

The Effect of AI-Driven Personalization, Chatbot Interaction, and Dynamic Pricing on Consumer Purchase Decisions through Trust in AI Systems

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Abstract: The rapid adoption of Artificial Intelligence (AI) in digital marketing has changed how consumers interact with brands, particularly through personalized recommendations, chatbot services, and dynamic pricing. However, although these AI-based features are widely used on digital platforms, consumers may still question their reliability, fairness, and transparency. This study aims to examine the effects of AI-driven personalization, AI-enabled chatbot interaction, and AI-based dynamic pricing on consumer purchase decisions through trust in AI systems. This research employed a quantitative approach using a cross-sectional survey of consumers who had experience using AI-based features on digital platforms in Indonesia. Data was analyzed using PLS-SEM. The results show that AI-driven personalization and chatbot interaction positively influence purchase decisions, while dynamic pricing has no direct effect. Trust in AI systems significantly mediates the relationship between AI-based marketing features and purchase decisions. This study concludes that consumer trust is essential in converting AI-driven marketing strategies into purchase behavior.

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INTRODUCTION

Artificial Intelligence (AI) has rapidly transformed contemporary marketing practices by enabling firms to personalize offerings, automate customer interactions, and optimize pricing strategies at an unprecedented scale. Recent industry reports indicate that over 80% of companies worldwide have adopted at least one form of AI-based marketing technology, with personalization and conversational AI being the most widely implemented applications (Chui et al., 2023). Moreover, empirical evidence shows that 71% of consumers expect personalized interactions from brands, and 80% are more likely to make a purchase when such personalization is provided (Deloitte, 2023). These figures highlight the growing strategic importance of AI-driven marketing in influencing consumer purchase behavior.

One prominent application of AI in marketing is AI-driven personalization, which utilizes machine learning algorithms to tailor product recommendations, promotional content, and user experiences based on individual consumer data. Prior studies demonstrate that personalized recommendations significantly enhance perceived relevance and reduce information overload, leading to higher purchase intentions (Grewal et al., 2020). Firms implementing AI-based personalization have reported sales increases ranging from 10% to 30%, underscoring its tangible impact on consumer decision-making (Chui et al., 2023).

In parallel, AI-enabled chatbot interactions have become a dominant channel for customer engagement. Chatbots powered by natural language processing provide real-time assistance, streamline

information search, and reduce service response times. Research further indicates that chatbot responsiveness and perceived human-likeness positively influence trust and purchase intention by reducing uncertainty during online transactions (Chung et al., 2020).

Another increasingly prevalent AI application is dynamic pricing, where algorithms adjust prices in real time based on demand, competition, and consumer behavior. While dynamic pricing has been shown to improve revenue performance by approximately 5–15%, it also raises concerns regarding perceived fairness and transparency (Kumar et al., 2022). Empirical findings suggest that consumers may react negatively to AI-driven price discrimination when algorithmic decision processes are not clearly communicated, thereby undermining trust in the system (Xia et al., 2004).

Across these AI-driven marketing practices, consumer trust in AI systems emerges as a critical mediating mechanism. Trust reflects consumers' beliefs regarding the reliability, fairness, and transparency of AI technologies and has been identified as a key determinant of technology acceptance and usage behavior (Gefen et al., 2003). Recent studies confirm that insufficient trust—particularly related to data privacy and algorithmic opacity—can weaken the positive effects of AI personalization, chatbot interaction, and dynamic pricing on purchase decisions.

Given the rapid diffusion of AI in marketing and the simultaneous rise of consumer concerns regarding data usage and algorithmic decision-making, a deeper empirical investigation is required. Therefore, this study aimed to examine the effect of AI-driven personalization, chatbot interaction, and dynamic pricing on consumer purchase decisions, with trust in AI systems positioned as a mediating variable. By adopting a quantitative approach, this research contributes to the growing literature on AI marketing by clarifying the psychological mechanism through which AI influences consumer behavior.

Previous empirical studies have investigated the role of AI personalization, chatbot services, and algorithmic pricing independently. However, limited studies have simultaneously examined these three AI-driven marketing mechanisms within a single integrated framework while considering trust in AI systems as a mediating variable, particularly in the context of digital consumers in emerging markets such as Indonesia.

RESEARCH METHOD

Research Design

This study adopts a quantitative research approach with a causal explanatory design to examine the effects of AI-driven personalization, AI-enabled chatbot interaction, and AI-based dynamic pricing on consumer purchase decisions, both directly and indirectly through trust in AI

systems. A quantitative approach is appropriate as this study aims to test theoretically grounded hypotheses and measure relationships among latent constructs using statistical modeling techniques (Hair et al., 2022). The research employs a cross-sectional survey design, in which data are collected at a single point in time to capture consumers' perceptions and behavioral responses toward AI-based marketing practices. To ensure clarity, respondents were instructed to evaluate their experiences with e-commerce or digital platforms that utilize AI-based recommendation systems, AI-powered chatbots, and algorithmic pricing mechanisms that specifically are used in Indonesia, such as e-commerce marketplace (e.g., Tokopedia, Shopee, Lazada), supper-apps (e.g., Gojek, Grab), and fintech platforms (e.g., OVO, Dana).

Population and Sample

The population of this study comprises consumers who have prior experience using AI-based features on digital platforms, such as personalized product recommendations, AI-powered chatbots, and dynamic pricing mechanisms. Given the specificity of the research context, this study applies a purposive sampling technique, a form of non-probability sampling that allows researchers to select respondents who meet predefined criteria relevant to the study objectives (Etikan et al., 2016).

To ensure adequate statistical power for Structural Equation Modeling (SEM), the minimum sample size follows the recommendation of (Hair et al., 2022), which suggests a sample size of at least ten times the maximum number of structural paths directed at any endogenous construct. Considering the complexity of the proposed model, a minimum sample size of 200 respondents is deemed sufficient for reliable estimation and hypothesis testing.

Data Collection Procedure

Primary data are collected using a self-administered structured questionnaire distributed online through digital channels (Google Form). Online surveys are considered effective for capturing consumer perceptions in digital and AI-driven contexts, as they enable broad reach and efficient data collection (Saunders et al., 2023).

Measurement of Variables

The research model consists of five latent constructs: three independent variables, one mediating variable, and one dependent variable.

1. AI-Driven Personalization is measured through indicators reflecting perceived relevance, accuracy, usefulness, and overall evaluation of personalized recommendations (Huang & Rust, 2021).
2. AI-Enabled Chatbot Interaction is measured by indicators related to responsiveness, informativeness, interaction quality, and overall evaluation of chatbot services.
3. AI-Based Dynamic Pricing is measured using indicators capturing perceived price fairness, transparency, consistency, and acceptance (Xia et al., 2004).
4. Trust in AI Systems is measured through perceptions of reliability, integrity, competence, and overall trust of AI technologies (Shin, 2021).
5. Consumer Purchase Decision is measured by indicators reflecting purchase intention, confidence in decision-making, likelihood, and overall willingness of completing a purchase.

The survey instructed respondents to reflect on AI features they experienced on Indonesian platforms.

Table 2. Respondents' Reference Platforms for AI Feature Experience

Platform	AI Personalization	Chatbot	Dynamic Pricing
E-Commerce Marketplace			
Tokopedia	V	V	X
Shopee	V	V	X
Lazada	V	V	X
Supper Apps			
Gojek	V	V	V
Grab	V	V	V
Fintech			
OVO	V	V	X

Dana	V	V	X
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Questionnaire Item Indicators

All items are measured using a five-point Likert scale, ranging from 1 (strongly disagree) to 5 (strongly agree).

Data Analysis Technique

Data analysis is conducted using Structural Equation Modeling with the Partial Least Squares approach (PLS-SEM), employing statistical software such as SmartPLS 4. PLS-SEM is particularly suitable for this study due to its predictive orientation, ability to handle complex mediation models, and robustness with relatively large numbers of indicators (Hair et al., 2022).

The analysis procedure consists of two main stages. First, the measurement model (outer model) is evaluated by assessing convergent validity, discriminant validity, and internal consistency reliability (construct reliability). Second, the structural model (inner model) is assessed by examining path coefficients using bootstrapping techniques, coefficient of determination (R^2), effect size (f^2), and predictive relevance (Q^2) (Hair et al., 2022).

Hypothesis Testing

Hypotheses H1–H6 and H10 are tested through the evaluation of direct effects among constructs, while hypotheses H7–H9 are tested using mediation analysis to assess the indirect effects of trust in AI systems. A hypothesis is considered supported if the path coefficient is statistically significant at a p-value < 0.05, consistent with established SEM research standards (Hair et al., 2022).

Ethical Considerations

Ethical considerations are addressed by ensuring voluntary participation, informed consent, and anonymity of respondents. Respondents are informed that their data will be used solely for academic research purposes, and no personal identifiable information is collected.

RESULTS AND DISCUSSION

Measurement Model

Convergent Validity

Tabel 2. Loading Factor Result

	AI-Driven Personalization	AI-Enabled Chatbot Interaction	AI-Based Dynamic Pricing	Trust in AI Systems	Consumer Purchase Decision	Descriptions
AP1	0.888					Valid
AP2	0.744					Valid
AP3	0.820					Valid
AP4	0.826					Valid
CB1		0.754				Valid
CB2		0.853				Valid
CB3		0.930				Valid
CB4		0.904				Valid
DP1			0.858			Valid
DP2			0.807			Valid

DP3	0.926	Valid
DP4	0.891	Valid
TR1	0.807	Valid
TR2	0.915	Valid
TR3	0.878	Valid
TR4	0.845	Valid
PD1	0.872	Valid
PD2	0.913	Valid
PD3	0.865	Valid
PD4	0.905	Valid

Table 3. Average Variance Extracted (AVE)

	Average Variance Extracted (AVE)	Descriptions
AI-Driven Personalization	0.674	Valid
AI-Enabled Chatbot Interaction	0.745	Valid
AI-Based Dynamic Pricing	0.760	Valid
Trust in AI Systems	0.790	Valid
Consumer Purchase Decision	0.743	Valid

The convergent validity assessment demonstrates that all measurement indicators satisfy the recommended thresholds for PLS-SEM analysis. Table 2 shows that all indicator outer loadings exceed the minimum threshold of 0.70, indicating strong correlations between the indicators and their respective latent constructs (Hair et al., 2022). The loading values range from 0.744 to 0.930, confirming that each indicator adequately represents its intended construct. Furthermore, Table 3 presents the Average Variance Extracted (AVE) values for each construct, ranging from 0.674 to 0.790. All AVE values exceed the recommended minimum criterion of 0.50, suggesting that each construct explains more than half of the variance of its indicators (Fornell & Larcker, 1981). These results confirm that the measurement model achieves satisfactory convergent validity across all constructs.

Discriminant Validity

Table 4. Cross Loading Result

	AI-Driven Personalization	AI-Enabled Chatbot Interaction	AI-Based Dynamic Pricing	Trust in AI Systems	Consumer Purchase Decision	Keterangan
AP1	0.888	0.191	0.586	0.543	0.588	Valid
AP2	0.744	0.126	0.495	0.388	0.444	Valid
AP3	0.820	0.155	0.468	0.400	0.512	Valid
AP4	0.826	0.429	0.478	0.506	0.581	Valid
CB1	0.081	0.754	0.269	0.423	0.330	Valid
CB2	0.152	0.853	0.243	0.441	0.284	Valid
CB3	0.336	0.930	0.428	0.601	0.465	Valid
CB4	0.344	0.904	0.437	0.520	0.511	Valid
DP1	0.580	0.29	0.858	0.625	0.498	Valid
DP2	0.462	0.393	0.807	0.548	0.486	Valid
DP3	0.543	0.381	0.926	0.616	0.609	Valid

DP4	0.566	0.377	0.891	0.578	0.612	Valid
TR1	0.470	0.522	0.635	0.872	0.596	Valid
TR2	0.530	0.493	0.660	0.913	0.692	Valid
TR3	0.577	0.542	0.552	0.865	0.648	Valid
TR4	0.433	0.520	0.566	0.905	0.655	Valid
PD1	0.497	0.416	0.428	0.628	0.807	Valid
PD2	0.598	0.510	0.621	0.650	0.915	Valid
PD3	0.590	0.439	0.591	0.610	0.878	Valid
PD4	0.560	0.263	0.540	0.630	0.845	Valid

Table 5. Latent Variable Correlation Result

	AI-Driven Personalization	AI-Enabled Chatbot Interactions	AI-Based Dynamic Pricing	Trust in AI Systems	Consumer Purchase Decision	AVE2	Descriptions
AI-Driven Personalization	1	0.284	0.618	0.652	0.567	0.821	Valid
AI-Enabled Chatbot Interaction	0.284	1	0.413	0.475	0.584	0.863	Valid
AI-Based Dynamic Pricing	0.618	0.413	1	0.635	0.679	0.872	Valid
Trust in AI Systems	0.652	0.475	0.635	1	0.729	0.862	Valid
Consumer Purchase Decision	0.567	0.584	0.679	0.729	1	0.889	Valid

Discriminant validity was assessed using cross-loading analysis and the Fornell–Larcker criterion. Table 4 demonstrates that each indicator has the highest loading on its respective construct compared to the loadings on other constructs. This result indicates that all indicators are more strongly associated with their intended latent variables than with other constructs in the model, thereby confirming adequate discriminant validity (Hair et al., 2022). In addition, Table 5 presents the results of the Fornell–Larcker criterion analysis. The square root of the Average Variance Extracted (AVE) for each construct is higher than the correlations between constructs. These findings indicate that each latent variable possesses sufficient discriminant validity and is empirically distinct from the other constructs in the model (Fornell & Larcker, 1981). Therefore, the measurement model successfully differentiates the dimensions of AI-driven personalization, AI-enabled chatbot interaction, AI-based dynamic pricing, trust in AI systems, and consumer purchase decision.

Construct Reliability

Table 6. Reliability Test Results

	Cronbach's alpha	Composite reliability (rho_c)	Keterangan
AI-Driven Personalization	0.838	0.892	Reliable

AI-Enabled Chatbot Interaction	0.884	0.921	Reliable
AI-Based Dynamic Pricing	0.894	0.927	Reliable
Trust in AI Systems	0.911	0.938	Reliable
Consumer Purchase Decision	0.884	0.920	Reliable

Reliability analysis indicates strong internal consistency across all constructs in the measurement model. Table 6 presents Cronbach's alpha values ranging from 0.838 to 0.911 and composite reliability values ranging from 0.892 to 0.938. All values exceed the recommended threshold of 0.70, demonstrating satisfactory construct reliability (Hair et al., 2022). These findings confirm that the measurement instruments consistently and reliably capture their respective latent constructs.

Model Fit and Predictive Relevance

Table 7. Model Fit and Predictive Relevance Results

Measurement	Rule of Thumb	Result	Descriptions
SRMR	Less than 0.10	0.075	Fit
NFI	Approaching value of 1	0.8	Fit
Goodness of Fit (GoF)	Small (0.1), moderate (0.25), strong (0.36)	0.686	Fit (Good)
Q2 Predictive Relevance	Q2 > 0 : Have a predictive relevance	Q2 Trust in AI Systems 0.573 > 0	Predictive (Strong)
	Small (0.02), moderate (0.15), strong (0.35)	Q2 Purchase Decisions 0.532 > 0	

The model fit assessment demonstrates that the proposed model achieves an acceptable level of fit and predictive relevance. Table 7 reports an SRMR value of 0.075, which is below the recommended cut-off value of 0.10, indicating a good model fit (Hu & Bentler, 1999). The NFI value of 0.80 approaches the ideal value of 1, suggesting an acceptable comparative fit of the structural model. Table 7 also presents a Goodness of Fit (GoF) value of 0.686, which exceeds the threshold of 0.36 for the good model fit category. This indicates that the overall model has substantial robustness, as GoF values above 0.36 are generally interpreted as an indication of good model fit in PLS-SEM analysis (Akter et al., 2011, as cited in (Aghimien et al., 2022)). In terms of predictive relevance, the Q² values for Trust in AI Systems (0.573) and Consumer Purchase Decision (0.532) are greater than zero. As Q² values above 0.50 indicate substantial or large predictive relevance, these findings confirm that the model has strong predictive capability for the endogenous constructs (Hair et al., 2019; Wang et al., 2024).

Structure Model (Inner Model)

R Square (R²)

Table 8. Coefficient of Determination (R²) Results

	R-square	R-square adjusted	Descriptions
PD	0.664	0.652	Moderate
TR	0.602	0.596	Moderate

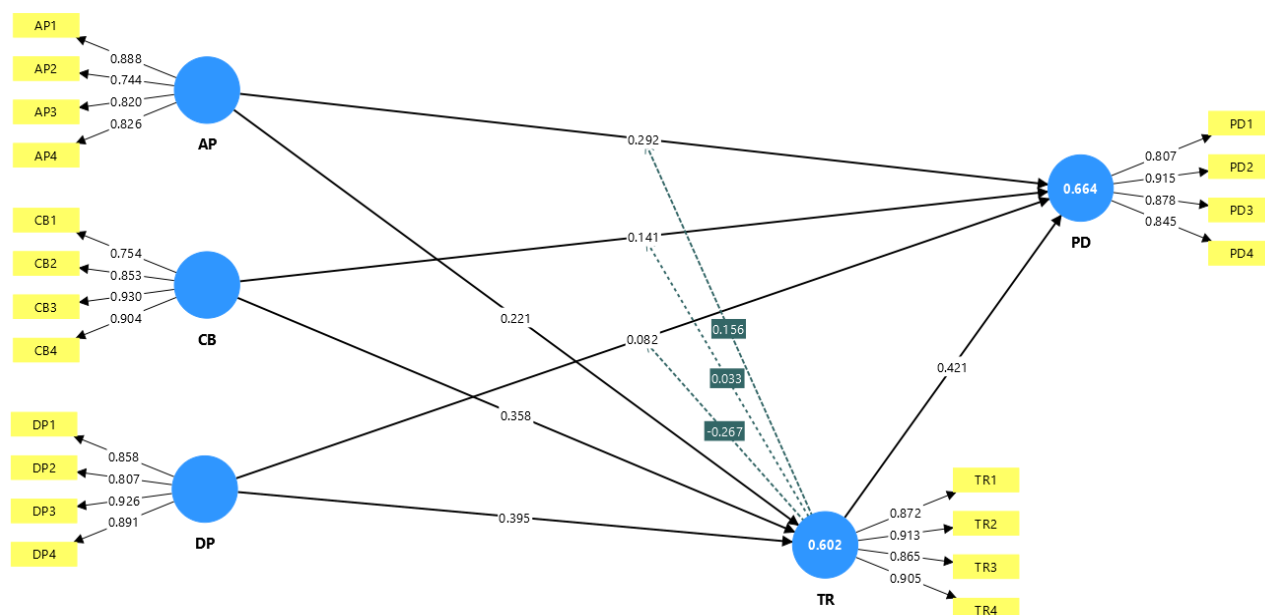


Figure 1. Structural Model Evaluation Results

The coefficient of determination (R^2) assessment indicates that the structural model demonstrates moderate explanatory power. Table 8 reports an R^2 value of 0.664 for Consumer Purchase Decision, indicating that 66.4% of the variance in consumer purchase decisions is explained by AI-driven personalization, AI-enabled chatbot interaction, AI-based dynamic pricing, and trust in AI systems. In addition, Table 8 presents an R^2 value of 0.602 for Trust in AI Systems, suggesting that AI-driven personalization, AI-enabled chatbot interaction, and AI-based dynamic pricing collectively explain 60.2% of the variance in consumer trust toward AI systems. Figure 1 further illustrates the structural relationships among the constructs within the proposed research model. Based on the PLS-SEM evaluation criteria, R^2 values above 0.50 indicate moderate explanatory power, demonstrating that the model adequately captures the key determinants of consumer trust formation and purchase decision behavior in AI-based marketing contexts (Hair et al., 2022).

Effect Size (F^2)

Table 9. Effect size (f^2) Analysis Result

	AI-Driven Personalization	AI-Enabled Chatbot Interactions	AI-Based Dynamic Pricing	Consumer Purchase Decision	Trust in AI Systems
AI-Driven Personalization				0.134	0.076
AI-Enabled Chatbot Interaction				0.029	0.267
AI-Based Dynamic Pricing				0.008	0.218
Consumer Purchase Decision					0.206
Trust in AI Systems				0.206	
TR X AP				0.034	

TR X CB	0.004
TR X DP	0.096

The effect size (f^2) analysis evaluates the relative contribution of each exogenous construct to the endogenous variables within the structural model. Table 9 indicates that Trust in AI Systems exerts a moderate effect on Consumer Purchase Decision ($f^2 = 0.206$), emphasizing the important role of trust in shaping consumer purchase behavior through reduced perceived risk and increased decision confidence (Gefen et al., 2003; Longoni et al., 2019). Table 9 also shows that AI-driven personalization has a small-to-moderate effect on Consumer Purchase Decision ($f^2 = 0.134$), whereas AI-enabled chatbot interaction ($f^2 = 0.029$) and AI-based dynamic pricing ($f^2 = 0.008$) demonstrate relatively small effects. Regarding Trust in AI Systems as the endogenous construct, AI-enabled chatbot interaction ($f^2 = 0.267$) and AI-based dynamic pricing ($f^2 = 0.218$) produce moderate effect sizes, while AI-driven personalization shows a small effect ($f^2 = 0.076$). Based on the established effect size thresholds of 0.02 (small), 0.15 (medium), and 0.35 (large), the findings suggest that trust represents the most influential determinant of consumer purchase decisions. In addition, chatbot interaction and dynamic pricing contribute more substantially to the development of consumer trust in AI systems (Hair et al., 2022).

Hypothesis Testing

Path Coefficient Bootstrapping Direct Effect

Table 10. Bootstrapping Results of Direct Effects

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (O/STDEV)	P values
AP -> PD	0.292	0.291	0.065	4.469	0.000
AP -> TR	0.221	0.222	0.054	4.090	0.000
CB -> PD	0.141	0.141	0.065	2.181	0.015
CB -> TR	0.358	0.351	0.086	4.177	0.000
DP -> PD	0.082	0.080	0.066	1.243	0.107
DP -> TR	0.395	0.401	0.077	5.110	0.000
TR -> PD	0.421	0.423	0.074	5.705	0.000
TR x AP -> PD	0.156	0.148	0.057	2.736	0.003
TR x CB -> PD	0.033	0.033	0.036	0.917	0.180
TR x DP -> PD	-0.267	-0.258	0.060	4.434	0.000

Table 10 also indicates that AI-enabled chatbot interaction positively and significantly influences Consumer Purchase Decision ($\beta = 0.141$, $p = 0.015$), supporting H2. This result suggests that responsive and informative chatbot interactions reduce consumer uncertainty and strengthen decision confidence during the purchasing process. In contrast, AI-based dynamic pricing does not significantly affect Consumer Purchase Decision ($\beta = 0.082$, $p = 0.107$), resulting in the rejection of H3. This finding implies that AI-generated price adjustments may not directly encourage purchasing behavior because consumers remain sensitive to issues of price fairness and transparency (Xia et al., 2004). Regarding trust formation, Table 10 shows that AI-driven personalization ($\beta = 0.221$, $p < 0.001$), AI-enabled chatbot interaction ($\beta = 0.358$, $p < 0.001$), and AI-based dynamic pricing ($\beta = 0.395$, $p < 0.001$) each exert significant positive effects on Trust in AI Systems, thereby supporting H4, H5, and H6. Among these predictors, AI-based dynamic pricing demonstrates the strongest influence on trust, indicating that perceptions of fairness and algorithmic

transparency play an important role in shaping consumer trust toward AI technologies (Kumar et al., 2022; Shin, 2021). Furthermore, Table 10 confirms that Trust in AI Systems significantly and positively affects Consumer Purchase Decision ($\beta = 0.421$, $p < 0.001$), supporting H10. This result highlights the central role of trust in reducing perceived risk and encouraging consumers to rely on AI-driven recommendations, chatbot interactions, and pricing mechanisms during the decision-making process (Gefen et al., 2003; Longoni et al., 2019).

Path Coefficient Bootstrapping Indirect Effect

Table 11. Bootstrapping Results of Indirect Effects

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (O/STDEV)	P values
DP -> TR -> PD	0.166	0.17	0.046	3.595	0.000
AP -> TR -> PD	0.093	0.095	0.031	2.982	0.001
CB -> TR -> PD	0.151	0.147	0.041	3.691	0.000

The mediation analysis demonstrates the important role of Trust in AI Systems in explaining the indirect relationships between AI-based marketing features and Consumer Purchase Decision. Table 11 indicates that Trust in AI Systems significantly mediates the relationship between AI-driven personalization and Consumer Purchase Decision ($\beta = 0.093$, $p = 0.001$), as well as the relationship between AI-enabled chatbot interaction and Consumer Purchase Decision ($\beta = 0.151$, $p < 0.001$). These findings support H7 and H8, suggesting that AI-driven personalization and chatbot interaction influence consumer purchase decisions both directly and indirectly through the development of trust in AI systems (Hair et al., 2022). Table 11 also shows that Trust in AI Systems significantly mediates the relationship between AI-based dynamic pricing and Consumer Purchase Decision ($\beta = 0.166$, $p < 0.001$), thereby supporting H9. Considering that the direct effect of AI-based dynamic pricing on Consumer Purchase Decision is not statistically significant, the mediation result indicates a full mediation effect. This finding suggests that AI-driven pricing strategies can influence consumer purchasing behavior only when consumers develop trust in the AI system responsible for generating pricing decisions (Xia et al., 2004). In addition, the moderation analysis reveals a significant negative interaction effect between Trust in AI Systems and AI-based dynamic pricing on Consumer Purchase Decision ($\beta = -0.267$, $p < 0.001$). This result indicates that higher levels of trust may increase consumer sensitivity toward perceived unfair pricing practices.

Discussion

Overall, the findings support the Stimulus–Organism–Response (S–O–R) framework, in which AI-driven marketing features act as external stimuli, trust in AI systems represents an internal psychological state, and consumer purchase decisions constitute behavioral responses (Shin, 2021). The positive effect of AI-driven personalization on consumer purchase decisions indicates that consumers value relevant and customized recommendations because they simplify information processing and improve decision efficiency. This finding aligns with the Technology Acceptance Model (TAM), which explains that perceived usefulness influences consumer acceptance of technology-based features in digital purchasing contexts (Davis, 1989). The results are also consistent with (Bhojwani et al., 2026), who found that AI-enabled features such as recommendation engines significantly enhance consumer confidence, satisfaction, and perceived usefulness in product evaluation, ultimately supporting purchase intention. Their study further highlights that AI

technologies can strengthen consumer decision-making when the systems are perceived as transparent and reliable. In addition, (Jiang et al., 2024) emphasized that AI-generated content (AIGC) has strong potential to improve content personalization, consumer engagement, and trust when marketers prioritize content quality, transparency, and relevance in AI-driven communication strategies.

Similarly, AI-enabled chatbot interaction directly and indirectly influences purchase decisions by providing responsive and informative communication that reduces uncertainty and strengthens decision confidence during online transactions. In contrast, AI-based dynamic pricing does not directly influence purchase decisions, suggesting that consumers may respond cautiously to algorithm-based price adjustments when fairness and transparency are unclear. Therefore, dynamic pricing requires trust as a prerequisite to positively affect consumer behavior, as consumers are more likely to accept AI-generated prices when they perceive the system as reliable and fair (Gefen et al., 2003; Xia et al., 2004). This finding is also supported by (Bhojwani et al., 2026), who emphasized that concerns related to privacy risks, overreliance on technology, and decision fatigue continue to shape consumer trust and technology adoption. Furthermore, (Jiang et al., 2024) explained that consumer trust in AI-driven marketing is strongly influenced by transparency, ethical AI practices, personalized content delivery, and effective consumer engagement strategies. Their study also noted that consumers are more willing to interact with AI-generated marketing content when AI systems are perceived as trustworthy, explainable, and capable of maintaining user privacy and authenticity.

CONCLUSION

This study concludes that AI-driven personalization and AI-enabled chatbot interaction positively influence consumer purchase decisions, both directly and indirectly through trust in AI systems. While AI-based dynamic pricing does not directly affect purchase decisions, it exerts an indirect influence by enhancing consumers' trust in AI technologies. These findings highlight the critical role of trust as a psychological mechanism linking AI-driven marketing practices to consumer behavior. The study contributes to the AI marketing literature by integrating personalization, chatbot interaction, and dynamic pricing within a single framework and demonstrating the mediating role of trust in AI systems. Practically, the results suggest that organizations should prioritize transparency, reliability, and user-centered AI implementation to strengthen consumer trust and improve marketing effectiveness in increasingly digitalized business environments.

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This study concludes that AI-driven personalization, AI-enabled chatbot interaction, and trust in AI systems play important roles in influencing consumer purchase decisions in digital marketing contexts. The findings reveal that AI-driven personalization and chatbot interaction positively affect purchase decisions both directly and indirectly through trust in AI systems, while AI-based dynamic pricing does not directly influence purchase decisions but significantly affects consumer trust. Furthermore, trust in AI systems is proven to be a central psychological mechanism that mediates the relationship between AI-based marketing practices and consumer purchase behavior. These findings contribute to the development of marketing and consumer behavior literature by integrating the Stimulus–Organism–Response (S–O–R) framework, Technology Acceptance Model (TAM), and Trust Theory in explaining consumer responses toward AI-driven

marketing technologies. From a managerial perspective, companies should not only focus on implementing advanced AI technologies, but also prioritize transparency, fairness, responsiveness, and reliability to strengthen consumer trust and improve purchase outcomes. In particular, businesses should ensure that AI-driven pricing strategies are perceived as fair and understandable to minimize consumer skepticism. Future studies are recommended to examine other AI-related variables, broader demographic contexts, or different digital platform categories to enrich understanding of consumer behavior toward AI technologies.

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