

## AI-Generated Content and Perceived Personalization on Purchase Intention of Generation Z: The Mediating Role of Brand Credibility

Hadiansyah Ma'sum<sup>1</sup>, Ratih Hurriyati<sup>2</sup>, Heny Hendrayati<sup>3\*</sup>, Mokh Adib Sultan<sup>4</sup>, Amirul Afif Muhamat<sup>5</sup>

<sup>1,2,3,4</sup> Fakultas Pendidikan Ekonomi dan Bisnis, Universitas Pendidikan Indonesia, Bandung, Indonesia

<sup>5</sup> Faculty of Business and Management, Universiti Teknologi MARA, Selangor, Malaysia

\*Corresponding Author: [henyhendrayati@upi.edu](mailto:henyhendrayati@upi.edu)

Received: 10/01/2026 | Revised: 08/02/2026 | Accepted: 27/03/2026 | Published: 29/03/2026

**Abstract:** This study examines the effects of AI-Generated Content and Perceived Personalization on Purchase Intention, with Brand Credibility as a mediating variable, in the context of digital marketing. A quantitative approach was employed using primary data collected from 168 respondents across several provinces in Indonesia. The data were analyzed using Structural Equation Modeling (SEM) with AMOS to test the proposed hypotheses and relationships among variables. The results indicate that AI-Generated Content and Perceived Personalization significantly influence Brand Credibility, and that Brand Credibility also significantly influences Purchase Intention. Furthermore, AI-Generated content directly affects Purchase Intention. However, Perceived Personalization does not have a direct effect on Purchase Intention; instead, it influences Purchase Intention indirectly through Brand Credibility, indicating a full mediation effect. These findings highlight the important role of Brand Credibility in bridging digital marketing strategies and consumer behavior. Therefore, companies should optimize AI-driven content while strengthening brand credibility to enhance consumers' purchase intent, whereas personalization strategies should focus on building consumer trust.

**Keywords:** *AI-Generated content, perceived personalization, brand credibility, purchase intention, digital marketing*

**How to Cite:** Ma'sum, H., Hurriyati, R., Hendrayati, H., Sultan, M. A., & Muhamat, A. A. (2026). AI-Generated Content and Perceived Personalization on Purchase Intention of Generation Z: The Mediating Role of Brand Credibility. *Journal of Economics and Management*, 4(1), 77-89. <https://doi.org/10.70716/ecoma.v4i1.563>

### INTRODUCTION

The rapid advancement of digital technology has significantly reshaped contemporary marketing practices, particularly through the integration of artificial intelligence (AI). Organizations increasingly utilize AI-driven approaches to enhance customer engagement, optimize communication efficiency, and deliver more personalized experiences. AI-Generated content, as part of generative AI development, enables firms to produce scalable, data-driven, and contextually relevant marketing communication (Feuerriegel et al., 2024; Thakur, 2025). At the same time, Perceived Personalization has emerged as a critical factor in enhancing consumer experience by tailoring content to individual preferences, thereby increasing perceived relevance and engagement (Ameen et al., 2022; Hardcastle et al., 2025).

Despite the growing adoption of AI and personalization strategies, the mechanisms through which these factors influence consumer behavior remain insufficiently understood. Prior studies suggest that personalization can enhance customer experience and loyalty; however, its direct impact on purchase intention often produces inconsistent results and depends on mediating psychological factors such as trust and satisfaction (Dwivedi et al., 2021; Hassan et al., 2025). Similarly, AI-Generated content has been shown to improve digital marketing performance and consumer engagement, yet its direct and indirect influence on purchase intention remains under empirical validation (Hendrayati et al., 2024; Sands et al., 2022).

One important construct that may explain these relationships is Brand Credibility. Brand credibility reflects consumers' perceptions of a brand's reliability and trustworthiness, which play a crucial role in reducing uncertainty and influencing purchase decisions (Erdem & Swait, 2004). In digital environments characterized by information overload and AI-driven communication, credibility becomes even more critical in shaping consumer responses (Guerra-Tamez et al., 2024). However, few studies have examined AI-Generated content and perceived personalization within a unified brand credibility framework, highlighting a significant gap in the literature.

Furthermore, prior research has largely examined AI marketing, personalization, and purchase intention in isolation (Mohamed & Ünsalan, 2025; Yang & Hu, 2022), without integrating these variables into a comprehensive structural model. This fragmented approach limits understanding of how different digital marketing strategies operate through both direct and indirect pathways to influence consumer behavior. Therefore, a more integrative framework is needed to explain the interplay among AI-generated content, personalization, and brand credibility in shaping purchase intention.

Based on these gaps, this study aims to examine the influence of AI-Generated Content and Perceived Personalization on Purchase Intention, with Brand Credibility as a mediating variable. This research contributes to the literature by integrating perspectives on artificial intelligence and personalization within a brand credibility framework, offering a more comprehensive understanding of digital consumer behavior. The findings are expected to provide both theoretical contributions and practical insights for organizations in designing effective AI-driven marketing strategies.

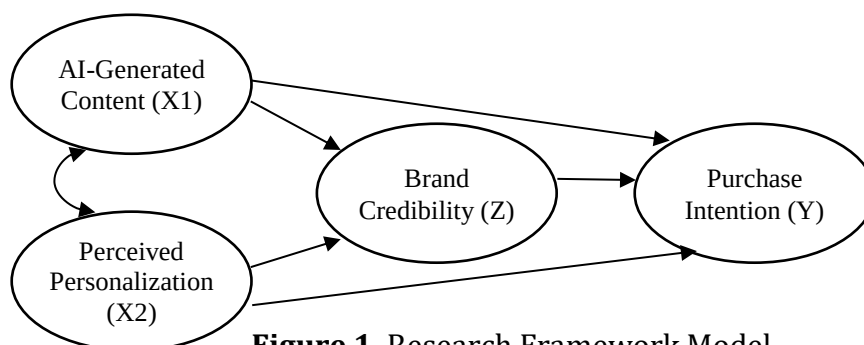
This study offers novelty by integrating AI-Generated content and perceived personalization within a brand credibility framework to explain purchase intention in the context of digital marketing.

To address these gaps, the present study integrates several theoretical frameworks to explain how AI-Generated Content and Perceived Personalization operate through Brand Credibility to influence Purchase Intention. The Elaboration Likelihood Model (ELM) suggests that the quality and credibility of information are critical determinants of consumer attitude formation (Cacioppo et al., 1986). In this context, AI-generated content that is accurate, relevant, and transparent is expected to enhance consumers' perceptions of brand credibility. Prior empirical evidence confirms that interactions with AI-driven marketing systems can build or erode brand trust depending on perceived authenticity and information quality (Guerra-Tamez et al., 2024; Sands et al., 2022). Although Generation Z consumers tend to scrutinize machine-generated content more critically (Wortel et al., 2024), well-crafted AI-generated content has been shown to strengthen brand credibility and deepen consumer engagement (Feuerriegel et al., 2024; Hendrayati et al., 2024). Accordingly, this study proposes that AI-Generated Content has a positive effect on Brand Credibility (H1).

Perceived personalization refers to consumers' subjective perception that marketing messages are tailored to their individual needs and preferences (An & Ngo, 2025). In AI-driven digital environments, personalization has emerged as a key strategy to enhance communication relevance and foster emotional connections between consumers and brands (Hardcastle et al., 2025; Hurriyati & Gunarto, 2021). Prior research demonstrates that effective personalization enhances perceived value and information quality (Zeithaml, 1988), thereby strengthening consumer trust in a brand. Hassan et al. (2025) found that personalized recommendations significantly improve consumer trust in e-commerce contexts. Nevertheless, excessive or intrusive personalization may produce the opposite effect due to privacy concerns, known as the personalization–privacy paradox (Ameen et al., 2022). Therefore, the effectiveness of personalization in enhancing brand credibility depends on balancing relevance with transparency in data usage. Based on this reasoning, Perceived Personalization is expected to affect Brand Credibility (H2) positively.

Brand credibility, defined as consumers' perceptions of a brand's ability and willingness to fulfill its promises (Erdem & Swait, 2004), plays a pivotal role in reducing perceived risk and influencing consumer decision-making, particularly in digital environments characterized by information overload (Guerra-Tamez et al., 2024). According to the Theory of Planned Behavior (Ajzen, 1991), purchase intention is shaped by consumer attitudes and beliefs, with brand credibility serving as a key attitudinal determinant. Empirical studies consistently show that credible brands are more likely to be chosen by consumers, as credibility reduces uncertainty and enhances confidence in purchase decisions (Lee & Chen, 2021; Mohamed & Ünsalan, 2025; Silalahi et al., 2022; Yang & Hu, 2022). It is therefore proposed that Brand Credibility positively affects Purchase Intention (H3).

Grounded in the Stimulus–Organism–Response (SOR) framework, this study positions AI-Generated Content and Perceived Personalization as external stimuli (S) that shape consumers' internal psychological state — Brand Credibility — as the organism (O), which subsequently drives Purchase Intention as the behavioral response (R). Prior studies have increasingly examined AI marketing and personalization as isolated constructs (Davenport et al., 2020; Hendrayati et al., 2024; Luckyardi, 2023), yet few have simultaneously integrated these variables within a unified brand credibility framework. The growing strategic importance of AI in marketing further underscores the need for integrative models that capture both direct and indirect pathways of influence (Huang & Rust, 2021). This study addresses that gap by offering an integrative structural model that captures both direct and indirect pathways through which AI-driven digital marketing strategies influence consumer purchase intention. The proposed research framework is illustrated in Figure 1.



**Figure 1.** Research Framework Model

## RESEARCH METHODS

This study employs a quantitative research approach to examine the causal relationships among the variables in the research model: AI-Generated Content, Perceived Personalization, Brand Credibility, and Purchase Intention. The quantitative approach is selected as it enables objective measurement and facilitates empirical hypothesis testing through statistical analysis (Hair et al., 2022).

The data source in this study consists of primary data collected through a questionnaire distributed to respondents categorized as Generation Z. The sampling technique is non-probability purposive sampling, targeting respondents who meet specific criteria: active users of digital platforms and individuals who have been exposed to AI-based marketing content. The total sample size in this study is 168 respondents, which meets the minimum requirements for Structural Equation Modeling (SEM) analysis (Anderson & Gerbing, 1988; Hair et al., 2022).

The research instrument is developed as a structured questionnaire using a five-point Likert scale from 1 (strongly disagree) to 5 (strongly agree). The measurement indicators for each construct are adapted from relevant prior studies to ensure construct validity and reliability (Fornell & Larcker, 1981).

The demographic characteristics of respondents include gender, age, occupation, domicile, and the digital platforms used. Data collection was conducted between January and March 2026. The distribution of respondents indicates a dominance of Generation Z aged 17–20 years, with the majority being students. This finding aligns with the characteristics of Generation Z as digital natives who are highly engaged with digital technology (Priporas et al., 2017). Detailed demographic characteristics of respondents are presented in Table 1.

**Table 1.** Demographic Characteristics of Respondents

| Characteristics | Description        | Frequency | Percentage (%) |
|-----------------|--------------------|-----------|----------------|
| Gender          | Male               | 62        | 36.9%          |
|                 | Female             | 106       | 63.1%          |
| Age             | 13–16 years        | 1         | 0.6%           |
|                 | 17–20 years        | 100       | 59.5%          |
|                 | 21–24 years        | 54        | 32.1%          |
|                 | 25–29 years        | 13        | 7.7%           |
|                 |                    |           |                |
| Occupation      | Student            | 148       | 88.1%          |
|                 | Employee           | 18        | 10.7%          |
|                 | Lecturer           | 1         | 0.6%           |
|                 | Entrepreneur       | 1         | 0.6%           |
| Region          | Aceh               | 2         | 1.2%           |
|                 | Jakarta            | 3         | 1.8%           |
|                 | Jambi              | 1         | 0.6%           |
|                 | West Java          | 127       | 75.6%          |
|                 | Central Java       | 1         | 0.6%           |
|                 | East Java          | 3         | 1.8%           |
|                 | Central Kalimantan | 1         | 0.6%           |
|                 |                    |           |                |

| Characteristics | Description                           | Frequency | Percentage (%) |
|-----------------|---------------------------------------|-----------|----------------|
| Platform Usage  | South Sulawesi                        | 1         | 0.6%           |
|                 | West Sumatra                          | 29        | 17.3%          |
|                 | Shopee / Tokopedia / Marketplace      | 43        | 25.6%          |
|                 | TikTok, Instagram, WhatsApp, Facebook | 125       | 74.4%          |

Source: Processed primary data (2026)

The data analysis in this study employs Structural Equation Modeling (SEM) to examine the relationships among latent constructs simultaneously. SPSS was utilized for descriptive statistics and preliminary analyses, while AMOS was used to estimate the measurement and structural models and to test the proposed hypotheses. The SEM procedure was conducted in two stages: (1) evaluation of the measurement model to ensure construct validity and reliability, and (2) assessment of the structural model to analyze the causal relationships among variables (Hair et al., 2022).

## RESULTS AND DISCUSSION

### Results

The data analysis in this study used Structural Equation Modeling (SEM) to evaluate both the measurement and structural models. The analysis began with assessing the measurement model to ensure construct validity and reliability, followed by evaluating the structural model to test the proposed hypotheses.

### Measurement Model Assessment

The measurement model was first evaluated to ensure the validity and reliability of the constructs. Convergent validity was assessed using factor loadings, Composite Reliability (CR), and Average Variance Extracted (AVE). These indicators are essential to confirm that each construct adequately represents its measurement items. The results of the measurement model assessment are presented in Table 2.

**Table 2.** Measurement Model Assessment Results

| Construct                      | Indicator | Loading | CA    | CR    | AVE   |
|--------------------------------|-----------|---------|-------|-------|-------|
| AI-Generated Content (AIGC)    | X1.1      | 0.747   | 0.902 | 0.918 | 0.692 |
|                                | X1.2      | 0.744   |       |       |       |
|                                | X1.3      | 0.863   |       |       |       |
|                                | X1.4      | 0.867   |       |       |       |
|                                | X1.5      | 0.840   |       |       |       |
| Perceived Personalization (PP) | X2.1      | 0.847   | 0.923 | 0.938 | 0.753 |
|                                | X2.2      | 0.901   |       |       |       |
|                                | X2.3      | 0.843   |       |       |       |
|                                | X2.4      | 0.851   |       |       |       |
|                                | X2.5      | 0.797   |       |       |       |
| Brand Credibility (BC)         | Z1        | 0.759   | 0.929 | 0.949 | 0.789 |
|                                | Z2        | 0.869   |       |       |       |
|                                | Z3        | 0.896   |       |       |       |

| Construct               | Indicator | Loading | CA    | CR    | AVE   |
|-------------------------|-----------|---------|-------|-------|-------|
| Purchase Intention (PI) | Z4        | 0.932   |       |       |       |
|                         | Z5        | 0.867   |       |       |       |
|                         | Y1        | 0.841   | 0.912 | 0.932 | 0.774 |
|                         | Y2        | 0.748   |       |       |       |
|                         | Y3        | 0.895   |       |       |       |
|                         | Y4        | 0.865   |       |       |       |

Source: Data processing with AMOS, 2026

The measurement model assessment results indicate that all constructs demonstrate strong convergent validity and internal consistency. All indicator loadings exceed the recommended threshold of 0.70, confirming adequate item reliability. The Composite Reliability (CR) values range from 0.918 to 0.949, exceeding the minimum threshold of 0.70, indicating strong internal consistency. Furthermore, the Average Variance Extracted (AVE) values range from 0.692 to 0.789, which exceed the recommended threshold of 0.50, confirming that the constructs explain a substantial portion of the variance in their indicators. These results suggest that the measurement model is both valid and reliable (Hair et al., 2022).

### Discriminant Validity

After establishing convergent validity, discriminant validity was assessed to ensure that each construct is empirically distinct from the others. The Fornell-Larcker criterion was used, comparing the square root of AVE with inter-construct correlations. The results of this analysis are presented in Table 3.

**Table 3.** Discriminant Validity (Fornell-Larcker Criterion)

| Variable                       | AIGC  | PP           | BC           | PI           |
|--------------------------------|-------|--------------|--------------|--------------|
| AI-Generated Content (AIGC)    | 0.832 |              |              |              |
| Perceived Personalization (PP) | 0.698 | <b>0.868</b> |              |              |
| Brand Credibility (BC)         | 0.671 | 0.825        | <b>0.888</b> |              |
| Purchase Intention (PI)        | 0.732 | 0.737        | 0.843        | <b>0.880</b> |

Source: Data processing with AMOS, 2026

Table 3 presents the discriminant validity results using the Fornell-Larcker criterion. The diagonal values in the table represent the square root of the Average Variance Extracted (AVE) for each construct. Specifically, AI-Generated content has a value of 0.832, Perceived Personalization 0.868, Brand Credibility 0.888, and Purchase Intention 0.880. These values are higher than the corresponding inter-construct correlations in their respective rows and columns. This indicates that each construct accounts for more variance among its indicators than among those of other constructs, thereby confirming adequate discriminant validity. All constructs in this study are empirically distinct and suitable for further analysis (Hair et al., 2022).

### Collinearity Assessment

Prior to testing the structural model, it is essential to assess potential multicollinearity among the predictor variables. Multicollinearity was evaluated using the Variance Inflation Factor (VIF) to ensure that the independent variables do not exhibit high intercorrelations that could bias the estimation results. A VIF value below



the recommended threshold indicates the absence of multicollinearity. The results of the collinearity assessment are presented in Table 4.

**Table 4.** Collinearity Statistics (VIF)

| Construct                      | AIGC  | PP    | BC    | PI    |
|--------------------------------|-------|-------|-------|-------|
| AI-Generated Content (AIGC)    | -     | 1.696 |       |       |
| Perceived Personalization (PP) | 1.696 | -     |       |       |
| Brand Credibility (BC)         |       |       | -     | 1.000 |
| Purchase Intention (PI)        |       |       | 1.000 | -     |

Source: Data processing with SPSS, 2026

The collinearity statistics were evaluated using the Variance Inflation Factor (VIF) to assess multicollinearity among the predictor variables in the structural model. As presented in Table 4, the VIF values for AI-Generated Content (AIGC) and Perceived Personalization (PP), which act as predictors of Brand Credibility (BC), are both 1.696. This indicates that the two independent variables do not exhibit high intercorrelation and are statistically independent in explaining Brand Credibility. The relatively low VIF values further suggest that both variables represent different explanatory aspects within the model, allowing their effects to be interpreted clearly without causing instability in the estimation results.

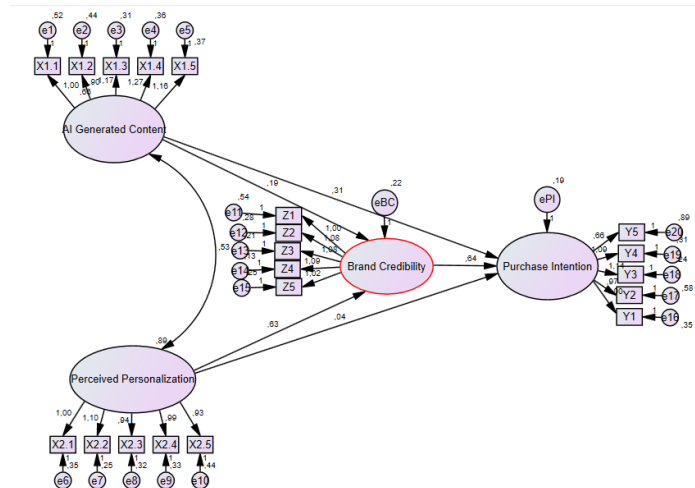
Furthermore, the VIF value for Brand Credibility (BC) as a predictor of Purchase Intention (PI) is 1.000, indicating no multicollinearity. This suggests that Brand Credibility independently contributes to explaining Purchase Intention without any redundancy or overlap with other predictors. A VIF value equal to 1.000 shows that there is no linear dependency issue involving the construct in the regression model. As a result, Brand Credibility can be considered a stable predictor that contributes directly to explaining variations in Purchase Intention.

All VIF values in this study are well below the commonly accepted threshold of 5 (Hair et al., 2022), and even below the more conservative threshold of 3, indicating a very low level of multicollinearity. This confirms that each construct contributes uniquely to the model and that path coefficient estimates are not biased by collinearity. In addition, the low collinearity values indicate that the independent variables explain the dependent constructs without creating overlapping effects within the structural model.

These results demonstrate that the structural model is free of multicollinearity, thereby ensuring the robustness and reliability of the regression estimates. The model is suitable for further hypothesis testing and structural analysis (Hair et al., 2022).

### Structural Model and Hypothesis Testing

The subsequent analysis stage examined the structural model by analysing the path coefficients to test the proposed hypotheses regarding the direct relationships among constructs. The significance of each hypothesized path was evaluated using the critical ratio (t-statistic) and the P-value obtained from the AMOS estimation results. A path is considered statistically significant when the t-statistic is greater than 1.96, and the P-value is less than 0.05 (Hair et al., 2022). In this context, the structural model represents the relationships among AI-Generated Content, Perceived Personalization, Brand Credibility, and Purchase Intention. The results of the structural model are illustrated in Figure 2.



**Figure 2.** Structural Model

After ensuring the adequacy of the measurement model, the structural model was evaluated to test the proposed hypotheses. The significance of the relationships was determined using the t-statistic (CR) and the P-value. The results of the direct effects are presented in Table 5.

**Table 5.** The Result of Path Coefficient (Direct Effects)

| Path      | Original Sample (O) | Sample Mean (M) | Standard Deviation | t-statistic | P-value |
|-----------|---------------------|-----------------|--------------------|-------------|---------|
| PP → BC   | 0.631               | 0.631           | 0.085              | 7.393       | ***     |
| AIGC → BC | 0.195               | 0.195           | 0.082              | 2.381       | 0.017   |
| BC → PI   | 0.641               | 0.641           | 0.114              | 5.634       | ***     |
| AIGC → PI | 0.314               | 0.314           | 0.085              | 3.700       | ***     |
| PP → PI   | 0.036               | 0.036           | 0.097              | 0.376       | 0.707   |

Source: Data processing with AMOS, 2026

Table 5 presents the results of the path coefficient analysis examining the direct relationships among the constructs in the structural model. The findings indicate that Perceived Personalization has a positive and significant effect on Brand Credibility ( $\beta = 0.631$ ,  $p < 0.001$ ), followed by AI-Generated content, which also shows a significant influence on Brand Credibility ( $\beta = 0.195$ ,  $p < 0.05$ ). Furthermore, Brand Credibility demonstrates a strong and significant effect on Purchase Intention ( $\beta = 0.641$ ,  $p < 0.001$ ), indicating its important role as a key predictor in the model.

In addition, AI-Generated content is found to have a significant direct effect on Purchase Intention ( $\beta = 0.314$ ,  $p < 0.001$ ). However, the effect of Perceived Personalization on Purchase Intention is not statistically significant ( $\beta = 0.036$ ,  $p > 0.05$ ). These results suggest that while Perceived Personalization significantly enhances Brand Credibility, it does not directly influence Purchase Intention, highlighting Brand Credibility's mediating role in the relationship.

### Indirect Effect Analysis

To further examine the mediating role of Brand Credibility, an indirect effect analysis was conducted. The indirect effects were calculated as the difference between the total and direct effects for each relationship. This analysis aims to determine whether Brand Credibility significantly mediates the relationship between AI-Generated



Content, Perceived Personalization, and Purchase Intention. The results of the indirect effect analysis are presented in Table 6.

**Table 6.** Indirect Effect

| Path           | Original Sample (O) | Sample Mean (M) | Standard deviation | t-statistic | P-value |
|----------------|---------------------|-----------------|--------------------|-------------|---------|
| AIGC → BC → PI | 0.115               | 0.115           | 0.085              | 1.353       | 0.176   |
| PP → BC → PI   | 0.428               | 0.428           | 0.097              | 4.412       | ***     |

Source: Data processing with AMOS, 2026

As shown in Table 6, the indirect effect of Perceived Personalization on Purchase Intention through Brand Credibility is positive and statistically significant ( $\beta = 0.428$ ,  $t = 4.412$ ,  $p < 0.001$ ). This indicates that Brand Credibility fully mediates the relationship between Perceived Personalization and Purchase Intention. In other words, Perceived Personalization influences Purchase Intention primarily by affecting Brand Credibility.

In contrast, the indirect effect of AI-Generated Content on Purchase Intention through Brand Credibility is not statistically significant ( $\beta = 0.115$ ,  $t = 1.353$ ,  $p > 0.05$ ). This finding suggests that Brand Credibility does not mediate the relationship between AI-Generated Content and Purchase Intention. Therefore, the effect of AI-Generated Content on Purchase Intention occurs more directly rather than through Brand Credibility.

### Total Effect

To provide a comprehensive understanding of the relationships among the constructs, a total effect analysis was conducted. The total effect represents the combined influence of a variable's direct and indirect effects on other variables. This analysis is important to capture the overall impact of AI-Generated Content and Perceived Personalization on Purchase Intention, including the mediating role of Brand Credibility. The results of the total effect analysis are presented in Table 7.

**Table 7.** Total Effect

| Path      | Original Sample (O) | Sample Mean (M) | Standard Deviation | t-statistic | P-value |
|-----------|---------------------|-----------------|--------------------|-------------|---------|
| PP → BC   | 0.631               | 0.631           | 0.085              | 7.424       | ***     |
| AIGC → BC | 0.195               | 0.195           | 0.082              | 2.378       | 0.017   |
| BC → PI   | 0.641               | 0.641           | 0.114              | 5.623       | ***     |
| AIGC → PI | 0.439               | 0.439           | 0.085              | 5.165       | ***     |
| PP → PI   | 0.441               | 0.441           | 0.097              | 4.546       | ***     |

Source: Data processing with AMOS, 2026

As shown in Table 7, Perceived Personalization has a strong and significant total effect on Brand Credibility ( $\beta = 0.631$ ,  $p < 0.001$ ), followed by AI-Generated content ( $\beta = 0.195$ ,  $p < 0.05$ ). This indicates that both variables play an important role in enhancing Brand Credibility.

Furthermore, Brand Credibility has a significant total effect on Purchase Intention ( $\beta = 0.641$ ,  $p < 0.001$ ), confirming its central role in consumer decision-making. In addition, both AI-Generated Content and Perceived Personalization have significant total effects on Purchase Intention, with coefficients of 0.439 and 0.441, respectively.

Interestingly, although Perceived Personalization does not have a significant direct effect on Purchase Intention, its total effect becomes significant due to the mediating

role of Brand Credibility. This finding highlights the importance of Brand Credibility as a key mechanism through which perceived personalization influences purchase intention. Meanwhile, AI-Generated content affects Purchase Intention both directly and indirectly, indicating a complementary role of both pathways.

### Discussion

The findings of this study provide significant theoretical and managerial insights into the role of AI-Generated Content and perceived personalization in shaping Purchase Intention through Brand Credibility. This study extends existing literature by demonstrating that digital marketing strategies do not operate uniformly, but rather through distinct direct and indirect mechanisms.

These findings suggest that the effectiveness of AI-driven marketing strategies depends not only on technological capability but also on the ability to build consumer trust through credible brand communication.

First, the significant effect of AI-Generated Content on Brand Credibility confirms that AI-driven marketing content can enhance consumer trust when it delivers relevant and reliable information. This finding extends prior research by demonstrating that AI-Generated content not only enhances communication effectiveness but also strengthens brand credibility in AI-driven marketing environments and enhances consumer engagement (Feuerriegel et al., 2024; Hendrayati et al., 2024)

Second, Perceived Personalization demonstrates a strong influence on Brand Credibility, indicating that personalized communication enhances consumer trust. This result aligns with prior research suggesting that personalization improves perceived value and strengthens brand relationships (Ameen et al., 2022; Hassan et al., 2025).

Third, Brand Credibility significantly influences Purchase Intention, confirming its role as a key determinant in consumer decision-making. This finding is consistent with established theories emphasizing the importance of trust and credibility in reducing perceived risk (Erdem & Swait, 2004).

Interestingly, Perceived Personalization does not directly influence Purchase Intention; rather, it exerts its effect indirectly through Brand Credibility. This indicates that trust acts as a necessary mechanism through which personalization influences consumer behavior. This finding provides a nuanced understanding of personalization strategies and highlights the importance of credibility as a mediating factor.

Meanwhile, AI-Generated content influences Purchase Intention both directly and indirectly, suggesting that AI-driven strategies can impact consumer decisions through multiple pathways. This reinforces the growing importance of artificial intelligence in digital marketing.

### CONCLUSION AND RECOMMENDATIONS

This study was conducted to address the research problem concerning how AI-Generated Content and Perceived Personalization influence Purchase Intention, particularly through the mediating role of Brand Credibility in the context of digital marketing. In the era of artificial intelligence, understanding the mechanisms through which digital strategies affect consumer behavior becomes increasingly important.

The findings reveal that both AI-Generated Content and Perceived Personalization significantly influence Brand Credibility, which in turn plays a crucial role in driving Purchase Intention. Additionally, AI-Generated content has a direct and significant effect on Purchase Intention, whereas Perceived Personalization does not directly affect Purchase Intention but exerts its influence indirectly through Brand Credibility. This

indicates that Brand Credibility acts as a full mediator in the relationship between Perceived Personalization and Purchase Intention, while AI-Generated Content operates through both direct and indirect pathways.

These findings provide important theoretical implications by integrating artificial intelligence and personalization within the framework of brand credibility and consumer behavior. From a managerial perspective, the results suggest that organizations should prioritize developing AI-driven content strategies while simultaneously strengthening brand credibility to enhance consumer trust and purchase intention. Moreover, personalization strategies should be designed to build credibility first, rather than directly targeting purchase behavior.

To effectively address the research problem, the key strategy is to leverage AI-generated content to deliver relevant and engaging communication while ensuring that personalization efforts build strong brand credibility. This combination enables firms to influence consumer decision-making both directly and indirectly.

This study highlights that brand credibility is not merely an outcome of digital marketing strategies, but a critical mechanism that transforms technological engagement into actual consumer behavior.

Despite its contributions, this study has several limitations, particularly regarding the sample scope and the contextual setting. Therefore, future research is recommended to expand the model by incorporating additional variables, such as consumer trust, perceived value, or digital engagement, and to apply different analytical approaches and broader, more diverse samples to enhance generalizability.

## REFERENCES

- Ajzen, I. (1991). The theory of planned behavior. *Organizational Behavior and Human Decision Processes*, 50(2), 179–211.
- Ameen, N., Hosany, S., & Paul, J. (2022). The personalisation-privacy paradox: Consumer interaction with smart technologies and shopping mall loyalty. *Computers in Human Behavior*, 126, 106976. <https://doi.org/10.1016/j.chb.2021.106976>
- An, G. K., & Ngo, T. T. A. (2025). AI-powered personalized advertising and purchase intention in Vietnam's digital landscape: The role of trust, relevance, and usefulness. *Journal of Open Innovation: Technology, Market, and Complexity*, 11(3), 100580. <https://doi.org/10.1016/j.joitmc.2025.100580>
- Anderson, J., & Gerbing, D. (1988). Structural Equation Modeling in Practice: A Review and Recommended Two-Step Approach. *Psychological Bulletin*, 103, 411–423. <https://doi.org/10.1037/0033-2909.103.3.411>
- Cacioppo, J., Petty, R., Chuan, F., & Rodriguez, R. (1986). Central and Peripheral Routes to Persuasion: An Individual Difference Perspective. *Journal of Personality and Social Psychology*, 51, 1032–1043. <https://doi.org/10.1037/0022-3514.51.5.1032>
- Davenport, T. H., Guha, A., Grewal, D., & Bressgott, T. (2020). How artificial intelligence will change the future of marketing. *Journal of the Academy of Marketing Science*, 48(1), 24–42. <https://doi.org/10.1007/s11747-019-00696-0>
- Dwivedi, Y. K., Ismagilova, E., Hughes, D. L., Carlson, J., Filieri, R., Jacobson, J., Jain, V., Karjaluoto, H., Kefi, H., Krishen, A. S., Kumar, V., Rahman, M. M., Raman, R., Rauschnabel, P. A., Rowley, J., Salo, J., Tran, G. A., & Wang, Y. (2021). Setting the future of digital and social media marketing research: Perspectives and research propositions. *International Journal of Information Management*, 59, 102168. <https://doi.org/10.1016/j.ijinfomgt.2020.102168>

- Erdem, T., & Swait, J. (2004). Brand credibility, brand consideration, and choice. *Journal of Consumer Research*, 31(1), 191–198. <https://doi.org/10.1086/383434>
- Feuerriegel, S., Hartmann, J., Janiesch, C., & Zschech, P. (2024). Generative AI. *Business and Information Systems Engineering*, 66(1), 111–126. <https://doi.org/10.1007/s12599-023-00834-7>
- Fornell, Claes, & Larcker, David F. (1981). Evaluating Structural Equation Models with Unobservable Variables and Measurement Error. *Journal of Marketing Research*, 18(1), 39–50. <https://doi.org/10.1177/002224378101800104>
- Guerra-Tamez, C. R., Kraul Flores, K., Serna-Mendiburu, G. M., Chavelas Robles, D., & Ibarra Cortés, J. (2024). Decoding Gen Z: AI's influence on brand trust and purchasing behavior. *Frontiers in Artificial Intelligence*, 7. <https://doi.org/10.3389/frai.2024.1323512>
- Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2022). *A primer on partial least squares structural equation modeling (PLS-SEM) (3rd ed.)*. Sage.
- Hardcastle, K., Vorster, L., & Brown, D. M. (2025). Understanding Customer Responses to AI-Driven Personalized Journeys: Impacts on the Customer Experience. *Journal of Advertising*, 54(2), 176–195. <https://doi.org/10.1080/00913367.2025.2460985>
- Hassan, N., Abdelraouf, M., & El-Shihy, D. (2025). The moderating role of personalized recommendations in the trust–satisfaction–loyalty relationship: an empirical study of AI-driven e-commerce. *Future Business Journal*, 11(1). <https://doi.org/10.1186/s43093-025-00476-z>
- Hendrayati, H., Achyarsyah, M., Marimon, F., Hartono, U., & Putit, L. (2024). The Impact of Artificial Intelligence on Digital Marketing: Leveraging Potential in a Competitive Business Landscape. *Emerging Science Journal*, 8(6), 2343–2359. <https://doi.org/10.28991/ESJ-2024-08-06-012>
- Huang, M. H., & Rust, R. T. (2021). Artificial intelligence in service. *Journal of Service Research*, 24(1), 3–15. <https://doi.org/10.1177/1094670520902266>
- Hurriyati, R., & Gunarto, M. (2021). Digital marketing strategy. *Journal of Distribution Science*, 19(6), 25–34. <https://doi.org/10.15722/jds.19.6.202106.25>
- Lee, C., & Chen, C. (2021). The Impact of Live Streaming on Online Purchase Intention. *Information*, 12(6), 241–254.
- Luckyardi, S. (2023). Consumer Behavior and Digital Marketing Strategy in the Era of Artificial Intelligence. *Jurnal Ekonomi, Bisnis, Dan Manajemen (JEBM)*, 6(3), 201–219. <https://doi.org/10.37715/jebm.v6i3.6942>
- Mohamed, Z. A., & Ünsalan, M. (2025). Does AI marketing efforts affect brand loyalty of Gen Z consumers? Mediating role of brand image and brand experience. *Cogent Business and Management*, 12(1). <https://doi.org/10.1080/23311975.2025.2542428>
- Priporas, C. V., Stylos, N., & Fotiadis, A. K. (2017). Generation Z consumers' expectations of interactions in smart retailing: A future agenda. *Computers in Human Behavior*. *Computers in Human Behavior*, 77, 374–381. <https://doi.org/10.1016/j.chb.2017.01.058>
- Sands, S., Campbell, C. L., Plangger, K., & Ferraro, C. (2022). Unreal influence: leveraging AI in influencer marketing. *European Journal of Marketing*, 56(6), 1721–1747. <https://doi.org/10.1108/EJM-12-2019-0949>
- Silalahi, I. V., Hurriyati, R., Rahayu, A., Gaffar, V., Wibowo, L. A., Dirgantari, P. D., & Warlin, L. (2022). Digital Way To Increase Consumer Purchase Intention for Local Fashion Products in Developing Country. *Journal of Eastern European and Central*

- Asian Research*, 9(5), 838–850. <https://doi.org/10.15549/jeecar.v9i5.1070>
- Thakur, C. (2025). Exploring the Influence of Generative Ai on Consumer Experiences and Behavioral Responses: a Systematic Literature Review and Future Research Agenda. *Academy of Marketing Studies Journal*, 29(6), 1–41.
- Wortel, C., Vanwesenbeeck, I., & Tomas, F. (2024). Made with Artificial Intelligence: The Effect of Artificial Intelligence Disclosures in Instagram Advertisements on Consumer Attitudes. *Emerging Media*, 2(3), 547–570. <https://doi.org/10.1177/27523543241292096>
- Yang, C., & Hu, J. (2022). When do consumers prefer AI-enabled customer service? The interaction effect of brand personality and service provision type on brand attitudes and purchase intentions. *Journal of Brand Management*, 29(2), 167–189. <https://doi.org/10.1057/s41262-021-00261-7>
- Zeithaml, V. A. (1988). Consumer Perceptions of Price, Quality, and Value: A Means-End Model and Synthesis of Evidence. *Journal of Marketing*, 52(3), 2–22. <https://doi.org/10.1177/002224298805200302>