# From Preference to Recommendation: The Role of AI Stimuli and Perceived Marketing Innovation

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**Abstract**

**Research purpose:**

*This research examines the influence of Artificial Intelligence stimuli, specifically perceived personalization and perceived interactivity, on consumers' brand preferences and brand recommendations. Drawing on Arousal theory, the study explores how perceived marketing innovation influences these relationships. It indicates that customers are inclined to establish a strong brand preference and promote it when they see the brand's marketing efforts as innovative and exciting.*

**Research motivation:**

*This study is driven by the increasing use of AI technologies in brand marketing, particularly in enhancing user personalization and interactivity. Despite the widespread adoption, little is known about how these AI-driven elements shape consumer brand preference and their recommendation of the brand to others. Drawing on Arousal theory, this research explores how stimulating brand experiences can influence consumer behavior.*

**Research design, approach, and method:**

*This study examined 260 valid questionnaires collected from mature consumers, with a focus on those who had previously encountered or were familiar with such brands and had adopted AI initiatives. The analysis was carried out using SPSS 26 and SmartPLS 3 statistical software.*

**Main findings:**

*The research finds that Artificial stimuli, namely perceived personalization and perceived interactivity, have a positive influence on brand preference, subsequently enhancing consumers' intention to recommend the brand. Moreover, perceived marketing innovation plays a significant moderating role, with the strongest effect observed in the relationship between perceived personalization and brand preference. Brand preference also mediates the relationship between perceived personalization and brand recommendation, along side with the relationship between perceived interactivity and brand recommendation.*

**Practical/managerial implications:**

*This research outlines directions for marketers by providing the important role AI technologies that enhance personalization and interactivity. Brand can be strengthened through engage some emotionally activity and let customer have tech-enabled experiences.*

**Keywords**: artificial intelligence, brand preference, brand recommendation, perceived marketing innovation, perceived personalization, perceived interactivity.

## 1. INTRODUCTION

Artificial intelligence (AI) has become one of the most important driving forces changing how people live, work, and interact (Gao & Liu, 2023). Over the past twenty years, AI has had a significant impact on various industries, including biotechnology, teaching and learning, industrial engineering, banking and finance, and public health, which equally applies to marketing (Huang & Rust, 2018; Rust, 2020). In marketing, AI applications are expanding rapidly. Businesses now use AI tools to create personalized customer experiences and analyze consumer data to create an advertising strategy that attracts customers (Huseynov, 2023). These advanced techniques enable companies to deliver intelligent, customized experiences that influence consumer preferences, purchasing decisions, and brand loyalty (Behera et al., 2024; Mariani et al., 2022). The rapid growth of AI is truly impressive and exciting. It's amazing to see how quickly this technology is advancing and the new possibilities it opens up for all of us impressive. The global AI market will hit USD 244.22 billion by 2025 and is expected to increase at a steady annualized growth rate (CAGR) of 26.6% from 2025 to 2031 (Statista,2025). In the U.S. alone, the AI market was valued at USD 146.09 billion in 2024 and is forecasted to reach USD 173.56 billion in 2025 (Precedence Research, 2024). These numbers really show how quickly AI is advancing and all the exciting possibilities ahead potential.

Enhancing customer experience is a primary motivation for brands to adopt AI (Ho & Chow, 2024). Today, companies increasingly incorporate AI technologies into frontline operations to automate and personalize consumer interactions (de Ruyter et al., 2020; Silva & Bonetti, 2021). However, marketing AI innovation faces unique challenges because it depends not just on technological abilities but also on how consumers perceive interactivity and emotional connection. In particular, how well an AI system can quickly solve problems and provide helpful support can really shape how satisfied users feel (Yeo et al., 2022). Consumers generally prefer AI agents that feel more human and relatable, rather than those that seem just mechanical or robotic (Garvey et al., 2022). Therefore, achieving success with AI in marketing means beautifully balancing its practical features with warm, human-like qualities like personalization and interactivity. This blend helps create truly meaningful connections between brands and people interactions.

Although there's increasing research on how AI interacts with customer engagement (Hollebeek et al., 2021; Huang & Rust, 2022; Xiao & Kumar, 2021), only a few research specifically look into how AI influences this connection or through what mechanisms it does so. Most current literature mainly addresses AI's instrumental role, concentrating on the way perceived usefulness and ease of use impact customer retention (Sheng & Teo, 2012; Kim et al., 2016; Fang & Fang, 2016). These studies, built upon models like the Technology Acceptance Model (TAM), emphasize rational decision-making and efficiency, providing valuable insights but mainly concentrating on technological and operational aspects. Few empirical investigations examine how AI influences the consumer-brand relationship (Ahmed et al., 2025). Additionally, brand recommendation has gained scholarly attention, especially in sports, due to its strong effect on audience behavior and visibility. It is equally important to explore this in marketing contexts, where intelligent systems increasingly influence consumer experiences. A further gap is the limited investigation of contextual or brand-level factors, such as perceived marketing innovation, that could enhance or hinder AI's effectiveness. These gaps underscore the need for a more emotionally focused approach in AI marketing research.

Building on Berlyne's (1960) Arousal Theory, which highlights that certain stimuli can trigger emotional responses influencing behavior, this research conceptualizes perceived marketing innovation as a moderating construct capable of enhancing or reducing the influence of AI stimuli. Existing studies show that personalized recommendations often lead to higher conversion rates and sales, as consumers tend to prefer offers aligned with their preferences and needs (Kumar & Reinartz, 2016). By applying Arousal Theory to AI-driven marketing, this research offers a deeper understanding of how emotional and perceptual factors influence long-term brand success. It explores how AI enhances consumer engagement, brand loyalty, and advocacy in the digital age. The present study is designed to explore the following research questions:

RQ1: How do AI stimuli (perceived personalization and perceived interactivity) influence the preference of consumers towards brands that utilize AI?

RQ2: How does brand preference influence the relationship between AI stimuli and brand recommendations?

RQ3: How does perceived marketing innovation moderate the relationships between AI stimuli, brand preference, and brand recommendation?

## 2. LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

### 2.1. Arousal theory

Arousal theory highlights how external environmental factors impact individuals' emotional states (Berlyne, 1960). These factors activate our perceptual processes, increasing arousal levels that then influence our behaviors in a meaningful way. (Loewen & Suedfeld, 1992). In business research, this theory often helps us understand how environmental cues influence consumer emotions and behaviors, offering valuable insights into how they make decisions (Wirtz et al., 2018). Previous studies also show that these influences shape both the physical feelings and the psychological experiences of tourists, highlighting how interconnected and impactful these factors are (Wang et al., 2020). Building on this, the current study explores how AI-driven marketing acts as an external stimulus that influences consumer perceptions and brand preferences, ultimately shaping brand recommendations. By adopting this approach, we can more effectively grasp how technology shapes and guides consumer choices.

According to arousal theory, elements like novelty, complexity, and ambiguity can boost arousal levels. When arousal reaches a moderate, optimal level, it often results in feelings of interest and enjoyment, making experiences more engaging and rewarding enjoyment. In today's service environments, digital technologies act as social stimuli that influence customer experiences by inspiring perceptual and behavioral responses (Parise et al., 2016). The study highlights perceived personalization and perceived interactivity as important AI-driven service stimuli. Perceived personalization provides consumers with a fresh, personally relevant cue that signals an individualized brand experience engagement. At the same time, perceived interactivity makes things more engaging and invites a deeper level of participation through

lively, responsive interactions. These stimuli are designed to deliver the perfect level of excitement, capture attention, evoke emotional reactions, and help build a stronger preference for the brand.

Previous research has shown that in digital settings, using arousal theory can really enhance how we connect with content. Features like personalized content and interactive elements are especially effective at increasing engagement and evoking emotional responses (e.g., Gao et al., 2022; Gao & Liu, 2023; Li et al., 2024; Belanche et al., 2014). This study takes a different look by exploring not just how AI stimuli work functionally, but also how they influence social and emotional responses from consumers. It's interesting to note that most previous research mostly focused on short-term outcomes like satisfaction or engagement, so this approach offers a fresh perspective. This study builds on arousal theory by looking at how it affects long-term brand outcomes, like how much people prefer a brand and recommend it to others. It also looks at perceived marketing innovation as a helpful factor that can either boost or lessen the arousal effects of AI stimuli.

### 2.2. Hypothesis development

#### 2.2.1. AI Stimuli

This research on AI-driven marketing explores how AI stimuli make consumers feel their personal needs are met and encourage interactive engagement through AI marketing efforts. It highlights two main aspects: perceived personalization and perceived interactivity. Perceived personalization shows how much consumers feel AI provides content, promotions, or messages that are customized to their unique traits and preferences (Li & Unger, 2012). Perceived interactivity looks at how much consumers feel they can actively engage, influence, and get responses from AI-powered brand interactions or interfaces (Yadav & Pavlou 2014).

According to arousal theory (Berlyne, 1960), external stimuli such as novelty, complexity, or unpredictability can create a psychological state of arousal. In digital marketing, AI-driven personalization and interactivity serve as these stimulating factors by providing consumers with personalized and dynamic brand experiences that foster greater cognitive and emotional engagement. When these stimuli reach an ideal level of excitement, they're more likely to bring about positive responses, such as liking a brand more or preferring it over others. Personalized AI content shows that a brand understands individual needs, making interactions feel less intrusive (Keyzer et al., 2022). This personalized approach helps reinforce consumers' personal attachment to the brand, fostering more positive feelings and attitudes toward the brand (Keyzer et al., 2022). It also makes use of interactive AI tools like chatbots and recommendation systems, which warmly invite users to participate more actively and feel a greater sense of control. This friendly approach naturally encourages more engagement and loyalty. As supported by previous research, personalization and interactivity in digital environments help improve user experience and strengthen emotional connections, leading to higher engagement and loyalty (Gao et al., 2022; Li et al., 2024). Built upon arousal theory and existing studies, the subsequent hypotheses are developed.

**H1:** Perceived personalization has a positive (+) influence on brand preference.

**H2:** Perceived interactivity has a positive (+) influence on brand preference.

#### 2.2.2. Brand Preference

Brand preference, as explained by Hellier et al. (2003), refers to how consumers tend to favor their current service provider more than other similar options in the market. Building on this idea, Chang and Liu (2009) describe brand preference as a positive feeling towards a brand, influenced by emotional connections, past experiences, perceived quality, and overall satisfaction. This shows that both thoughts and feelings play a role in how consumers choose. Chowdhury and Khare (2011) highlight that the way consumers act is strongly guided by their preferred brands. It develops through personal connections and emotional bonds with the brand. In service marketing, creating positive customer experiences helps build favorable perceptions, which can lead to increased brand loyalty and even influence current market trends. Belén del Río et al. (2001) highlight that strong brand preferences often go hand-in-hand with positive word-of-mouth, as loyal customers love to recommend their favorite brands. Zameer's research further supports this idea, showing that a person's preference for a brand is a good predictor of whether they'll recommend it, since those who favor a brand are more inclined to endorse it. This study views brand preference as a key stepping stone towards brand recommendation.

**H3:** Brand preference has a positive (+) influence on brand recommendation.

#### 2.2.3. Perceived Marketing Innovation

According to the OECD, marketing innovation represents a significant progression marked by the adoption of novel marketing approaches that comprise of exciting changes in areas like product design, packaging, placement, promotion, or pricing. It's all about finding new ways to connect with customers and make a positive impact (OECD/Eurostat, 2005; p. 49). A firm's ongoing success in competitive markets really relies on how effectively creative ideas are converted into impactful marketing strategies that produce products meeting customers' shifting needs and expectations.. A brand communicates its marketing innovations through a variety of channels, such as advertising and promotional activities, to connect with and engage its audience (Gupta et al., 2016). Additionally, as highlighted by Grönroos (2017) and Grönroos

and Voima (2013), the key way to shape how customers see a company's innovations and its creativity is by introducing changes together through the launch of new solutions.

Perceived marketing innovation plays a key mediator explaining how AI-driven stimuli can shape and influence your preferred brands, making the connection more understandable and relatable. For instance, Li et al. (2020) found that personalized marketing not only makes the user experience better but also enhances perceptions of a brand's innovation. This can lead to more positive attitudes and greater engagement from consumers. Based on Arousal Theory (Berlyne, 1960), specific stimulus features like novelty, complexity, and ambiguity can increase arousal, which helps draw more attention and emotional involvement. Similarly, when digital environments are interactive, they tend to be seen as more innovative (Lemon & Verhoef, 2016), which enhances both emotional and functional appreciation. These findings suggest that when consumers see AI-powered personalization or interactivity, they tend to associate these features with innovative marketing strategies. This connection often makes them more favorably inclined towards the brand.

Recent research by Hwang and Hyun (2015) highlighted the innovativeness of the companies they choose. It shows that when travelers perceive a firm as innovative, it enhances their educational experiences, entertainment, aesthetics, and sense of escapism. These feelings, in turn positively impacts their perception of luxury, making their cruise experience feel even more special. Likewise, Kim et al. (2014) showed that when mobile phone companies highlight both practical and symbolic benefits of innovation, they can offer greater value to their customers. This often leads to higher satisfaction and a more positive experience. Within the scope of AI-driven marketing, perceived innovation serves as a wonderful sign of a brand's technological leadership and flexibility. It not only helps build stronger preferences among consumers by highlighting the value they see in the brand, but also drives individuals to express their positive experiences by recommending the brand to others.

**H4a:** Perceived marketing innovation positively (+) moderates the relationship between perceived personalization and brand preference

**H4b:** Perceived marketing innovation positively (+) moderates the relationship between perceived interactivity and brand preference

**H4c:** Perceived marketing innovation positively (+) moderates the relationship between brand preference and brand recommendations

### 2.2.4. The mediating role of Brand Preference

According to this study, brand preference serves as a crucial link between brand recommendations and AI stimuli like perceived personalization and interactivity. When consumers perceive personalization, it makes them feel recognized as individuals, as if their unique needs and preferences are truly understood and valued by the brand. For example, Tran et al. (2020) discover that personalized brand ads really boost how consumers identify with the brand and feel connected to it, which in turn helps strengthen the overall value of the brand. Similarly, Shanahan et al. (2019) highlight how personalization on social media greatly boosts customer engagement and emotional connection with the brand. This positive impact encourages a stronger perception of brand quality and fosters greater loyalty among customers. These results suggest that experiences tailored to individuals tend to foster more positive feelings towards a brand, meaning they develop a stronger preference for it. Additionally, when consumers perceive interactivity, they feel more involved with AI-powered brand interfaces, which boosts their sense of control and the value they see in co-creating. This, in turn, helps to deepen their brand loyalty (Liu & Shrum, 2002).

Brand preference really matters when it comes to encouraging consumers to recommend a brand. When people like a brand, this increases their likelihood of promoting the brand through positive word-of-mouth and personal recommendations. (Zameer et al., 2019; Belén del Río et al., 2001). Research shows that the emotional and mental connection people feel with a brand, known as brand preference, plays a vital role in turning personalized and interactive experiences into positive recommendations (Schivinski et al., 2019). So, this study posits that brand preference mediates the relationship between AI stimuli (perceived personalization and perceived interactivity) and consumers' behavioral intentions, helping us understand how AI stimuli can inspire people to recommend a brand.

**H5a:** Brand preference mediates the relationship between perceived personalization and brand recommendation

**H5b:** Brand preference mediates the relationship between perceived interactivity and brand recommendation

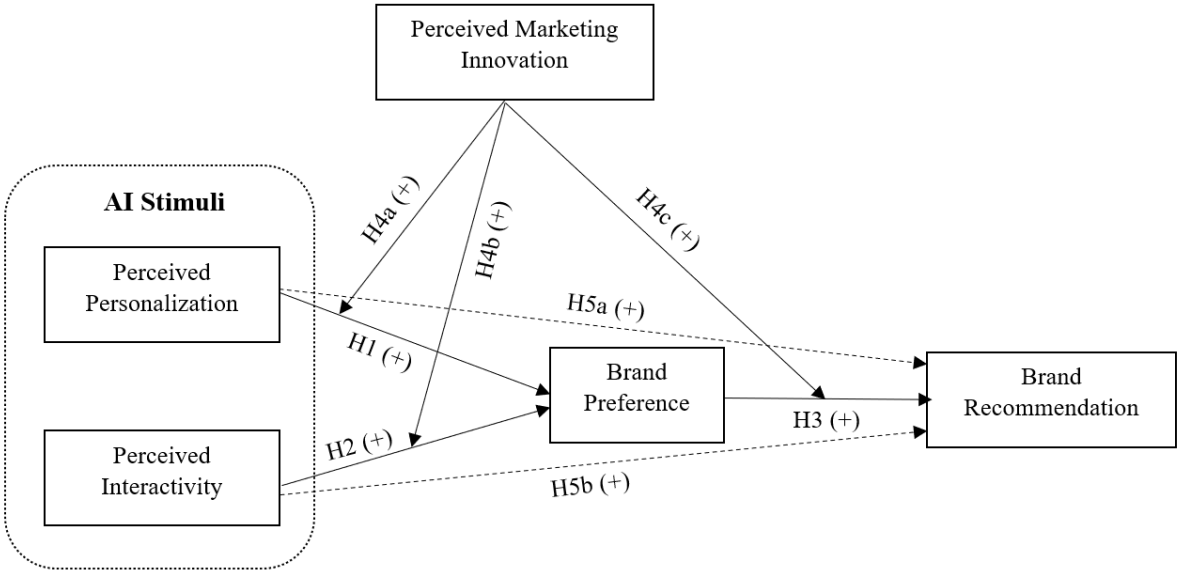



**Figure 1.** Proposed research model

## 3. METHODOLOGY

### 3.1. Sampling and data collection

The current study investigated how AI stimuli and perceived marketing innovation influence people's brand preferences and recommendations by using a quantitative survey method. To gather enough insights, a Google Form survey was shared through social media platforms like discussion forums, class groups, and personal networks across Vietnam. We focused on participants who were familiar with or had experience with AI-based advertising, making data collection smoother. After reviewing the responses, we removed 38 incomplete or inconsistent replies, leaving 260 valid responses in the final data set. This sample size was just right for using structural equation modeling (SEM) and provided enough statistical power for a thorough analysis.

Our study included 260 respondents, the majority of whom were women (70.4%) and belonged to Generation Z (89.2%), a group known for their high exposure to AI technologies and marketing. Many participants (61.2%) had a bachelor's degree, indicating a possible link between higher education and engagement with AI-driven marketing. Income levels varied, with 68.8% earning less than 5 million VND per month, while others had moderate to higher incomes. This group reflects findings that younger, educated individuals are key targets for AI-based marketing efforts aimed at shaping brand preferences and recommendations (see Table 1).

**Table 1.** Demographic information

| Code | Level | Frequency | Percentage |
|---|---|---|---|
| Gender | Male | 77 | 29.6 |
| | Female | 183 | 70.4 |
| Generation | Generation Z | 232 | 89.2 |
| | Generation Y | 24 | 9.2 |
| | Others | 4 | 1.5 |
| Education | High school | 78 | 30.0 |
| | Associate college/Job apprentice | 9 | 3.5 |
| | Bachelor’s | 159 | 61.2 |
| | Post-graduate | 14 | 5.4 |

| Code | Level | Frequency | Percentage |
|---|---|---|---|
| Income | < 5 million/month | 179 | 68.8 |
| | 5-10 million/month | 45 | 17.3 |
| | 10-15 million/month | 19 | 7.3 |
| | > 15 million/month | 17 | 6.5 |

### 3.2. Measurement

The measurement items were modified to suit the circumstances of this study after being taken from earlier research. Perceived personalization was measured with four items by Li et al. (2024), like "AI-based marketing stores my preferences and offers me extra services based on my preferences". Perceived interactivity was evaluated using four items from Li et al. (2024), such as "AI-based marketing can effectively promote two-way communication with customers". Perceived marketing innovation was measured with four items from Gupta et al. (2016) and Im and Workman (2004), such as "Brand X takes initiative on developing new channels for marketing channels." Brand preference was measured with seven items from Zameer et al. (2019); Mourad and Ahmed (2012), such as "It makes sense always to choose products of this brand, even if other products are better than this brand". Finally, brand recommendation was measured with four items by Zameer et al. (2019); Hightower et al. (2002); Raajpoot and Ghilni-Wage (2019), such as "I will recommend others to buy products of brand X". A five-point Likert scale, ranging from "strongly disagree" (1) to "strongly agree" (5), was used to rate each item.

### 3.3. Reliability and validity

Evaluating the reliability and validity of the measurement scale is essential to ensure that it consistently and accurately captures the underlying research constructs, thereby supporting rigorous data analysis. This study employed SmartPLS 3 to analyze a complex structural equation model (SEM) involving multiple latent constructs and interrelated variables. As previously noted, content validity was established by adopting measurement items from established literature on AI and marketing innovation. Item reliability, convergent validity, and discriminant validity were then used to assess the validity and reliability of the measurement model. Internal consistency was verified using reliability indicators such as Cronbach's alpha and composite reliability (Hair et al., 2017). Convergent validity was confirmed through factor loadings, average variance extracted (AVE) (Fornell & Larcker, 1981), and composite reliability (CR) (Bagozzi & Yi, 1988). Both the heterotrait-monotrait (HTMT) ratio and the Fornell-Larcker criterion were used to assess discriminant validity (Henseler et al., 2015). Variance inflation factor (VIF) values were computed to account for potential multicollinearity, ensuring that predictor variables were not excessively correlated (Hair et al., 2017). Together, these indicators demonstrate the measurement model's strong reliability and validity, thereby reinforcing the methodological rigor of the study. Lastly, the correlation matrix was interpreted based on threshold values to determine the strength of inter-construct relationships.

### 3.4. Structural equation modeling

A second-generation multivariate method called structural equation modeling (SEM) was designed to estimate and analyze complex interrelationships among multiple variables within a single framework (Haenlein & Kaplan, 2004). By incorporating both observed indicators and latent constructs, SEM facilitates the assessment of hypothesized causal relationships using quantitative data and correlation-based assumptions. In this study, SmartPLS 3 software was to implement the Partial Least Squares SEM (PLS-SEM) methodology. To improve the validity, reliability, and robustness of the parameter estimations and to determine the statistical significance of the suggested model, a bootstrapping process using 5,000 resamples was carried out. The use of PLS-SEM combined with bootstrapping offers valuable insights for assessing the measurement and structural components within the research model.

## 4. RESULTS AND DISCUSSION

### 4.1. Measurement model results

#### Factor loadings and reliability results

To evaluate internal consistency, both Cronbach's Alpha (α) and Composite Reliability (CR) were utilized. All constructs exceeded the commonly accepted thresholds of $\alpha \geq 0.70$ and $CR \geq 0.70$, confirming satisfactory reliability (Hair et al., 2021). Specifically, Perceived Personalization ($\alpha = 0.846$, $CR = 0.897$) and Perceived Marketing Innovation ($\alpha = 0.786$, $CR = 0.862$) were found reliable, whereas the other constructs recorded high internal consistency ($CR > 0.9$), thus enhancing the robustness of the measures. Perceived Interactivity (PI1 = 0.873) had the highest factor loadings, which means it was well explained by the model. All factor loadings are higher than 0.7, indicating that the items represent the constructs very well (Sarstedt et al., 2017) (see Table 2).

**Convergent validity assessment**

Convergent validity was evaluated through the Average Variance Extracted (AVE), adopting the recommended cut-off value of AVE ≥ 0.50 (Fornell & Larcker, 1981). All constructs met this criterion (AVE range: 0.609–0.735), indicating that all constructs were able to account for the variance of their indicators. Notably, Perceived Interactivity (AVE=0.735) stands out for demonstrating strong convergent validity.

**Table 2.** Factor loadings and reliability assessments

| **Constructs** | **Factor loadings** | **α** | **CR** | **AVE** |
|---|---|---|---|---|
| **Perceived Personalization** | | 0.846 | 0.897 | 0.684 |
| PP1 | 0.811 | | | |
| PP2 | 0.816 | | | |
| PP3 | 0.854 | | | |
| PP4 | 0.827 | | | |
| **Perceived Interactivity** | | 0.880 | 0.917 | 0.735 |
| PI1 | 0.873 | | | |
| PI2 | 0.860 | | | |
| PI3 | 0.854 | | | |
| PI4 | 0.843 | | | |
| **Perceived Marketing Innovation** | | 0.786 | 0.862 | 0.609 |
| MI1 | 0.794 | | | |
| MI2 | 0.772 | | | |
| MI3 | 0.793 | | | |
| MI4 | 0.762 | | | |
| **Brand Preference** | | 0.913 | 0.930 | 0.656 |
| BP1 | 0.815 | | | |
| BP2 | 0.815 | | | |
| BP3 | 0.808 | | | |
| BP4 | 0.795 | | | |
| BP5 | 0.801 | | | |
| BP6 | 0.830 | | | |
| BP7 | 0.805 | | | |
| **Brand Recommendation** | | 0.855 | 0.902 | 0.696 |
| BR1 | 0.825 | | | |
| BR2 | 0.829 | | | |
| BR3 | 0.842 | | | |

| Constructs | Factor loadings | α | CR | AVE |
|---|---|---|---|---|
| BR4 | 0.841 | | | |

Note: BP: brand preference, BR: brand recommendation, MI: perceived marketing innovation, PP: perceived personalization, PI: perceived interactivity.

**Discriminant validity assessment**

Discriminant validity determines whether constructs are empirically distinct by evaluating their inter-correlations (Henseler et al., 2015). Table 3 indicates that the Fornell–Larcker criterion is satisfied, as the square root of each construct's AVE is greater than its correlations with other constructs (Hair et al., 2017). Furthermore, the Heterotrait-Monotrait Ratio (HTMT) was analyzed, and all HTMT values were found to be below the recommended threshold of 0.90 (Table 4). These findings affirm the discriminant validity of the model and confirm that the constructs are conceptually and empirically distinct.

**Table 3.** Fornell-Larcker Criterion

| | BP | BR | MI | PI | PP |
|---|---|---|---|---|---|
| BP | 0.810 | | | | |
| BR | 0.370 | 0.834 | | | |
| MI | 0.056 | 0.538 | 0.780 | | |
| PI | 0.503 | 0.454 | -0.011 | 0.857 | |
| PP | 0.514 | -0.182 | -0.142 | -0.095 | 0.827 |

Note: BP: brand preference, BR: brand recommendation, MI: perceived marketing innovation, PP: perceived personalization, PI: perceived interactivity.

**Table 4.** Heterotrait-monotrait ratio (HTMT) – Matrix

| | BP | BR | MI | PI | PP |
|---|---|---|---|---|---|
| BP | | | | | |
| BR | 0.417 | | | | |
| MI | 0.096 | 0.651 | | | |
| PI | 0.558 | 0.523 | 0.096 | | |
| PP | 0.584 | 0.215 | 0.194 | 0.112 | |

Note: BP: brand preference, BR: brand recommendation, MI: perceived marketing innovation, PP: perceived personalization, PI: perceived interactivity.

**Multicollinearity assessment**

Variance Inflation Factor (VIF) values were assessed to test for multicollinearity, and all fell below the recommended cut-off of 3 (Hair et al., 2017). The highest VIF observed was 1.343, indicating that the independent variables were not strongly intercorrelated. As a result, the model's parameter estimates can be considered reliable and are free from concerns about multicollinearity.

**Table 5.** Inner model - Matrix (VIF)

| | BP | BR | MI | PI | PP |
|---|---|---|---|---|---|
| BP | | 1.003 | | | |
| BR | | | | | |
| MI | 1.092 | 1.006 | | | |

| | BP | BR | MI | PI | PP |
|---|---|---|---|---|---|
| PI | 1.042 | | | | |
| PP | 1.343 | | | | |

Note: BP: brand preference, BR: brand recommendation, MI: perceived marketing innovation, PP: perceived personalization, PI: perceived interactivity.

**Correlations assessment**

Only paired correlations between constructs were analyzed, and the results were all less than 0.8, which serves to enhance the validity of the constructs. The highest correlation noted (0.538 between Perceived Marketing Innovation and Brand Recommendation) was well within the acceptable range, confirming that each construct measures a distinct theoretical concept.

**Table 6.** Paired correlations

| | BP | BR | MI | PI | PP |
|---|---|---|---|---|---|
| BP | 1.000 | | | | |
| BR | 0.370 | 1.000 | | | |
| MI | 0.056 | 0.538 | 1.000 | | |
| PI | 0.503 | 0.454 | -0.011 | 1.000 | |
| PP | 0.514 | -0.182 | -0.142 | -0.095 | 1.000 |

Note: BP: brand preference, BR: brand recommendation, MI: perceived marketing innovation, PP: perceived personalization, PI: perceived interactivity.

### 4.2. Structural equation model results

As Table 7 shows, all six hypotheses proposed were approved. Specifically, perceived personalization and perceived interactivity had a positive influence on brand preference ($\beta = 0.548$, p-value $< 0.000$; $\beta = 0.567$, p-value $< 0.000$, respectively), supporting H1 and H2. Additionally, brand preference had a positive impact on brand recommendation ($\beta = 0.340$, p-value $< 0.000$), supporting H3. Besides, in the aspect of moderators, perceived marketing innovation positively moderated three relationships: (1) the relationship between perceived personalization and brand preference, (2) the relationship between perceived interactivity and brand preference, (3) the relationship between brand preference and brand recommendation ($\beta = 0.149$, p-value $< 0.016$; $\beta = 0.120$, p-value $< 0.007$; $\beta = 0.125$, p-value $< 0.004$, respectively), supporting H4a, H4b, and H4c. The results model was presented in Figure 2.

The bootstrap method was also used to test for the mediation of brand preference (H5a, H5b) via SmartPLS. There were two indirect effects in this model. The first (PP → BP → BR) was 0.193, the second (PI → BP → BR) was 0.186. Mediation is indicated by the significance level of the indirect effect from perceived personalization and perceived interactivity to brand recommendation through brand preference as indicated by the p-value. Therefore, brand preference partially mediated the relationship between perceived personalization and brand recommendation, as well as the relationship between perceived interactivity and brand recommendation ($\beta = 0.193$, p-value $< 0.000$; $\beta = 0.186$, p-value $< 0.000$, respectively), supporting H5a and H5b.

**Table 7.** Hypotheses results

| **Ho** | **Relationships** | **β** | **St.dv** | **T-value** | **P values** | **Results** |
|---|---|---|---|---|---|---|
| H1 | PP → BP | 0.548 | 0.054 | 10.182 | 0.000 | Approved |
| H2 | PI → BP | 0.567 | 0.045 | 12.578 | 0.000 | Approved |
| H3 | BP → BR | 0.340 | 0.049 | 6.920 | 0.000 | Approved |
| H4a | PP*MI → BP | 0.149 | 0.062 | 2.412 | 0.016 | Approved |
| H4b | PI*MI → BP | 0.120 | 0.044 | 2.713 | 0.007 | Approved |

| Ho | Relationships | β | St.dv | T-value | P values | Results |
|---|---|---|---|---|---|---|
| H4c | BP*MI → BR | 0.125 | 0.043 | 2.912 | 0.004 | Approved |
| H5a | PP → BP → BR | 0.193 | 0.038 | 5.006 | 0.000 | Approved |
| H5b | PI → BP → BR | 0.186 | 0.029 | 6.387 | 0.000 | Approved |

Note: BP: brand preference, BR: brand recommendation, MI: perceived marketing innovation, PP: perceived personalization, PI: perceived interactivity.

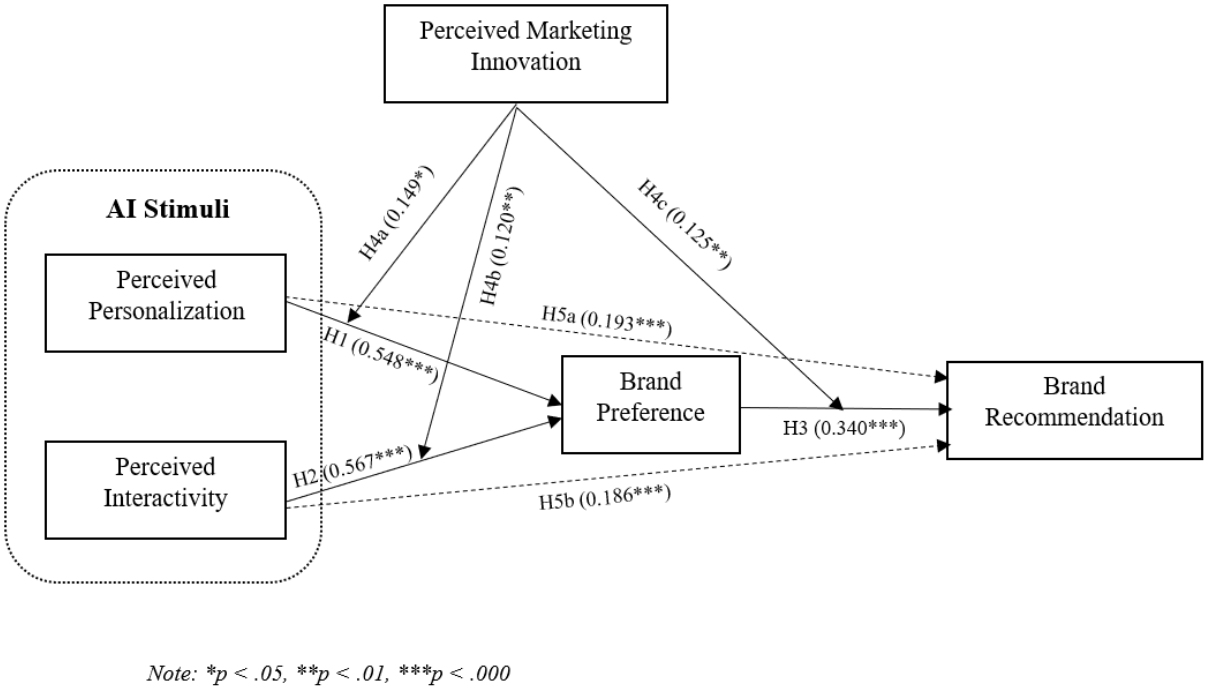



**Figure 2.** Result of the research model

### 4.4. Discussion

This study looks at how consumers' brand preferences and intention to recommend the brand are affected by AI stimuli. It also looks into how perceived marketing innovation affects the relationships between AI stimuli and brand preferences and between brand preferences and intention to recommend the brand. The findings generally validate the proposed model and suggest that all hypotheses are supported. In particular, it demonstrates that both AI stimulus constructs - namely, perceived personalization and perceived interactivity positively influence brand preference, thereby enhancing brand recommendation. Furthermore, three relationships are positively moderated by perceived marketing innovation, with the strongest effect on the relationship between perceived personalization and brand preference.

The results show that consumers' brand preferences are greatly increased by perceived personalization and perceived interactivity. This means that when a consumer feels that a brand's AI tools provide personalized experiences and allow for responsive interaction, they are more likely to form positive attitudes towards the brand. This aligns with previous research by Gao et al. (2022) and Li et al. (2024), which found that AI stimuli can enhance user experience and emotional connection, resulting in stronger customer engagement and stickiness. Furthermore, in line with Hellier et al. (2003), who conceptualized brand preference as a customer's inclination towards a favored provider, and Chang and Liu (2009), who emphasized the psychological and emotional dimensions of this bias, our study confirms that AI-enhanced interactions help strengthen this preference. Moreover, as Chowdhury and Khare (2011) noted, emotional connections formed through brand experiences play a crucial part in shaping preferences. Additionally, the positive relationship between brand preference and brand recommendation is consistent with previous studies, such as Zameer's findings, which suggest a direct link between preference and recommendation. In our study, consumers with a high level of brand preference, driven by AI stimuli, exhibit a stronger intent to recommend the brand, suggesting that preferences have a significant influence on digital platforms.

In terms of perceived marketing innovation, a notable finding from this study is the moderating effect of this construct in both key relationships: between AI stimuli and brand preference, and between brand preference and brand

recommendation. Among these, the moderation effect of perceived marketing innovation was strongest in the relationship between perceived personalization and brand preference, indicating that innovative marketing efforts significantly enhance the impact of personalized AI experiences on consumers' preferences towards a brand. This suggests that when customers see marketing communications, commercials, or product recommendations adapted to their interests, they may interpret these messages as evidence of the company's innovativeness, reinforcing their preference for the brand. One reason for this could be explained by the work of An and Ngo (2025), which indicates that personalization shows customers that the brand understands and respects them. Given that personalization is a very visible and recognizable form of innovation, this builds a foundation of trust because the customer feels the brand is dedicated to providing content that is relevant to them. This aligned with the previous research of Li et al. (2020), whose results show that tailored marketing enhances user experience while also bolstering opinions about a brand's inventiveness, which in turn increases brand preference and intent to recommend. Additionally, this was followed by the moderating effect on the link between brand preference and brand recommendation, suggesting that perceived marketing innovation also reinforces how brand linking translates into consumers' intention to recommend it to others. Lastly, the moderation effect was comparatively weaker in the relationship between perceived interactivity and brand preference, though still statistically significant, implying a more modest role of innovation in strengthening interactive experiences.

Our findings support both H5a and H5b, revealing that brand preference strongly modulates the link between AI stimuli and brand endorsement. More specifically, brand preference has a large mediating effect on the relationship between perceived customization and brand endorsement. This conclusion is consistent with past research showing the significance of brand preference as a crucial psychological process that converts pleasant brand experiences into advocacy behaviors, such as the work of Shanahan et al. (2019), which shows that personalization on social media substantially increases customer brand engagement and attachment. Therefore, this evidence aligns with our findings that personalized AI experiences have a notable influence on brand preference and ultimately, on brand recommendations. Furthermore, the mediating effect of brand preference on the relationship between perceived interactivity and brand recommendation is also worth mentioning. As Liu and Shrum (2002) explained, interactivity primarily enhances consumers' perceived control and co-creation value, which strengthens brand preference. As a result, both AI stimuli appear to be dominant drivers that foster recommendations through brand preference.

Lastly, this study offers helpful insights into how AI-driven marketing innovations, especially creative approaches, can improve consumer brand preference and their intention to recommend. Through the integration of cutting-edge technologies, brands can enhance brand preference and customer recommendations by effectively communicating their practices and cultivating deeper emotional connections with consumers.

## 5. CONCLUSION

### 5.1. Implications

#### 5.1.1. Theoretical implications

This research contributes to the expanding literature on consumer behavior in AI-driven marketing by employing Arousal Theory to examine the effects of AI stimuli, brand preference, and perceived marketing innovation. While prior research has focused primarily on the technical and experiential aspects of virtual environments, this study highlights the emotional and cognitive mechanisms that shape consumer engagement within these contexts.

This study bridges a research gap by exploring how AI-enabled personalization and interactivity act as arousal triggers influencing consumers' preferences and subsequent behaviors. For instance, Li et al. (2020) found that personalized marketing not only enhances user experience but also boosts perceptions of a brand's innovativeness, supporting the relevance of integrating perceived marketing innovation as a key moderator. Moreover, Zameer (2020) and Del Rio et al. (2001) demonstrated that brand preference is a strong predictor of brand recommendation, providing a foundation for our model's assumptions.

Our data also suggest that brand preference mediates the link between AI stimuli and brand recommendation. While prior studies have mainly focused on the direct impact of personalization or interactivity on factors such as engagement and attachment (Chowdhury & Khare, 2011; Shanahan et al., 2019), this study extends the literature by showing that these effects are transmitted through brand preference. This highlights that preference can act as a key psychological mechanism through which AI-driven experiences translate into advocacy behaviors such as recommendations, which is worth examining.

Differing from earlier studies that treated user experience, innovation, or technology acceptance in isolation, this research provides a more nuanced understanding of how emotional arousal, marketing innovation, and AI-driven interactions jointly influence consumers' preferences towards a brand's innovative approaches and their intention to recommend it to others. By doing so, it offers new theoretical insight into how immersive and emotionally engaging brand experiences, mediated by perceived innovation, can strengthen long-term consumer-brand relationships.

#### 5.1.2. Managerial implications

For marketers looking to increase brand preference and advocacy through AI-enabled strategies, this study offers helpful advice. The findings highlight the necessity for brands to use AI tools that produce tailored and captivating customer experiences since they show that perceived personalization and interactivity greatly influence brand preference. For example, personalization engines that adapt content, offers, or product recommendations based on user behavior can significantly boost consumer engagement and emotional connection to the brand (Li et al., 2020). Given that personalization emerges as a critical factor, managers should prioritize AI-enabled personalization, as it exerts a strong influence on building brand preference and converting it into recommendation behaviors. Likewise, interactivity remains valuable for fostering engagement, therefore, it is also important to create interactive experiences for customers to enhance their advocacy behaviors.

Second, the moderating role of perceived marketing innovation highlights the importance of not only implementing AI features but also effectively communicating the brand's innovative efforts. This means that, beyond deploying new technologies, brands must position themselves as forward-thinking and consumer-centric. The persuasive impact of AI-based advertising can be increased by marketers who effectively communicate the innovative nature of their business, which will improve consumer attitudes and buy intentions.

Third, the strong link between brand preference and recommendation intention underscores the importance of fostering long-term emotional bonds with customers. Marketing strategies should therefore go beyond transactional interactions and focus on delivering consistent, emotionally resonant experiences that build trust and advocacy.

Lastly, managers should continuously monitor consumer perceptions of innovation, as they shape how effectively AI stimuli translate into brand loyalty and word-of-mouth. By aligning technological investments with perceived innovation and emotional value, brands can create sustainable competitive advantages in an increasingly digital marketplace.

### 5.2. Limitations and Future Research Directions

Future researchers should look into and address the limitations of this work. The study does not take into consideration other significant factors like trust in AI, perceived risk, privacy, or ethical concerns; instead, it concentrates on two aspects of AI stimulus: perceived personalization and perceived interactivity. Future studies could gain a better understanding of how consumers react to AI-based brand marketing by incorporating these factors.

Moreover, perceived marketing innovation was treated as a single construct in the current model. Future studies could disaggregate this variable into more specific forms, such as product innovation, communication innovation, or technological innovation, to examine their unique impacts. Additionally, individual differences such as consumer innovativeness, technology readiness, or emotional involvement could be explored as potential moderating factors to clarify the observed relationships further.

Third, the number of valid responses collected was relatively limited in both size and demographic diversity. It remains uncertain whether the conclusions drawn from this sample would be consistent when applied to larger or more diverse populations. Future studies are encouraged to adopt broader sampling strategies to enhance the reliability and generalizability of the findings. By addressing these issues, future studies will be able to create a more thorough and sophisticated framework for comprehending brand-consumer interactions in AI-enabled settings.

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