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Artificial Intelligence and the Transformation of Personalized Marketing: An Empirical Study of Consumer Behavior

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A B S T R A C T

This study examines the role of AI usefulness in shaping purchase intention within AI-driven personalised marketing. A quantitative explanatory design was employed using an online survey of 400 e-commerce consumers in DKJ Jakarta collected June 2025 to August 2025. Data were analysed using SEM-PLS to test direct and mediating effects among AI usefulness, consumer trust, perceived risk, consumer knowledge, and purchase intention. The findings reveal that AI usefulness significantly increases consumer trust and knowledge while reducing perceived risk, but does not directly influence purchase intention. Purchase intention is driven by trust and knowledge, with significant indirect effects identified. The study highlights the importance of trust-building and knowledge enhancement in maximising AI-based marketing effectiveness

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INTRODUCTION

The rapid development of Artificial Intelligence (AI) has significantly reshaped contemporary marketing practices, particularly through the emergence of AI-driven personalised marketing within digital ecosystems. Firms increasingly utilise intelligent systems to deliver tailored recommendations and predictive analytics that enhance customer engagement and operational efficiency (Davenport, 2020). In e-commerce environments, algorithmic systems continuously analyse consumer data to generate customised product suggestions, positioning AI as a strategic driver of competitive advantage rather than merely a supporting tool.

Globally, AI adoption across business functions continues to accelerate. A recent industry report published by McKinsey & Company reports a substantial increase in organisational AI integration between 2017 and 2025 (Singla et al., 2025). As illustrated in Figure 1, the percentage of organisations adopting AI has increased consistently over time, reflecting growing confidence in AI's strategic value.

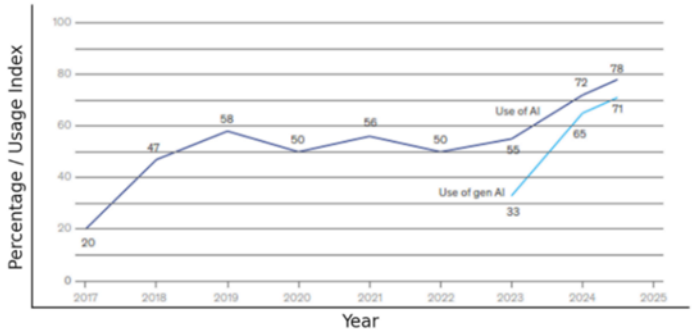

Figure 1. Global Organisational AI Adoption Trend (2017–2025)
Source: McKinsey & Company (2025)

Figure 1 shows that AI adoption increased from 20 percent in 2017 to 47 percent in 2018 and further to 58 percent in 2019, with continued growth through 2025. This upward trajectory indicates accelerating digital transformation across industries. However, increasing adoption rates do not necessarily reflect uniform implementation depth. Many organisations remain at early deployment stages, suggesting that the effectiveness of AI in marketing depends not only on technological capability but also on consumer evaluation and behavioural response.

In Indonesia, the digital economy has expanded rapidly, particularly within the e-commerce sector (Google et al., 2024). Jakarta, as the country's primary economic and digital hub, represents a mature urban digital environment supported by relatively strong infrastructure and digital literacy.

This context provides a relevant niche sample for examining AI-based personalised marketing in an emerging market setting. Nevertheless, consumer acceptance is not automatically guaranteed. Concerns regarding privacy and system reliability continue to influence trust formation in AI-enabled interactions (Kaplan & Haenlein, 2019).

From a theoretical perspective, perceived usefulness remains a primary determinant of technology acceptance (Mariani et al., 2022). Trust links technological evaluation to behavioural outcomes (Wang et al., 2023), whereas perceived risk may inhibit online purchase intention (Pappas, 2016). Consumer knowledge further shapes how individuals interpret information and evaluate uncertainty (Babatunde et al., 2024). Although these constructs have been examined individually, limited studies integrate AI usefulness, trust, perceived risk, and consumer knowledge into a unified structural framework within emerging digital markets.

Therefore, this study contributes to knowledge enrichment by integrating these constructs into a comprehensive behavioural model tested within a niche urban digital sample in Jakarta. This research aims to examine whether AI usefulness directly influences purchase intention or operates through the mediating mechanisms of consumer trust, perceived risk, and consumer knowledge among e-commerce consumers in Jakarta.

THEORETICAL REVIEW

Technology Acceptance Model (TAM)

The Technology Acceptance Model (TAM) was developed by Fred D. Davis (1989) to explain the factors influencing technology adoption. The model posits that technology acceptance is primarily determined by perceived usefulness and perceived ease of use. Perceived usefulness refers to the extent to which an individual believes that using a particular system enhances their performance, while perceived ease of use reflects the degree to which the system is perceived as effortless to use.

In this study, perceived usefulness is conceptualised as AI Usefulness, representing the extent to which consumers perceive that artificial intelligence enhances their shopping experience. AI-based personalisation not only improves efficiency but also facilitates access to relevant product information, thereby strengthening consumer understanding and decision-making confidence.

Previous research supports the central role of perceived usefulness in shaping behavioural outcomes. Linh and Huyen (2025) demonstrate that perceived usefulness positively influences trust in digital technology adoption. Similarly, Sipos (2025) finds that AI-powered personalisation enhances consumer trust and purchase intention. Gupta (2025) further shows that AI-driven personalisation improves consumer knowledge through adaptive information delivery, while Ruiz-Herrera et al. (2023) confirm that perceived usefulness positively affects behavioural intention through cognitive evaluation.

Based on the theoretical foundation and empirical evidence, the following hypotheses are proposed:

H1: AI Usefulness has a positive and significant effect on Consumer Trust.
H3: AI Usefulness has a positive and significant effect on Consumer Knowledge.
H4: AI Usefulness has a positive and significant effect on Purchase Intention.
H16: AI Usefulness has a positive and significant effect on Purchase Intention through Consumer Knowledge.

Commitment-Trust Theory of Relationship Marketing

The Commitment-Trust Theory of Relationship Marketing was introduced by Robert M. Morgan and Shelby D. Hunt (1994). The theory emphasises that trust is the central mediating variable in establishing and maintaining long-term relationships between firms and consumers. Trust develops when consumers believe that a company acts with integrity, reliability, and transparency.

Within the context of AI technology, trust becomes a critical mechanism that links technological benefits to relational and behavioural outcomes. When consumers trust AI systems, they are more likely to rely on the information provided, deepen their understanding of the system, and demonstrate stronger purchasing tendencies.

Empirical evidence highlights the importance of trust in digital environments. Tian et al. (2023) find that perceived trust strengthens the relationship between technology perception and behavioural intention. Pirzado et al. (2025) demonstrate that high-quality AI interaction significantly enhances consumer trust and purchase intention. Sipos (2025) also reports that trust reinforces the relationship between AI personalisation and consumer responses. Accordingly, the following hypotheses are formulated:

H5: Consumer Trust has a positive and significant effect on Consumer Knowledge.

H6: Consumer Trust has a positive and significant effect on Purchase Intention.

H10: AI Usefulness has a positive and significant effect on Consumer Knowledge through Consumer Trust.

H11: AI Usefulness has a positive and significant effect on Purchase Intention through Consumer Trust.

H14: Consumer Trust has a positive and significant effect on Purchase Intention through Consumer Knowledge.

Theory of Planned Behavior (TPB)

The Theory of Planned Behavior was developed by Icek Ajzen (1991), proposing that behavioural intention is the primary determinant of actual behaviour. Intention is influenced by attitudes, subjective norms, and perceived behavioural control. Perceived behavioural control reflects individuals' perceptions of their capability to perform a behaviour and the extent of control over potential barriers.

In this study, perceived behavioural control is represented by Perceived Risk and Consumer Knowledge. Perceived Risk refers to the level of uncertainty or potential loss consumers associate with AI technology usage. Higher perceived risk may weaken confidence and reduce purchase intention. Conversely, Consumer Knowledge reflects the extent of consumers' understanding of AI systems, which strengthens their confidence and behavioural intention.

Empirical findings support these relationships. Joseph et al. (2025) report that effective AI implementation reduces perceived risk and enhances consumer confidence. Pirzado et al. (2025) find that responsive AI interaction decreases uncertainty and strengthens behavioural responses. Sipos (2025) further

indicates that privacy concerns may weaken the relationship between trust and purchase intention.

Based on TPB and prior evidence, the following hypotheses are proposed:
H2: AI Usefulness has a negative and significant effect on Perceived Risk.
H7: Perceived Risk has a negative and significant effect on Consumer Knowledge.
H8: Perceived Risk has a negative and significant effect on Purchase Intention.
H9: Consumer Knowledge has a positive and significant effect on Purchase Intention.
H12: AI Usefulness has a positive and significant effect on Consumer Knowledge through Perceived Risk.
H13: AI Usefulness has a positive and significant effect on Purchase Intention through Perceived Risk.
H15: Perceived Risk has a negative and significant effect on Purchase Intention through Consumer Knowledge.

Following the formulation of the hypotheses, this study presents the contextual framework to illustrate the conceptual relationships among the proposed variables. As a quantitative study, the framework visually demonstrates the structural linkages between AI Usefulness, Consumer Trust, Perceived Risk, Consumer Knowledge, and Purchase Intention. It clarifies the direction of influence, including both direct and mediating effects, among the variables examined in this research. The contextual framework therefore provides a systematic representation of the research model and serves as the basis for the empirical testing of the proposed hypotheses.

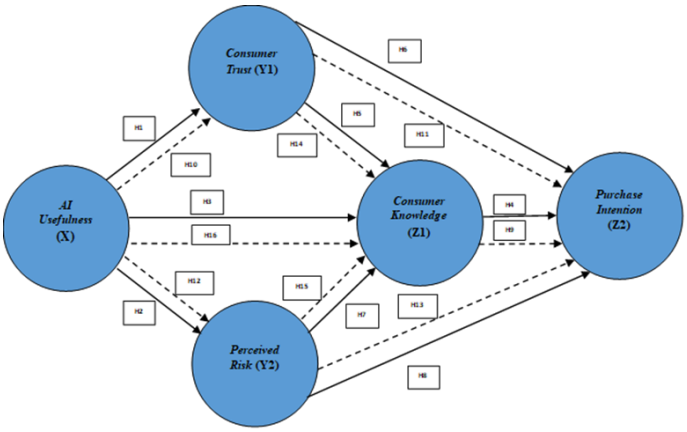

Figure 2. Conceptual Framework

METHODOLOGY

This study employs a quantitative research design, with data analysed using Partial Least Squares Structural Equation Modelling (PLS-SEM). The population consists of e-commerce consumers residing in DKJ Jakarta who have experienced AI-based marketing features. The sampling technique applied is purposive sampling, whereby respondents are selected based on specific criteria relevant to the research objectives. The minimum sample size was determined

using the Slovin formula with a 5 per cent margin of error, resulting in 400 respondents (Sekaran & Bougie, 2016).

Data collection was conducted online from June 2025 to August 2025 through the distribution of a structured questionnaire using Google Forms. The questionnaire was disseminated via social media platforms and digital communities. All respondents met the criteria of having conducted online transactions and interacted with AI-driven features such as product recommendations, chatbots, predictive analytics, or personalised advertisements in e-commerce platforms. The use of Partial Least Squares Structural Equation Modelling (PLS-SEM) is appropriate for analysing complex relationships between latent variables and prediction-oriented research models (Hair & Alamer, 2022).

RESEARCH RESULTS

Overview of Research Subjects

The total number of respondents in this study is 400, all of whom met the criteria of having prior experience interacting with Artificial Intelligence (AI) in e-commerce marketing, particularly in AI-driven personalized marketing activities. Respondents come from all areas of DKJ Jakarta, with 29.5% from South Jakarta, 28.25% from Central Jakarta, 21.5% from West Jakarta, 10.75% from North Jakarta, and 10% from East Jakarta. Female respondents dominate at 67.75%, while male respondents constitute 32.25%. Most respondents are young adults aged 17–25 years (84.75%) with high school education (74.25%) and monthly income below Rp 3,000,000 (54%).

Respondents are familiar with digital platforms and AI applications in e-commerce, including product recommendations, targeted promotions, and AI-based customer service, providing relevant assessments of AI usefulness, consumer knowledge, consumer trust, perceived risk, and purchase intention. Data collection was conducted online via questionnaires, allowing wide participation without temporal or spatial limitations.

Outer Model Test Results

The evaluation of the outer model was conducted using the Partial Least Squares–Structural Equation Modelling (PLS-SEM) approach to assess the validity and reliability of the constructs. Convergent validity was evaluated based on outer loading values and the Average Variance Extracted (AVE), while discriminant validity was assessed using cross loadings and the Fornell–Larcker criterion. Construct reliability was examined using Cronbach's alpha and Composite Reliability.

The results of the convergent validity test indicate that all indicators have outer loading values $\geqslant 0.70$, thereby meeting the criteria for convergent validity. In addition, the AVE values for all constructs exceed the minimum threshold of 0.50, namely Artificial Intelligence Usefulness (0.621), Consumer Knowledge (0.616), Consumer Trust (0.639), Purchase Intention (0.684), and Perceived Risk (0.599). This demonstrates that each construct explains more than 50% of the variance of its indicators.

Discriminant validity based on cross loadings shows that each indicator has the highest loading on its respective construct compared to other constructs.

Furthermore, the Fornell–Larcker test results reveal that the square root of the AVE for each construct is greater than the correlations between constructs, confirming that all constructs satisfy the discriminant validity criteria.

Furthermore, the reliability test results show that all constructs have Cronbach's alpha values ranging from 0.944 to 0.977 and Composite Reliability values ranging from 0.951 to 0.978, all of which exceed the recommended threshold of 0.70. Therefore, all constructs in this study are considered reliable.

Overall, the results of the outer model evaluation demonstrate that all indicators and constructs meet the requirements for convergent validity, discriminant validity, and reliability. Accordingly, the measurement model is deemed appropriate for further analysis.

Model Fit Test Results

The model fit assessment was conducted to evaluate the suitability of the structural model with the empirical data and to examine the predictive capability of the model. The evaluation employed several indicators, namely the Standardised Root Mean Square Residual (SRMR), Chi-square, Normed Fit Index (NFI), Goodness of Fit (GoF), and Q^2predict.

Table 1. Model Fit Test Results

Parameter	**Value**	**Criteria**	**Remarks**
SRMR	0.058	< 0.08	Fit
Chi-square	χ^2 estimated = 19,556.510; χ^2 saturated = 19,556.323	χ^2 estimated ≈ χ^2 saturated	Fit
NFI	0.600	≥ 0.90 (good); 0.80–0.90 (acceptable)	Less fit
GoF	0.538	> 0.36	Strong fit
Q^2predict (CK)	0.325	> 0	Moderate predictive relevance
Q^2predict (CT)	0.583	> 0	Strong predictive relevance
Q^2predict (PI)	0.305	> 0	Moderate predictive relevance

Q^2predict (PR)	0.123	> 0	Weak–moderate predictive relevance

Source: Data processed by the researcher, 2026

Based on the table above, the SRMR value indicates that the model meets the model fit criterion, while the Chi-square estimated value being close to the Chi-square saturated value suggests a good model fit. The GoF value of 0.538 reflects a strong overall model fit, and all Q^2predict values greater than zero indicate that the model possesses adequate predictive capability. Although the NFI value remains below the ideal threshold, overall the research model is considered acceptable and demonstrates good predictive performance.

Inner Model Test Results

The inner model assessment was conducted to evaluate the relationships among latent constructs and to test the research hypotheses using the bootstrapping procedure with a significance level of 0.05.

Table 2. Path Coefficient Results (Direct Effects)

Hypothesis	Relationship	Coefficient	t-statistic	p-value	Conclusion
H1	AU → CT	0.766	27.477	0.000	Accepted
H2	AU → PR	−0.360	7.609	0.000	Accepted
H3	AU → CK	0.259	3.979	0.000	Accepted
H4	AU → PI	−0.013	0.191	0.848	Rejected
H5	CT → CK	0.225	3.634	0.000	Accepted
H6	CT → PI	0.309	4.800	0.000	Accepted
H7	PR → CK	−0.408	9.437	0.000	Accepted
H8	PR → PI	0.022	0.643	0.520	Rejected
H9	CK → PI	0.592	10.679	0.000	Accepted

Source: Data processed by the researcher, 2026

The results indicate that Artificial Intelligence Usefulness has a significant effect on Consumer Trust, Perceived Risk, and Consumer Knowledge, but does not have a direct effect on Purchase Intention. In addition, Consumer Trust and Consumer Knowledge have significant positive effects on Purchase Intention, whereas Perceived Risk does not significantly influence Purchase Intention.

Table 3. Path Coefficient Results (Indirect Effects)

Hypothesis	Relationship	Coefficient	t-statistic	p-value	Conclusion
H10	AU → CT → CK	0.172	3.454	0.001	Accepted
H11	AU → CT → PI	0.237	4.449	0.000	Accepted
H12	AU → PR → CK	0.147	6.327	0.000	Accepted
H13	AU → PR → PI	−0.008	0.633	0.527	Rejected
H14	CT → CK → PI	0.133	3.378	0.001	Accepted
H15	PR → CK → PI	−0.241	7.082	0.000	Accepted
H16	AU → CK → PI	0.153	3.851	0.000	Accepted

Source: Data processed by the researcher, 2026

Overall, the inner model results demonstrate that most relationships among variables are significant, both directly and indirectly. Consumer Trust and Consumer Knowledge play crucial mediating roles in enhancing Purchase Intention, indicating that the research model is supported by strong empirical evidence.

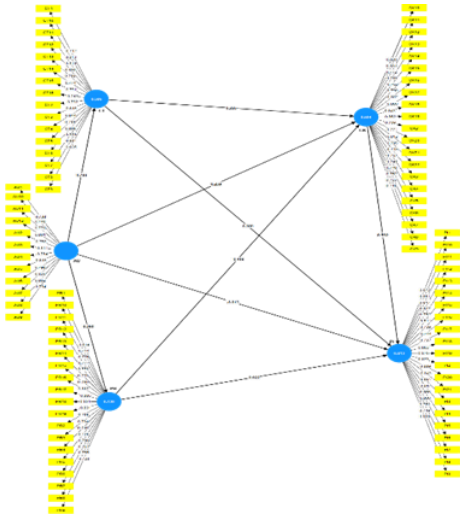

Figure 3. Structural Model Results

Figure 3 presents the structural model obtained from the PLS-SEM analysis, illustrating the relationships among Artificial Intelligence Usefulness, Consumer Trust, Perceived Risk, Consumer Knowledge, and Purchase Intention. The model shows the path coefficients and the direction of influence among constructs. Consumer Trust and Consumer Knowledge demonstrate strong direct effects on Purchase Intention, while Artificial Intelligence Usefulness influences Purchase Intention indirectly through mediating variables.

DISCUSSION

Artificial Intelligence Usefulness is proven to play an important role in shaping Consumer Trust, enhancing Consumer Knowledge, and reducing Perceived Risk. When AI systems are able to provide relevant recommendations, accurate information, and effective support in consumers' decision-making processes, consumers tend to perceive the technology as competent and reliable. This perception of usefulness creates a positive experience that strengthens trust and encourages consumers to be more open to accepting and utilising the information provided. In addition, the ability of AI to present information in a clear and personalised manner helps to reduce uncertainty and consumer concerns, thereby lowering perceived risk. These findings confirm that AI usefulness contributes to creating a more supportive and trustworthy digital environment, which facilitates consumers' interaction with AI-based marketing features.

Nevertheless, Artificial Intelligence Usefulness does not directly influence Purchase Intention. This finding indicates that technological usefulness alone is insufficient to stimulate purchase intention without the presence of supporting psychological factors. Consumers require confidence in the system as well as adequate understanding before forming an intention to purchase. Thus, AI

usefulness functions as a foundational factor that enhances consumer perceptions and experience, while its influence on purchase intention operates through mediating variables such as Consumer Trust and Consumer Knowledge. This suggests that the effectiveness of AI in influencing consumer behaviour depends not only on its functional performance but also on how it shapes consumers' psychological readiness.

Consumer Trust is confirmed as a key factor in increasing Consumer Knowledge and Purchase Intention. Trust creates a sense of security and confidence in the system, making consumers more willing to explore features, accept information, and engage in transactions. When consumers trust AI-based systems, they are more receptive to recommendations and information provided, which enhances their understanding of products and services. This condition ultimately strengthens their confidence in making purchase decisions. Trust also reduces psychological resistance and uncertainty, thereby facilitating consumers' transition from information evaluation to behavioural intention.

Conversely, Perceived Risk acts as an inhibiting factor in enhancing Consumer Knowledge, as consumers who perceive higher risk tend to limit their interaction and engagement with the system. Consumers who feel uncertain about privacy, security, or the reliability of AI recommendations are less likely to actively explore and utilise available information. However, Perceived Risk does not directly affect Purchase Intention, suggesting that consumers place greater emphasis on perceived benefits, trust, and knowledge rather than risk considerations when forming purchase intentions. This finding indicates that the presence of positive factors, particularly trust and knowledge, plays a more dominant role in influencing consumer decisions compared to perceived risk.

Consumer Knowledge emerges as a primary determinant in increasing Purchase Intention. Consumers with a better understanding of products, AI features, and transaction processes feel more confident and capable of making informed decisions. Adequate knowledge reduces uncertainty, strengthens consumers' evaluation of product value, and increases their readiness to engage in transactions. This finding highlights the importance of informational clarity and consumer understanding in supporting AI-based marketing effectiveness, as knowledgeable consumers are more likely to convert their evaluation into actual purchase intention.

Furthermore, the mediating roles of Consumer Trust and Consumer Knowledge confirm that the influence of Artificial Intelligence Usefulness on Purchase Intention operates indirectly through these psychological mechanisms. AI usefulness enhances trust and knowledge, which subsequently encourage consumers to develop stronger purchase intention. This finding emphasises that the success of AI-based marketing does not rely solely on technological capability, but also on its ability to build trust and improve consumer understanding. These mediating relationships demonstrate that psychological factors serve as essential bridges connecting technological perceptions and behavioural outcomes.

Overall, the findings of this study indicate that Artificial Intelligence Usefulness serves as a fundamental factor in building trust, enhancing knowledge,

and reducing consumers' perceived risk. However, its influence on Purchase Intention occurs indirectly through Consumer Trust and Consumer Knowledge.

This confirms that trust and knowledge are the key mechanisms linking the usefulness of AI technology to the formation of consumers' purchase intention in the context of AI-based e-commerce. These findings also highlight the importance for e-commerce platforms to focus not only on improving AI functionality, but also on strengthening consumer trust and facilitating consumer understanding in order to effectively increase purchase intention.

CONCLUSIONS AND RECOMMENDATION

This study concludes that Artificial Intelligence Usefulness plays an important role in shaping Consumer Trust, enhancing Consumer Knowledge, and reducing Perceived Risk within the context of AI-based personalised marketing. However, Artificial Intelligence Usefulness does not directly influence Purchase Intention; instead, its effect operates through mediating mechanisms, particularly Consumer Trust and Consumer Knowledge.

Consumer Trust is proven to enhance both Consumer Knowledge and Purchase Intention, indicating that trust is a crucial factor in encouraging consumers' readiness to make purchases. In contrast, Perceived Risk has a negative effect on Consumer Knowledge, demonstrating that perceived risk can hinder consumers' understanding of the system and products.

Consumer Knowledge emerges as the most dominant factor in increasing Purchase Intention, highlighting that consumers' understanding of AI-based products and systems is the key driver of purchase intention. Overall, these findings confirm that the effectiveness of AI in increasing consumers' purchase intention depends on its ability to build trust and enhance consumer knowledge.

Companies are encouraged to develop AI systems that are not only functional but also capable of strengthening consumer trust and understanding. This can be achieved by providing accurate recommendations, clear information, and systems that are transparent and easy to use. In addition, companies should minimise perceived risk by improving data security, enhancing system transparency, and maintaining consistent service quality. These strategies will help to strengthen consumer trust and knowledge, which in turn will increase Purchase Intention.

FURTHER STUDY

Future research is recommended to extend the model by incorporating additional variables, such as perceived personalisation, perceived value, or consumer engagement, in order to obtain a more comprehensive understanding of the factors influencing Purchase Intention in the context of AI. Furthermore, future studies may employ different populations and contexts to enhance the generalisability of the research findings.

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