



**THE INFLUENCE OF ARTIFICIAL INTELLIGENCE ON BRAND
PREFERENCE OF SYARIAH BANKING CUSTOMERS IN BANDUNG
RAYA**

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Abstract

The rapid advancement of Artificial Intelligence (AI) technology has brought significant transformations across various industries and reshaped how consumers interact. This study highlights the role of AI-based chatbots and analytics in shaping marketing strategies and customer service. Chatbots enable round-the-clock service, support multiple languages, and reduce operational costs. Meanwhile, AI-driven marketing facilitates a more personalized approach by leveraging data to predict consumer needs, accelerate decision-making, and influence purchasing behavior, despite the inherent risk of bias. Grounded in the Stimulus-Organism-Response (S-O-R) model, this research focuses on the influence of AI on brand preference in the context of Islamic banking in Indonesia. The study aims to support Islamic banks in designing AI-driven marketing activities and formulating more effective branding and marketing strategies. A survey was conducted with over 400 respondents. The findings reveal that consumers appreciate the speed and personalization offered by AI-powered services; however, they remain aware of AI's limitations in emotional understanding. This indicates that while AI enhances engagement, further development is needed to create more emotionally intuitive AI-driven experiences.

Keywords: Artificial Intelligence, Brand Experience, Brand Preference



INTRODUCTION

Artificial Intelligence is a technology designed to be an assistant for humans, functioning like a robot but in a virtual form integrated into a computer system (Pratikno, 2017). AI provides solutions through the ability to analyze data on a large scale (Pangkey et al., 2019). This technology is able to imitate human behavior, including in the decision-making and problem-solving process, as applied to virtual assistants and chatbots (Bedy and Iwan, 2021). AI is developed to carry out tasks that require human intelligence, such as learning, reasoning, and problem solving (Wang and Wang, 2021). The growth of the AI market globally is very rapid. From \$207.9 billion in 2023, its value is predicted to jump almost 9 times to \$1,847.5 billion in 2030. This shows that AI is a strategic sector with enormous economic potential in the future, reflecting the widespread adoption of AI technology in various industries. Including AI in banking. Artificial intelligence (AI) can optimize banks' ability to achieve profits, create more personalized services, and create more rewarding experiences (Biswas et al. 2020).

In banking, Artificial Intelligence (AI) technology is applied through Natural Language Processing (NLP), such as chatbots and virtual assistants that are able to understand context and answer customer questions quickly and personally (Boustani, 2022). NLP features such as machine translation and speech recognition also increase service accessibility and enable interaction through voice commands. Machine Learning (ML) is used to analyze transaction data to recommend relevant services (Bapat & Sharma, 2020), and to group customers based on behavioral patterns for further personalization. In addition, Computer Vision supports security through facial recognition and administrative efficiency with automated document processing (Wilson et al., 2021).

The development of artificial intelligence (AI) in the banking sector is a major innovation in improving financial services. The application of AI includes chatbots, virtual assistants, fraud detection, credit risk analysis, and service personalization. With natural language processing technology, AI enables fast and efficient interactions without direct human involvement (Wilson et al., 2021) and provides objective responses (Boustani, 2022). In credit risk analysis, AI processes big data to accurately assess creditworthiness and reduce the risk of default through machine learning algorithms (LeCun et al., 2015). AI also recommends products based on customer preferences and behavior (Singh & Kaur, 2021), and is used in mobile banking for transactions, account management, and investment advice (Manser Payne et al., 2018). In Indonesia, around 51% of

financial institutions have adopted AI, in line with the growth of the digital economy, especially in fraud prevention, risk management, and automated customer service (Ventures, BCG & KADIN, 2024).

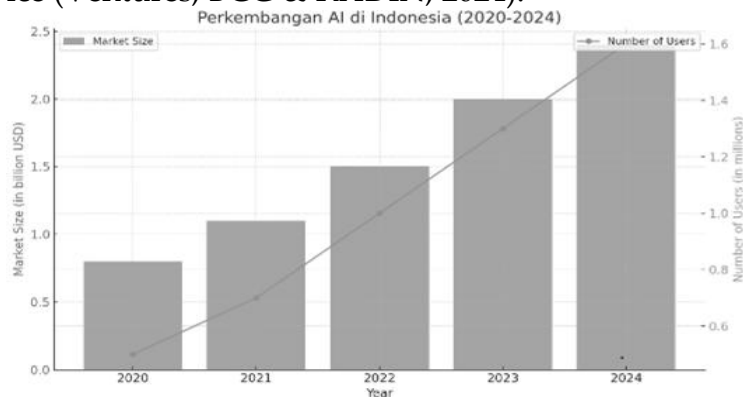


Figure 1.

AI Development in Indonesia

Based on reports from AC Ventures, Boston Consulting Group (BCG), the Indonesian Chamber of Commerce and Industry (Kadin), and survey results from the Indonesian Fintech Association (Aftech) 2024, more than half of financial institutions and fintechs in Indonesia have utilized AI. The graph shows an increase in revenue due to the use of AI from 2020 to 2024, where the original amount of USD 0.8 billion in 2020 increased to USD 2.4 billion in 2024. The number of AI users also grew from 0.5 million in 2020 to 1.6 million in 2024. This reflects a positive trend in the adoption and development of AI technology in Indonesia. The use of AI in Indonesian banking has experienced significant growth, especially in conventional banks that have adopted AI-based mobile and internet banking to understand customer preferences and provide appropriate solutions (Gupta & Dhiman, 2021). Services such as robo-advisory, facial recognition, and voice enable account opening and transactions from home (Soni et al., 2021). Examples of AI implementations include Veronika (BCA), Livin' Assistant and MITA (Bank Mandiri), SABRINA (BRI), VIRA (BCA), CINTA (BNI), and EVA (PermataBank). The larger number of conventional banks (105 banks, 24,276 offices; OJK, 2023) shows their dominance compared to Islamic banks, which face challenges of limited capital, access to technology, and the need for sharia compliance (Arif, 2022).

Therefore, AI serves as a bridge in addressing this gap by expanding the reach of digital services, increasing efficiency, transparency, and accuracy in accordance with sharia principles. AI also supports product personalization through chatbots, big data analysis, and facial recognition technology (Samsudin et al., 2021; Usman et al., 2022), thereby strengthening customer experience and



loyalty (Verhoef et al., 2019; Vijai, 2019). In Indonesia, several Islamic banks have implemented artificial intelligence, for example, PT Bank Muamalat Indonesia uses an AI-based chatbot named "Salma" to provide quick responses to customer questions, while Bank Syariah Indonesia (BSI) has a similar chatbot named "Aisyah" which helps customers access product and service information 24 hours a day. PT Bank Aladin Syariah, Tbk, which focuses on digital banking, has utilized AI for customer data analysis, fraud detection, and service personalization. PT BCA Syariah and several other banks, such as PT Bank Mega Syariah and PT Bank Panin Dubai Syariah, Tbk, also use AI technology to support operations. By utilizing AI technology, Islamic banks have a great opportunity to overcome existing challenges and increase public preference for their services. The use of AI technology, accompanied by more intensive socialization of the sharia system, can strengthen the competitiveness of sharia banks and encourage faster growth in the future. With this strategy, sharia banks can build a modern and trusted image that is able to compete equally with conventional banks in this digital era.

Although the use of AI is becoming a global trend, research related to the role of AI in brand experience and brand imaging is still limited, although there have been several studies in other countries, but in the context of sharia banking it is still very minimal. This is increasingly relevant, considering that the increasingly competitive industry requires a deep understanding of customer experience and preferences in order to be able to offer relevant and attractive products and services. Customer preferences cover various aspects, such as the type of product desired, service quality, to user experience. Theoretically, this study can contribute to the literature on AI, marketing, brand experience and brand preferences, by offering an understanding of the relationship between AI, customers, and brands in the context of sharia banking. Meanwhile, in practice, the results of this study are expected to be useful especially for marketing practitioners who want to build a strong brand through an AI-based marketing mix. Banks can utilize the results of this study to support banks in their application of AI (HKMA, 2019). With this background, this study aims to explore the role of AI in understanding and fulfilling the brand experience and brand preferences of Islamic bank customers in Indonesia, especially in Bandung City. It is hoped that this study can provide insight for Islamic banks in formulating more effective strategies to attract and retain customers, as well as improve the quality of services that are in accordance with customer expectations and needs.



RESEARCH METHOD

In this study, primary data collection was conducted through questionnaires to respondents using various Google Form platforms. The Likert scale was used to assess five aspects of respondents' responses to their behavior towards each question, where a score of 1 indicates a very low level and a score of 5 indicates a very high level. The sampling method used was convenience sampling, chosen because the population size of Islamic bank customers in Indonesia is quite large and is not known with certainty or is confidential. This approach allows researchers to flexibly select samples according to the characteristics of respondents who represent the population as a sample or data source. The characteristics of respondents are aged 18 to over 45 years, living in the Greater Bandung area, and have been Islamic banking customers for at least less than one year, with a sample size of 400 individuals. With several indicators: information, interaction, responses, customization, accessibility, and problem-solving, Brand Experience, and Brand Preference. The data in this study were analyzed using Smart-PLS software version 3.2.9, which is designed to process latent variables, namely variables that cannot be measured directly. Smart-PLS version 3.2.9 is software used for statistical analysis based on Partial Least Squares Structural Equation Modeling (PLS-SEM). Evaluation of the measurement model is carried out through three main stages, namely convergent validity, reliability, and discriminant validity. Convergent validity is examined through the loading factor value, which is ideally above 0.7, although a minimum value of 0.5 is still acceptable in exploratory studies (Hair et al., 2014; Henseler et al., 2016). Construct reliability is tested using Composite Reliability (CR), where values above 0.7 are considered reliable for confirmatory studies, and between 0.6 and 0.7 are still acceptable in exploratory studies (Gefen et al., 2000). Meanwhile, discriminant validity is analyzed through the Average Variance Extracted (AVE) value, which must be more than 0.5 and a higher cross-loading value on its own construct compared to other constructs (Fornell & Larcker, 1981).

At the structural model evaluation stage, several analysis tools are used. First, the Variance Inflation Factor (VIF) value is analyzed to detect multicollinearity, with an ideal value below 5 (Hair et al., 2018). Furthermore, hypothesis testing is carried out using the bootstrapping technique, and the hypothesis is accepted if the t-statistic exceeds 1.96 at a significance level of 5% (Sarstedt et al., 2019). The coefficient of determination (R^2) is used to see the strength of the model, where an R^2 value above 0.67 is considered strong, between 0.33–0.67 moderate, and below 0.33 weak (Chin, 1998). Finally, the model fit is



tested through the Standardized Root Mean Square Residual (SRMR) value, with a value below 0.08 indicating a good model, and between 0.08 and 0.10 still acceptable (Henseler et al., 2016).

RESULTS AND DISCUSSION

Of the total 403 questionnaires distributed, 401 were filled in according to the criteria and were declared eligible for analysis. This number was then used as a sample in this study because it met the data eligibility criteria. Data collection was carried out systematically in order to obtain accurate and scientifically accountable results. Respondent characteristics include various demographic and socio-economic backgrounds, such as gender, age, education level, and domicile. In addition, information related to employment, income level, status as a sharia bank customer, and utilization of artificial intelligence (AI)-based services were also the subject of questions in the distributed questionnaire. The majority of respondents were female (56.2%) and aged 25–34 years (58.9%). Most had a D-4/S-1 education (56.9%) and were domiciled in Cimahi City (36.2%) and West Bandung (28.9%). Most jobs were private employees (41.4%), and self-employed (24.2%). The most widely used Islamic bank is BSI (43.4%), while the most utilized AI services are customer service chatbots (27.1%) and virtual assistants (24.9%). The highest frequency of use is several times a week (35.4%). The highest monthly income is in the range of IDR 5–10 million (45.9%). Most respondents have been Islamic bank customers for 1–3 years (66.6%). Furthermore, a structural model was formed using the SEM-PLS approach with 42 statement items, and an analysis was carried out using the PLS algorithm to obtain convergent validity, composite reliability, and average variance extracted (AVE) values. Outer loading values less than 0.7 were eliminated from the model to ensure convergent validity, and after elimination, all latent variables such as AI marketing, brand experience, and brand preference had AVE values above 0.5 and high reliability values. Therefore, the model has met the convergent validity criteria. In the discriminant validity test, it ensures that each indicator has the highest loading value on its own construct compared to other constructs (cross loading), as evidence that each construct is truly separate and does not overlap with each other conceptually. To obtain validity values in the model, a series of analysis stages are carried out, one of which is by evaluating the outer loading value to measure convergent validity, as shown in Table 1. Indicators with outer loading values below 0.7 are eliminated from the mode. All latent constructs, namely AI

marketing, brand experience, and brand preference, show outer loading values that meet the minimum threshold, which is above 0.5 to 0.7.

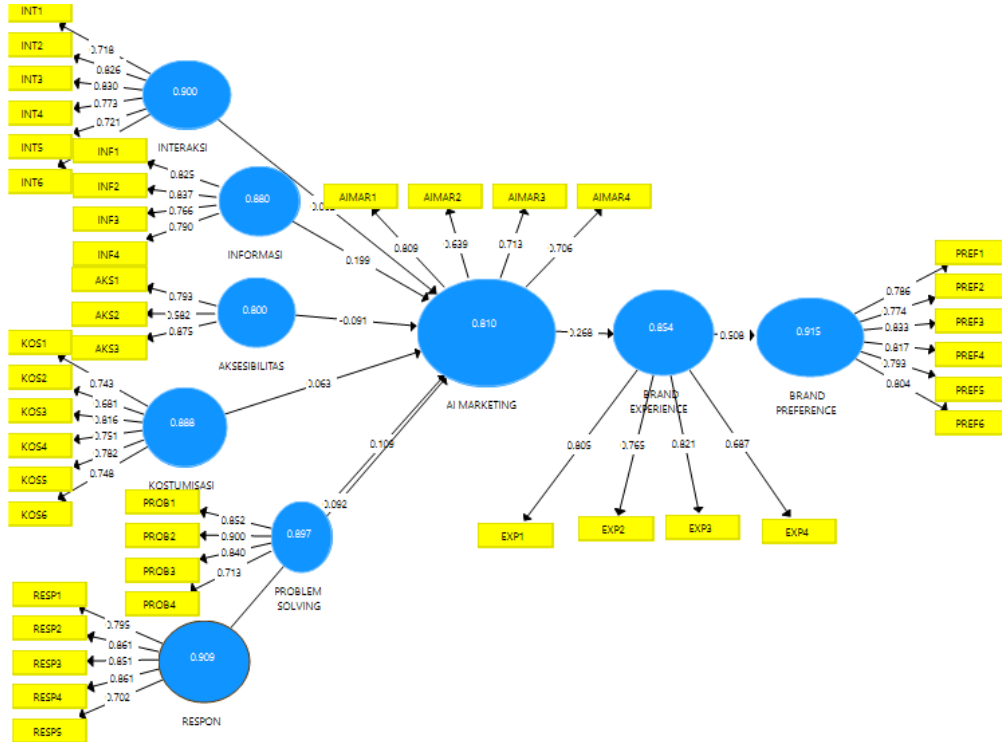


Figure 2.
Research Model

Next, a series of analysis stages are carried out, one of which is by evaluating the outer loading value, as shown in Table 1.

Table 1.
Outer Loading Value

	Ai Marketing	Accessib ility	Brand Exper ience	Brand Prefere nce	Infor mation	Intera ction	Custom ization	Probl em Solvi ng	Respon
AIMAR1	0.809								
AIMAR2	0.639								
AIMAR3	0.713								
AIMAR4	0.706								
AKS1		0.793							



AKS2		0.582							
AKS3		0.875							
EXP1			0.805						
EXP2			0.765						
EXP3			0.821						
EXP4			0.687						
INF1					0.825				
INF2					0.837				
INF3					0.766				
INF4					0.790				
INT1						0.718			
INT2						0.826			
INT3						0.830			
INT4						0.773			
INT5						0.721			
INT6						0.771			
KOS1							0.743		
KOS2							0.681		
KOS3							0.816		
KOS4							0.751		
KOS5							0.782		
KOS6							0.748		
PREF1				0.786					
PREF2				0.774					
PREF3				0.833					
PREF4				0.817					
PREF5				0.793					
PREF6				0.804					
PROB1								0.852	



PROB2								0.900	
PROB3								0.840	
PROB4								0.713	
RESP1									0.795
RESP2									0.861
RESP3									0.851
RESP4									0.861
RESP5									0.702

Source: Processed primary data, 2025

Based on the results of the cross-loading test, all indicators have the highest loading value on the measured construct compared to other constructs, which indicates that each indicator item better represents its own variable construct. This indicates that the model has met the criteria for discriminant validity, because there are no indicators that have a higher correlation with other constructs. Thus, each construct in the model, such as AI Marketing, Accessibility, Brand Experience, Brand Preference, Information, Interaction, Customization, Problem Solving, and Response, has adequate differentiation and can be clearly distinguished from each other's, so that the model can be declared discriminantly valid.

Table 2.
Validity and Reliability Constructs

	Cronbach's Alpha	rho_A	Composite Reliability	Average Variance Extracted (AVE)
AI Marketing	0.740	0.851	0.810	0.517
Accessibility	0.726	0.594	0.800	0.578
Brand Experience	0.775	0.772	0.854	0.595
Brand Preference	0.889	0.894	0.915	0.642
Information	0.820	0.828	0.880	0.648
Interaction	0.879	0.921	0.900	0.600
Customization	0.853	0.890	0.888	0.570
Problem Solving	0.853	0.897	0.897	0.687



Respon	0.875	0.901	0.909	0.667
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Source: Processed primary data, 2025

Based on the results of the validity and reliability tests, it can be concluded that all indicators in this model show good discriminant validity. Each indicator has the highest correlation to the construct it represents compared to other constructs, so that each variable of AI Marketing, Accessibility, Brand Experience, Brand Preference, Information, Interaction, Customization, Problem Solving, and Response, can be clearly distinguished, and there is no overlap between constructs.

Table 3.
T-Value

	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (O/STDEV)	P Values
AI Marketing -> Brand Experience	0.268	0.271	0.067	4.019	0.000
Accessibility> AI Marketing	-0.091	-0.036	0.112	0.808	0.420
Brand Experience -> Brand Preference	0.508	0.516	0.044	11.481	0.000
Information -> AI Marketing	0.199	0.196	0.058	3.430	0.001
Interaction -> AI Marketing	0.062	0.046	0.096	0.643	0.521
Customization-> AI Marketing	0.063	0.054	0.075	0.833	0.405
Problem Solving -> AI Marketing	0.109	0.110	0.068	1.598	0.111
Response -> AI Marketing	0.092	0.095	0.068	1.354	0.176

Source: Processed primary data, 2025

Based on the results of testing the relationship between variables in the model, it can be concluded that not all the hypotheses proposed are supported by the data. Only a few relationship paths are proven to be statistically significant (p-value < 0.05).

The Influence of AI Marketing on Brand Experience



The first research hypothesis in this study is "there is a significant influence between AI Marketing on Brand Experience for users of Islamic bank chatbot services". Based on the results of the statistical test in Table 3.3, a p-value of $0.000 < 0.05$ was obtained with a t-statistic value of 4.019, which means it is greater than the t-table. Therefore, H_0 is rejected and H_1 is accepted. These results indicate that there is a positive and significant influence between AI Marketing on Brand Experience. These findings indicate that the use of artificial intelligence in marketing services such as information personalization, chatbots, and customer preference analysis can be a new experience for customers towards Islamic bank brands. This is in line with Chatterjee, Rana, and Dwivedi (2020), which shows that AI technology improves consumer perceptions through ease and satisfaction of service. Huang and Rust (2021) also emphasized that AI contributes to creating a more relevant and contextual experience for users. Therefore, Islamic banks are advised to integrate AI technology into their digital marketing strategies to strengthen customer loyalty and brand value, with the support of digital capacity development from regulators and the government.

The Influence of Brand Experience has a positive and significant effect on Brand Preference

The second hypothesis is "Brand Experience has a positive and significant effect on Brand Preference for users of Islamic bank chatbot services". Based on the results of the analysis, a p-value of $0.000 < 0.05$ was obtained with a t-statistic value of 11.481, which is greater than the t-table. Thus, H_0 is rejected and H_2 is accepted. This proves that the higher the Brand Experience, the higher the Brand Preference. This finding indicates that positive brand experience contributes significantly to shaping brand preference. Brakus et al. (2009) stated that strong brand experience influences consumer attitudes and decisions.

In the context of sharia, experiences that are in line with Islamic values are an important factor in strengthening preferences. Iglesias et al. (2021) found that sensory and affective dimensions in brand experience can increase brand preference, especially if the experience evokes positive emotions. This suggests that users tend to choose brands that align with their religious identity. Furthermore, another study by Kumar and Nayak (2023) revealed that consistency of brand experience, including in the application of sharia values, is a strong predictor of long-term brand preference.

The Influence of Information from AI Marketing has a positive and significant effect on the perception of AI Marketing



The third hypothesis is that Information from AI Marketing has a positive and significant effect on the perception of AI Marketing on users of Islamic bank chatbot services". From the test results, a p-value of $0.001 < 0.05$ was obtained with a t-statistic of 3,430. Because the p-value < 0.05 and $t > t\text{-table}$, H_0 is rejected and H_3 is accepted. This means that the quality of information conveyed through AI Marketing has a significant influence in shaping user perceptions. The influence of information on the use of AI Marketing in Islamic digital services is proven to be significant, with a p-value of 0.040 (< 0.05), so H_0 is rejected and H_a is accepted. This shows that accurate and relevant information increases trust and facilitates the adoption of AI technology.

This finding is in line with Xu et al. (2020), who emphasized the importance of the effectiveness of information delivery in the acceptance of AI-based digital technology. Lankton et al. (2022) support this by finding that information transparency can increase user trust, especially in AI systems in financial services, including those based on sharia. Chen et al.'s (2021) study shows that education about AI mechanisms can increase technology acceptance, and the level of use is 2.3 times higher. Meanwhile, Abdullah et al. (2023) revealed that personalization of information is based on Sharia values. All of these findings strengthen the results of this study that the quality and relevance of information are key factors in encouraging the use of AI Marketing in the sharia digital ecosystem.

The Influence of Accessibility on AI Marketing does not have a positive and significant effect on the perception of AI Marketing

The fourth hypothesis is that the Accessibility of AI Marketing is not significant, with a p-value of 0.420 to 0.808, so the hypothesis is rejected. This shows that ease of access to chatbots has not contributed enough to shaping perceptions of AI Marketing strategies in Islamic banking services. Based on research findings and supported by the latest literature, it can be concluded that accessibility to AI Marketing, especially in the form of chatbot services in Islamic banks, has not had a significant effect on user perceptions. Although ease of access is available, this factor is not strong enough to shape positive perceptions of AI-based marketing strategies. Isnaini and Tulasmi's (2024) study shows that user habits are more dominant than accessibility in influencing chatbot usage intentions and behavior. In addition, research by Kagan et al. (2025) revealed the phenomenon of "gatekeeper aversion" and "algorithm aversion," which makes users hesitate to rely on chatbots even though they are easy to access. Therefore, improving the perception of AI Marketing requires a comprehensive approach



that not only focuses on accessibility, but also pays attention to aspects of trust, transparency, and emotional comfort of users.

The Influence of Interaction on AI Marketing does not have a positive and significant effect on the perception of AI Marketing

The fifth hypothesis is that Interaction from AI Marketing is not significant with a p value of 0.521 t 0.643, so the hypothesis is rejected. The results of the hypothesis test show that user interaction with digital platforms does not have a significant effect on the adoption of AI Marketing. This finding indicates that the intensity and quality of user interaction do not have a significant effect on the adoption of AI Marketing. This is in line with Cicco et al. (2020) who stated that interactions with automated systems often do not meet the emotional needs of users in the financial services sector. As-syiva and Nasution (2023) also revealed that although chatbots are able to answer basic questions, their limitations in responding to emotions make them less effective in building connections. Likewise, Sitanggang et al. (2023) stated that many users feel less interested in interacting with chatbots, especially when the response does not match expectations. Forbes' (2023) report shows that chatbots are used more for basic information, while complex questions are still handled by human services. Lin and Kim (2016) and Zhang et al. (2023) found that utilitarian factors such as convenience and efficiency play a greater role in technology adoption than interaction aspects. McLean et al. (2023) added that in the e-commerce sector, users prioritize accuracy and speed of information over in-depth interaction. Overall, these findings strengthen the research results that interaction is not yet a determining factor in the adoption of AI Marketing.

The Influence of Response to AI Marketing does not have a positive and significant effect on the perception of AI Marketing.

The sixth hypothesis is that the response from AI Marketing is not significant, with a p-value of 0.176 t 1354, so the hypothesis is rejected. The responsiveness of chatbots has not had a sufficient impact on the perception of AI-based marketing strategies. This study is in line with the findings of De Sá Siqueira et al. (2023), who stated that responses do not always match user needs due to technological limitations, and Araujo (2018), who found that even though chatbots are flexible, users prefer human assistance for complex problems. This finding is supported by research by Blut et al. (2021) and Lu et al. (2023), who stated that even though chatbots are fast, their failure to solve problems reduces the positive impact of speed. Følstad and Brandtzæg (2020) also showed that generic, fast responses can reduce user trust. Therefore, the results of this study strengthen the argument that companies should focus more on the quality of



content and personalization of AI services, as well as the system's ability to provide the right solutions, rather than just optimizing response speed.

**The Effect of Customization on AI Marketing does not have a positive and significant effect on the perception of AI Marketing**

The seventh hypothesis is that the customization of AI Marketing is not significant, with a p value of 0.405 to 0.833, so the hypothesis is rejected. The AI service customization feature has not shown a significant effect in increasing perceptions of the effectiveness of AI Marketing. The failure of chatbots to understand and solve complex problems and their inability to adapt services to user needs are major obstacles. This shows that despite customization efforts, chatbots often fail to provide a fully personalized experience, which can lead to user frustration (Zhang et al., 2024). Research also shows that consumers prefer human interaction for complex customer service, as chatbots tend not to be able to understand unique contexts (Statista Survey, 2023). Limitations in personalization by AI, such as only adjusting language or basic product recommendations, reduce the effectiveness of the customization offered. Furthermore, studies by Elsholz et al. (2019) and Gupta et al. (2024) show that even when customization is available, chatbots still struggle to provide a truly personalized experience. Furthermore, when the customization process is perceived as unfair or burdensome, this can actually decrease user satisfaction (Scholl-Grissemann et al., 2020). Thus, the results of this study confirm that customization does not have a significant effect on the use of AI Marketing.

The Influence of Problem Solving on AI Marketing does not have a positive and significant effect on AI Marketing

The eighth hypothesis is that Problem Solving from AI Marketing is not significant with a p-value of 0.111 t 1598, so the hypothesis is rejected. The ability of chatbots to solve problems is not strong enough to influence user assessments of AI Marketing. This finding shows that although AI is designed to solve marketing problems, users have not seen this aspect as a major factor in technology adoption. Lack of understanding of how AI works, as well as negative experiences such as less relevant solutions from chatbots, make users doubt its effectiveness (Zhang et al., 2024). This is contrary to the opinion of Huang and Rust (2021), who emphasize the importance of the role of problem-solving in AI-based marketing. Studies by Castelo et al. (2022) and Janson (2023) show that AI is still limited in understanding the context, emotions, and specific needs of users, which results in low trust and adoption. Lopez et al. (2023) added that the lack of transparency of AI, especially in Islamic banking, such as creditworthiness evaluation, causes anxiety and bias. Although AI is technically capable of solving problems, user perceptions of the effectiveness and relevance of its solutions remain barriers to adoption. This finding reinforces that AI's current problem-



solving capabilities are not yet convincing enough for users to be a deciding factor in adopting AI Marketing.

CONCLUSION

Based on the research results, it can be concluded that AI Marketing has a positive and significant influence on brand experience, which in turn has a significant impact on the brand preference of users of Islamic bank chatbot services. The quality of information delivered by AI has also been shown to play an important role in forming positive perceptions of AI Marketing. However, other variables such as accessibility, interaction, responsiveness, customization, and AI problem-solving capabilities did not show a significant influence on user perceptions, indicating that current AI technology still has limitations in meeting emotional expectations, personalization, and solving complex problems. Therefore, Islamic banks need to focus on improving the quality of information and brand experience based on Islamic values, while continuing to develop the sophistication of AI to provide services that are more adaptive and relevant to customer needs.

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