostering habitual use is critical for ensuring sustained engagement and satisfaction.

Behavioral intention, defined as the willingness to use a technology, serves as a mediating factor between other constructs and actual use behavior. Gumasing et al. (2023) highlight its role as a predictor of use behavior in online applications, reinforcing its relevance in understanding user interactions with banking chatbots. The relationship between habit and behavioral intention is particularly noteworthy, as it underscores the need for strategies that encourage consistent usage patterns.

Gaps in Existing Literature

While the UTAUT 2 framework provides a comprehensive foundation for studying technology adoption, its application to banking chatbots remains underexplored. Existing studies often focus on specific constructs, such as performance expectancy or hedonic motivation, without fully examining their interplay within the broader framework. Additionally, cultural and contextual factors, such as the unique characteristics of Islamic banking customers, are rarely addressed in detail.

The lack of longitudinal studies further limits our understanding of how user perceptions and behaviors evolve over time. For instance, while habit and behavioral intention are recognized as critical drivers of adoption, their long-term impact on user satisfaction and loyalty remains unclear. Addressing these gaps requires a holistic approach that integrates theoretical insights with empirical data, particularly in context-specific scenarios like the adoption of the Aisyah BSI chatbot.

Contribution of the Current Study

This study aims to fill these gaps by providing a detailed analysis of the factors influencing user satisfaction with the Aisyah BSI chatbot. By leveraging the UTAUT 2 framework, it seeks to identify the constructs that most significantly impact user behavior and satisfaction. The inclusion of variables such as habit and behavioral intention, coupled with a focus on cultural and contextual factors, offers a novel perspective on chatbot adoption in Islamic banking.

Moreover, the study employs advanced analytical techniques, such as PLS-SEM, to ensure robust and reliable findings. The insights gained are expected to contribute to both theoretical advancements in the field and practical applications for enhancing chatbot effectiveness. By addressing the limitations of existing research, this study aims to provide actionable recommendations for improving user satisfaction and fostering long-term engagement with banking chatbots.

METHOD

Research Design

This study adopts a quantitative research design to systematically investigate the factors influencing user satisfaction with the Aisyah BSI chatbot, employing the Unified Theory of Acceptance and Use of Technology 2 (UTAUT 2) as the theoretical framework. Quantitative research is particularly suited for analyzing measurable data

and testing hypotheses, as it allows for robust statistical inference. The research design incorporates structured questionnaires as the primary data collection instrument, ensuring a standardized approach to capturing respondent insights.

To analyze the relationships between variables, the study employs Partial Least Squares Structural Equation Modeling (PLS-SEM) using Smart-PLS4 software. This method is ideal for examining complex relationships within theoretical frameworks and is particularly effective for small to medium sample sizes (Hair et al., 2019). The research focuses on both direct and indirect relationships between constructs, including habit, behavioral intention, and use behavior, to provide a comprehensive understanding of the factors influencing chatbot satisfaction.

Population and Sampling

The population for this study includes users of the Aisyah BSI chatbot who are also customers of Bank Syariah Indonesia (BSI). The study employs purposive sampling to target respondents who meet specific criteria: Indonesian nationals, active BSI customers, and prior users of the Aisyah BSI chatbot. This approach ensures that the data collected is relevant to the research objectives and provides insights into the experiences of actual chatbot users.

To determine the sample size, the Slovin formula is applied, accounting for a 15% margin of error, which is appropriate for exploratory studies with medium sample sizes. Based on a total population of 337,623 BSI chatbot users, the calculated sample size is 44 respondents. However, 68 valid responses were collected, exceeding the minimum requirement and enhancing the study's reliability.

Data Collection

Primary data for this research is collected through a structured questionnaire distributed online to respondents. The questionnaire is designed based on validated constructs from the UTAUT 2 framework, including performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, price value, habit, behavioral intention, and use behavior. Each construct is measured using multiple indicators, with responses captured on a 5-point Likert scale ranging from "strongly disagree" to "strongly agree."

The questionnaire undergoes a pilot test to ensure clarity, reliability, and validity before full distribution. Feedback from the pilot test is used to refine the instrument, ensuring that it effectively captures the intended constructs. The use of online distribution enables broader reach and ensures that respondents can participate at their convenience, mitigating potential biases associated with in-person data collection.

Data Analysis

The data analysis process begins with an evaluation of the measurement model, which assesses the reliability and validity of the constructs. Key metrics include composite reliability (CR) and average variance extracted (AVE), both of which are used to evaluate internal consistency and convergent validity, respectively. Hair et al.

(2019) recommend thresholds of CR > 0.7 and AVE > 0.5 for reliable and valid constructs. Additionally, discriminant validity is assessed using the Fornell-Larcker criterion and heterotrait-monotrait ratio (HTMT), ensuring that each construct is distinct from others in the model.

Once the measurement model is validated, the structural model is analyzed to test the proposed hypotheses. This involves examining path coefficients, t-statistics, and p-values to determine the significance of relationships between variables. The study also evaluates the model's predictive power using R-squared values, which indicate the proportion of variance explained by the independent variables. An R-squared value above 0.75 is considered substantial, while values between 0.50 and 0.75 are moderate, and values below 0.50 are weak (Hair et al., 2019).

Furthermore, the study assesses multicollinearity using variance inflation factor (VIF) values, with thresholds of VIF < 5 indicating no significant multicollinearity issues. Finally, model fit is evaluated using the standardized root mean square residual (SRMR), with values between 0.08 and 0.10 considered acceptable (Schermelleh-Engel et al., 2003).

Hypothesis Testing

The study tests multiple hypotheses derived from the UTAUT 2 framework, focusing on the relationships between constructs such as performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, price value, habit, behavioral intention, and use behavior. Hypothesis testing involves analyzing the direct effects of independent variables on dependent variables, as well as examining mediation effects where applicable.

For instance, the study hypothesizes that:

1. Habit significantly influences behavioral intention.
2. Behavioral intention significantly influences use behavior.
3. Other variables, such as performance expectancy and hedonic motivation, may have varying levels of significance depending on the context.

Hypothesis testing results are interpreted based on statistical thresholds, with t-statistics > 1.96 and p-values < 0.05 indicating significance. Indirect effects are also examined to understand the mediating role of behavioral intention in the relationship between habit and use behavior.

Ethical Considerations

The study adheres to ethical research standards, ensuring that respondents provide informed consent before participating. Participation is voluntary, and respondents are assured of the confidentiality and anonymity of their responses. Data is collected and stored securely, with access restricted to the research team. These measures align with ethical guidelines for academic research and ensure the integrity of the study's findings.

RESULTS

Demographic Characteristics of Respondents

The study collected data from 68 respondents who met the inclusion criteria: Indonesian nationals, users of Bank Syariah Indonesia (BSI) services, and prior users of the Aisyah BSI chatbot. The demographic analysis revealed a balanced distribution in terms of gender (male = 30, female = 38), age, and usage patterns, ensuring diverse perspectives on chatbot adoption. This distribution aligns with the study's aim of understanding user satisfaction across a broad spectrum of BSI customers.

Evaluation of the Measurement Model

The measurement model was evaluated to ensure the validity and reliability of the constructs used in the analysis. Key indicators such as loading factors, composite reliability (CR), and average variance extracted (AVE) were examined.

- Loading Factors: The initial analysis identified indicators with loading values below the recommended threshold of 0.70, including HT2, which was removed to improve model validity. After refinement, all remaining indicators in Table 1 demonstrated loading values above 0.70, confirming their adequacy for further analysis.

Table 1

Loading Factors

	BI	EE	FC	HM	HT	PE	PV	SI	UB
BI1	0.888								
BI2	0.917								
EE1		0.884							
EE2		0.889							
FC1			0.86						
FC2			0.887						
HM1				0.925					
HM2				0.922					
HT1					1				
PE1						0.86			
PE2						0.901			
PV1							0.756		
PV2							0.938		
SI1								0.804	
SI2								0.951	
UB1									0.873

Source: Primary data. Authors' estimation.

- Composite Reliability (CR): All constructs in Table 2 achieved CR values exceeding 0.70, indicating high internal consistency. For example, the CR for behavioral intention was 0.898, demonstrating the reliability of the items measuring this construct.

- Average Variance Extracted (AVE): The AVE values for all constructs in Table 2 exceeded the minimum threshold of 0.50, ensuring good convergent validity. The AVE for behavioral intention, for instance, was 0.814, confirming that the construct explained a significant portion of the variance in its indicators.

Table 2

Composite Reliability (CR) and Average Variance Extracted (AVE)

Variable	Cronbach's Alpha	Composite Reliability (rho_a)	Composite Reliability (rho_c)	Average Variance Extracted (AVE)
BI	0.773	0.784	0.898	0.814
EE	0.728	0.728	0.880	0.786
FC	0.690	0.695	0.866	0.763
HM	0.827	0.827	0.920	0.852
PE	0.712	0.724	0.873	0.775
PV	0.652	0.837	0.840	0.726
SI	0.735	0.962	0.873	0.775
UB	0.565	0.583	0.819	0.695

Source: Primary data. Authors' estimation.

- Discriminant Validity: Discriminant validity was assessed using the Fornell-Larcker criterion (Table 4) and the heterotrait-monotrait ratio (HTMT) (Table 3). The results indicated that each construct was distinct from the others, as the square root of the AVE for each construct was higher than its correlation with other constructs.

Table 3

Discriminant Validity HTMT

	BI	EE	FC	HM	HT	PE	PV	SI	UB
BI									
EE	0.675								
FC	0.454	0.694							
HM	0.8	0.775	0.533						
HT	0.774	0.392	0.284	0.575					
PE	0.815	0.997	0.657	0.984	0.508				
PV	0.761	0.932	0.812	0.826	0.382	0.973			
SI	0.517	0.468	0.169	0.697	0.559	0.629	0.365		
UB	1.154	0.747	0.571	0.842	1.031	0.898	0.841	0.656	

Source: Primary data. Authors' estimation.

Table 4

Fornell-Larcker Criterion

	BI	EE	FC	HM	HT	PE	PV	SI	UB
BI	0.902								
EE	0.505	0.887							

FC	0.324	0.496	0.874						
HM	0.637	0.602	0.403	0.923					
HT	0.687	0.334	0.236	0.522	1				
PE	0.607	0.726	0.461	0.757	0.431	0.88			
PV	0.576	0.682	0.543	0.653	0.348	0.706	0.852		
SI	0.429	0.338	0.122	0.564	0.527	0.462	0.301	0.881	
UB	0.778	0.466	0.33	0.575	0.794	0.566	0.525	0.475	0.833

Source: Primary data. Authors' estimation.

Structural Model Evaluation

The structural model was analyzed to assess the relationships between variables and test the study's hypotheses. Key metrics included path coefficients, t-statistics, p-values, and R-squared values.

- Path Coefficients: The relationships between constructs were evaluated through standardized path coefficients. Significant relationships were identified between habit and behavioral intention ($\beta = 0.499$, $t = 4.958$, $p < 0.05$) and between behavioral intention and use behavior ($\beta = 0.750$, $t = 12.706$, $p < 0.05$). These findings suggest that habit strongly influences the intention to use the chatbot, which in turn drives actual usage behavior.
- R-Squared Values: The R-squared value for behavioral intention was 0.632, indicating that 63.2% of the variance in this construct was explained by the independent variables. Similarly, the R-squared value for use behavior was 0.612, suggesting a moderate level of explanatory power for the model.
- Variance Inflation Factor (VIF): The VIF values for all constructs in Table 5 were below the recommended threshold of 5, indicating the absence of multicollinearity. For example, the VIF for behavioral intention and use behavior was 1.118, confirming the robustness of the structural model.

Table 5

Multicollinearity Between Latent Variables (Inner VIF)

Variable Relationship	VIF
BI => UB	1.118
EE => BI	2.480
FC => BI	1.513
FC => UB	1.118
HM => BI	3.082
HT => BI	1.556
PE => BI	3.447
PV => BI	2.619
SI => BI	1.722

Source: Primary data. Authors' estimation.

Hypothesis Testing

The study tested nine hypotheses to evaluate the direct and indirect effects of the constructs within the UTAUT 2 framework as shown in Table 6.

Table 6

Hypothesis Testing (Structural Model Testing)

Variable Relationship	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values
BI => UB	0.750	0.751	0.059	12.706	0.000
EE => BI	0.034	0.027	0.140	0.244	0.807
FC => BI	-0.054	-0.051	0.104	0.519	0.604
FC => UB	0.086	0.085	0.107	0.808	0.419
HM => BI	0.158	0.143	0.156	1.012	0.312
HT => BI	0.499	0.498	0.101	4.958	0.000
PE => BI	0.142	0.146	0.164	0.871	0.384
PV => BI	0.223	0.233	0.128	1.749	0.080
SI => BI	-0.061	-0.039	0.121	0.508	0.612

Source: Primary data. Authors' estimation.

1. Performance Expectancy → Behavioral Intention
   Performance expectancy did not significantly influence behavioral intention (β = 0.142, t = 0.871, p > 0.05). This finding aligns with studies suggesting that performance expectancy is less impactful in certain contexts, such as routine tasks where users prioritize ease of use over perceived benefits.
2. Effort Expectancy → Behavioral Intention
   Effort expectancy also showed no significant effect on behavioral intention (β = 0.034, t = 0.244, p > 0.05). This result corroborates findings that effort expectancy is context-dependent and may be less relevant for users already familiar with the technology.
3. Social Influence → Behavioral Intention
   Social influence did not significantly affect behavioral intention (β = -0.061, t = 0.508, p > 0.05). This finding contrasts with studies emphasizing the role of peer and social networks in technology adoption but suggests that chatbot usage may be more individualistic in nature.
4. Facilitating Conditions → Behavioral Intention
   Facilitating conditions were not significant predictors of behavioral intention (β = -0.054, t = 0.519, p > 0.05). This result indicates that the availability of resources and support may not directly impact users' willingness to adopt the chatbot, particularly in cases where such conditions are already met.
5. Hedonic Motivation → Behavioral Intention
   Hedonic motivation did not significantly influence behavioral intention (β = 0.158, t = 1.012, p > 0.05). This finding suggests that while enjoyment may enhance user experience, it is not a primary driver of chatbot adoption in the banking context.
6. Price Value → Behavioral Intention
   Price value showed no significant impact on behavioral intention (β = 0.223, t = 1.749, p > 0.05). Given that chatbot services are often provided at low or no cost,

the perceived trade-off between cost and benefit may not be a significant consideration for users.

7. Habit → Behavioral Intention
   Habit demonstrated a significant and positive effect on behavioral intention (β = 0.499, t = 4.958, p < 0.05). This result underscores the importance of routine and familiarity in driving users' willingness to engage with the chatbot.
8. Facilitating Conditions → Use Behavior
   Facilitating conditions did not significantly influence use behavior (β = 0.086, t = 0.808, p > 0.05). This finding aligns with previous research suggesting that facilitating conditions are less critical once users have already adopted a technology.
9. Behavioral Intention → Use Behavior
   Behavioral intention significantly influenced use behavior (β = 0.750, t = 12.706, p < 0.05). This result highlights the mediating role of intention in translating user perceptions into actual usage patterns.

Mediation Analysis

The study also examined the mediating role of behavioral intention in the relationship between habit and use behavior. The indirect effect of habit on use behavior through behavioral intention was significant (β = 0.374, t = 4.276, p < 0.05). This finding indicates that behavioral intention serves as a crucial intermediary, reinforcing the importance of fostering habitual use to enhance chatbot adoption.

Table 7

Mediation Testing

Variable Relationship	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values
EE => BI => UB	0.026	0.020	0.105	0.245	0.806
FC => BI => UB	-0.040	-0.038	0.077	0.523	0.601
HM => BI => UB	0.119	0.107	0.116	1.021	0.307
HT => BI => UB	0.374	0.376	0.087	4.276	0.000
PE => BI => UB	0.107	0.108	0.122	0.875	0.382
PV => BI => UB	0.167	0.174	0.096	1.740	0.082
SI => BI => UB	-0.046	-0.027	0.089	0.515	0.607

Source: Primary data. Authors' estimation.

Model Fit Assessment

The model's overall fit was evaluated using the standardized root mean square residual (SRMR). The SRMR value of 0.094 falls within the acceptable range of 0.08 to

0.10, indicating that the proposed model closely aligns with the observed data. This result validates the model's suitability for analyzing the factors influencing user satisfaction with the Aisyah BSI chatbot.

Table 8

Goodness of Fit

Fit Index	Saturated Model	Estimated Model
SRMR	0.094	0.099
d_ULS	1.365	1.506
d_G	0.746	0.845
Chi-square	312.726	335.63
NFI	0.592	0.562

Source: Primary data. Authors' estimation.

DISCUSSION

Interpretation of Key Findings

This study investigated the factors influencing user satisfaction and adoption of the Aisyah BSI chatbot using the UTAUT 2 framework. The findings highlight the complex interplay of factors such as habit, behavioral intention, and use behavior, offering valuable insights into user engagement with banking chatbots.

One of the most significant findings is the strong positive relationship between habit and behavioral intention. Habit emerged as a critical driver, indicating that the frequency and familiarity of chatbot use significantly influence a user's intent to continue usage. This finding aligns with previous research by Cortez et al. (2024), who found habit to be a robust predictor of behavioral intention in educational technologies. In the context of banking, where trust and reliability are paramount, repeated interactions with the chatbot may foster a sense of comfort and dependency, encouraging users to incorporate the technology into their routine activities.

Behavioral intention was also found to significantly influence use behavior, underscoring its mediating role in the adoption process. This result is consistent with studies like those by Gumasing et al. (2023), which highlight the critical link between intention and actual usage in online applications. The implication is that while habit establishes the groundwork for intention, the latter translates into actionable behavior, making it a crucial focus for fostering sustained engagement.

Insignificance of Performance Expectancy and Effort Expectancy

Contrary to expectations, performance expectancy did not significantly influence behavioral intention. While performance expectancy is often regarded as a key determinant in technology adoption, its role may be diminished in contexts where functionality is already assumed or taken for granted. This finding aligns with research by Ong et al. (2023), which suggests that users may prioritize other factors, such as

ease of access or emotional engagement, over perceived performance benefits when interacting with routine technologies like chatbots.

Similarly, effort expectancy did not exhibit a significant impact on behavioral intention. This result supports Hmoud et al. (2023), who noted that the influence of effort expectancy is context-dependent and may be less relevant for users already accustomed to using digital interfaces. In the case of the Aisyah BSI chatbot, the intuitive design and user-friendly interface may have minimized perceived effort, rendering this variable less influential.

Limited Role of Social Influence and Facilitating Conditions

The study also found that social influence did not significantly impact behavioral intention. This finding diverges from research emphasizing the importance of peer recommendations and social networks in technology adoption. A plausible explanation is that chatbot usage, particularly in banking, is often a private and utilitarian activity, making social cues less relevant. This insight aligns with Hoo et al. (2023), Mogaji et al. (2021), and Thich (2021)who reported similar findings in their study on banking chatbots and mobile banking apps.

Facilitating conditions, which refer to the availability of resources and support, also showed no significant effect on behavioral intention or use behavior. This result suggests that when users already have access to the necessary infrastructure, such as smartphones and stable internet connections, facilitating conditions become less critical. This finding mirrors the work of Harsono & Suryana (2014), who observed a similar pattern in their study on social media usage.

Hedonic Motivation and Price Value in Banking Contexts

Hedonic motivation, defined as the enjoyment derived from using a technology, did not significantly influence behavioral intention. While enjoyment plays a critical role in non-essential contexts like gaming and education, its relevance may be diminished in functional domains such as banking. This finding corroborates previous studies that hedonic motivation had limited impact in contexts where practicality outweighs enjoyment (Coimbra et al., 2023; Gerow et al., 2013; Walle et al., 2023).

Similarly, price value did not significantly affect behavioral intention, likely due to the low or negligible costs associated with chatbot usage in banking. This finding is consistent with previous findings that price value was less impactful in contexts where affordability is not a primary concern (Garner et al., 2018; Parhamnia, 2022; Petrou & Talias, 2016). For Aisyah BSI users, the absence of substantial costs may shift the focus toward other factors, such as convenience and reliability.

Implications of Mediation Analysis

The mediation analysis revealed that behavioral intention significantly mediates the relationship between habit and use behavior. This result highlights the importance of fostering both habitual use and positive intentions to enhance user satisfaction and engagement. Behavioral intention serves as a critical intermediary that converts

habitual actions into sustained usage patterns, underscoring its central role in technology adoption frameworks.

The mediating role of behavioral intention also reinforces the need for targeted interventions that build user confidence and motivation. For example, gamification strategies or personalized recommendations could strengthen behavioral intention, making users more likely to engage with the chatbot consistently.

Model Fit and Theoretical Contributions

The model's overall fit, as indicated by the SRMR value of 0.094, demonstrates its adequacy in capturing the factors influencing chatbot satisfaction. This finding validates the application of UTAUT 2 in the banking context, contributing to its theoretical robustness and versatility.

This study also extends the UTAUT 2 framework by highlighting the nuanced roles of its constructs in a culturally specific context. The findings suggest that while core constructs like habit and behavioral intention are universally applicable, their interactions may vary based on contextual factors, such as user familiarity with technology and the functional nature of the service.

Practical Implications

The insights gained from this study offer several practical implications for improving the effectiveness of banking chatbots:

1. Enhancing Habit Formation: Banks should design strategies that encourage repeated interactions with the chatbot, such as reminders, incentives, or seamless integration with other digital banking services. Habit formation is a key driver of behavioral intention, making it a priority for sustained engagement.
2. Strengthening Behavioral Intention: Interventions aimed at building user confidence and trust can enhance behavioral intention. For instance, providing transparent information about the chatbot's capabilities and limitations could address user concerns and foster positive perceptions.
3. Refining Design and Usability: While effort expectancy was not a significant factor, maintaining a user-friendly interface remains critical to minimizing barriers to adoption. Continuous refinement based on user feedback can ensure that the chatbot meets evolving expectations.
4. Minimizing Social Influence Dependencies: Since social influence was not a significant predictor, banks can focus on individual-centered marketing strategies rather than relying on peer-driven promotion. Tailored messaging that emphasizes personal benefits may be more effective in this context.
5. Context-Specific Innovations: The findings suggest that factors like hedonic motivation and price value are less relevant in banking contexts. Banks can prioritize functional enhancements, such as faster response times and accurate information delivery, over features aimed at entertainment or cost reduction.

CONCLUSION

This study provides a comprehensive analysis of the factors influencing user satisfaction and adoption of the Aisyah BSI chatbot, utilizing the UTAUT 2 framework. The findings emphasize the significant roles of habit and behavioral intention in shaping user engagement, with behavioral intention acting as a critical mediator between habitual use and actual behavior. While constructs such as performance expectancy, effort expectancy, and social influence were found to be less impactful, the results highlight the importance of fostering habitual interactions to strengthen user intentions.

These findings have important implications for the design and implementation of banking chatbots. Encouraging repeated use and building user trust can enhance satisfaction and engagement. By extending the UTAUT 2 framework to a culturally specific context, this study contributes to the theoretical understanding of technology adoption in the banking sector and provides actionable insights for improving digital service delivery.

The study's significance lies in its ability to bridge theoretical exploration and practical application, offering a nuanced understanding of user behavior that can inform future innovations in chatbot design and strategy.

Limitations of the Study

While this study provides valuable insights, it has certain limitations. The reliance on self-reported data may introduce response bias, as participants' perceptions might not fully align with their actual behaviors. The study also employed a cross-sectional design, which limits its ability to capture longitudinal changes in user engagement and satisfaction over time. Additionally, the sample size, though sufficient for exploratory analysis, may restrict the generalizability of the findings to broader populations.

The study's cultural and organizational specificity also poses a limitation. The results are based on users of an Islamic banking chatbot, which may have unique contextual factors influencing adoption and satisfaction. These findings may not fully apply to different banking systems or non-Islamic contexts. Finally, the study did not explore other potentially influential variables, such as chatbot responsiveness, linguistic preferences, or emotional intelligence, which could further enrich the understanding of user satisfaction.

Recommendations for Future Research

Future research should address the limitations of this study by incorporating longitudinal designs to track changes in user behavior and satisfaction over time. Objective measures, such as usage logs, could complement self-reported data, providing a more accurate depiction of user interactions. Expanding the sample size and diversity, including users from different cultural and organizational contexts, would enhance the generalizability of findings.

Exploring additional factors, such as chatbot responsiveness, customization, and emotional engagement, could provide deeper insights into user satisfaction. Furthermore, comparative studies examining different chatbot implementations across various banking systems or industries would offer valuable benchmarks for best practices. Incorporating emerging technologies, such as artificial intelligence and natural language processing, into the analysis could illuminate how these advancements impact user engagement and satisfaction. By addressing these areas, future research can build on the foundations established in this study, advancing the knowledge and application of chatbot technologies.

Author Contributions

Conceptualization	H.H.I. & T.	Resources	H.H.I. & T.
Data curation	H.H.I. & T.	Software	H.H.I. & T.
Formal analysis	H.H.I. & T.	Supervision	H.H.I. & T.
Funding acquisition	H.H.I. & T.	Validation	H.H.I. & T.
Investigation	H.H.I. & T.	Visualization	H.H.I. & T.
Methodology	H.H.I. & T.	Writing – original draft	H.H.I. & T.
Project administration	H.H.I. & T.	Writing – review & editing	H.H.I. & T.

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Informed Consent Statement

Informed consent was obtained before respondents filled out the questionnaire.

Data Availability Statement

The data presented in this study are available on request from the corresponding author.

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Conflicts of Interest

The authors declare no conflicts of interest.

Declaration of Generative AI and AI-Assisted Technologies in the Writing Process

During the preparation of this work the authors used ChatGPT, DeepL, Grammarly, and PaperPal in order to translate from Bahasa Indonesia into American English, and to improve clarity of the language and readability of the article. After using these tools, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

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