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Consumer Behavior Toward AI-Driven Marketing: Insights from UTAUT and Uses and Gratifications Models

سلوك المستهلك تجاه التسويق المدعوم بالذكاء الاصطناعي رؤى من النظرية الموحدة لقبول واستخدام التقنية UTAUT ونظرية الاستخدامات والإشباعات Uses and gratifications

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Abstract:

Objectives: This study explores consumer perceptions of artificial intelligence (AI) in marketing, with a particular focus on its influence on buying behavior and ethical concerns, including data protection and privacy. The research aims to examine how AI technologies are received by consumers, assess the effectiveness of AI-driven ad personalization, and understand the factors that facilitate or hinder adoption.

Methods: A quantitative research design was employed, utilizing a structured survey to gather data from consumers. The reliability of the survey instruments was assessed using Cronbach's Alpha and Average Inter-Item Correlation. Chi-square analysis was applied to examine relationships between variables.

Results: The findings indicate that Effort Expectancy, the perceived ease of use, is a strong predictor of consumers' Behavioral Intention to adopt AI in marketing. However, Performance Expectancy is found to be non-significant, suggesting ongoing doubts about AI's predictive accuracy. Ethical concerns and trust deficits emerge as major barriers to adoption. Interestingly, Social Influence negatively affects Behavioral Intention, with consumers perceiving AI-driven marketing as potentially intrusive.

Conclusions: To fully leverage AI in marketing, strategies must prioritize usability, transparency, and ethical data practices. Customization based on demographic insights can enhance relevance and improve adoption rates. The study underscores the importance of aligning AI technology with consumer expectations and values to foster trust and long-term engagement.

Keywords*: AI marketing; UTAUT; Uses and Gratifications Theory; Integrated Model; AI Trust and Privacy.*

الملخص:

الأهداف: تهدف هذه الدراسة إلى استكشاف تصورات المستهلكين تجاه الذكاء الاصطناعي في مجال التسويق، مع التركيز بشكل خاص على تأثيره في سلوك الشراء والمخاوف الأخلاقية المتعلقة بحماية البيانات والخصوصية. وتسعى إلى تقييم مدى تقبّل المستهلكين لتقنيات الذكاء الاصطناعي، وتحليل فعالية تخصيص الإعلانات المدعومة بالذكاء الاصطناعي، وفهم العوامل التي تسهم في تبني هذه التقنيات أو تعيقها.

المنهجية: تم اعتماد تصميم بحثي كمي باستخدام استبيان منظم لجمع البيانات من المستهلكين. تم تقييم موثوقية أدوات القياس من خلال معامل كرونباخ ألفا ومتوسط الارتباط بين العناصر. كما تم استخدام تحليل كاي تربيع لفحص العلاقات بين المتغيرات.

النتائج: أظهرت النتائج أن "توقع الجهد" أي مدى سهولة استخدام التكنولوجيا كما يدركه المستهلك يُعد مؤشرًا قويًا على النية السلوكية لتبني الذكاء الاصطناعي في التسويق. في المقابل، لم يكن لـ"توقع الأداء" دلالة إحصائية، مما يشير إلى وجود شكوك مستمرة حول دقة تنبؤات الذكاء الاصطناعي. كما برزت المخاوف الأخلاقية ونقص الثقة كعوائق رئيسية أمام التبني. ومن اللافت أن "التأثير الاجتماعي" كان له تأثير سلبي على النية السلوكية، حيث ينظر المستهلكون إلى التسويق المدعوم بالذكاء الاصطناعي على أنه قد يكون تدخليًا.

الخلاصة: لتحقيق الاستفادة القصوى من الذكاء الاصطناعي في التسويق، ينبغي أن تركز الاستراتيجيات على سهولة الاستخدام، والشفافية، والممارسات الأخلاقية في التعامل مع البيانات. كما يمكن أن تعزز التخصيصات المستندة إلى البيانات الديموغرافية من الصلة بالسياق وتحسين معدلات التبني. وتؤكد الدراسة على أهمية مواءمة تقنيات الذكاء الاصطناعي مع توقعات وقيم المستهلكين لتعزيز الثقة وتحقيق التفاعل المستدام.

الكلمات المفتاحية: *التسويق بالذكاء الاصطناعي؛ نموذج التوحيد لتقبل التكنولوجيا؛ (UTAUT)؛ نظرية الاستخدامات والإشباعات؛ النموذج المتكامل؛ الثقة والخصوصية في الذكاء الاصطناعي.*

Citation

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1 Introduction

1.1 Background of the Study

Consumer behavior is the process of approaching, selecting, evaluating, and purchasing products and services, as well as the manner in which they use them. Classically, consumer behavior research in the marketing discipline has largely been concerned with identifying the antecedents to purchase decisions and how consumers distribute their scarce resources, such as time, money, and effort, in the marketplace (Cole, 2007). That is why traditional approaches, which dominate the market, have evolved due to the advent of artificial intelligence (AI). The use of AI in consumer behavior provides businesses with an opportunity to understand consumers, anticipate their preferences, and create the right engagement strategies that are impossible to achieve through conventional approaches (Edelman & Abraham, 2022).

The massive investment in AI shows how much it is valued, while the trends indicate that the AI and ML markets will grow in the future. According to McKinsey, AI usage across industries is expected to grow in the next few years to improve products, introduce new services, and strengthen customer bonds (Andrew, 2017). Marketing AI applications alone increased by 84% in 2020, and more expansion is expected as more brands focus on customer experience (Gera & Kumar, 2023). According to a Statista survey conducted in 2023, 61% of the participants are ready to buy products that are suggested by generative AI, and there is no significant variation between the generations.

While adopting AI in marketing has been beneficial in several ways, it is coupled with paramount issues of data privacy, ethical dealings, and consumer trust. The use of consumer data as the major source of insight brings issues of transparency, fairness, as well as accountability. These include issues of informed consent, bias in the developed algorithms, and impartiality toward all consumers (Dignum, 2018; Topol, 2019; Taddeo & Floridi, 2018). To overcome these challenges, attempts to improve the level of transparency should be regarded as urgent and indispensable.

Consequently, the study seeks to answer the following objectives to enhance knowledge on the application of AI in marketing as well as influence customer behavior. The objectives are defined as follows:

- To determine how insights from AI affect focused marketing tactics that suit the requirements and preferences of customers.
- To evaluate how well AI predicts the preferences and purchase behaviors of customers.
- To investigate how consumers from different demographic groupings view AI-assisted marketing recommendations.
- To identify obstacles that marketers encounter when implementing AI while balancing ethical considerations and customer trust.
- To determine whether utilizing AI-driven marketing improves customer engagement and brand loyalty over the long term by combining the modified constructs of Technology Perception, Social and Ethical Influence, and Behavioral Intentions with additional factors.

1.2 Problem Statement

The advancements in artificial intelligence in marketing have shifted the face of the market in the present digital environment by giving marketers unique insights into consumers and a chance to target them accordingly. AI solutions allow organizations to process enormous amounts of data and distinguish consumer trends more proficiently than conventional marketing strategies. Consequently, techniques like smart advertisements and promotional indications based on artificial neural networks form the core of present-day customer outreach. However, despite these advances offering major potential to enhance customer satisfaction and firm competitiveness, they raise emerging major ethical issues concerning user data protection, transparency, and trustworthiness.

Toward this end, this research aims to explore consumer attitudes toward marketing with AI technologies, including how and in what ways consumers consider AI as a factor in purchasing, consumers' perceptions of AI in their everyday lives, and key constraints that may hinder or limit AI's ability to build trust. Mitigating these gaps will prepare organizations that seek to capitalize on AI disclosure while sustaining clients' trust due to the rising impact of AI in the market.

1.3 Scope of the Study

This paper focuses specifically on how and to what extent AI affects consumer behavioral patterns in the marketing sphere, including personalization based on AI, recommendation systems, and AI interaction with the consumer. The research looks at consumers' attitudes toward AI and how applicable the utilization of this technology is in contemporary society. Also, due to the focus on personalization, the study questions involve the level of comfort regarding recommendations, the extent to which such recommendations affect decision-making, and the issues related to data sharing with businesses using AI in their marketing campaigns. Offline marketing channels and detailed discussions on AI regulation are not included in the scope of this research.

1.4 Significance of the Study

The study provides relevant information on the contribution of AI to changes in consumer behavior in marketing. Consumer insights from this study enable businesses to formulate more effective strategies and fashion their approach in a manner that ensures brand loyalty while utilizing data ethically. Briefly, this is a consumer behavior study on how AI-driven marketing is perceived and understood. Researching these factors helps provide insights into how AI is changing the face of marketing in the future, from understanding consumer expectations to identifying conflicts that businesses might face.

1.5 Organization of the Study

The first chapter introduces the topic. The second chapter reviews the existing literature and identifies the gaps in the literature related to the study. In the third chapter, the methodology is discussed, while chapter four presents the results and findings. To conclude the study, the conclusion is provided in chapter five.

2 Literature Review

2.1 Overview of Existing Research

Today, AI has become an integral part of our lives, and institutions and businesses have gained a stable competitive advantage in the global economy due to the digitalization process. AI not only promotes the branding strategies of services but also strengthens organizations' adaptability to new markets and enhances recovery and growth (Gülşen, 2019). Modern studies show that marketing has evolved from being a static process to an engaging and personalized digital process supported by AI. This shift helps brands harness AI for real-time client understanding, recommendations, and interaction, revolutionizing the nature of modern marketing strategies.

Artificial Intelligence has emerged as the key driver of digitalization, creating real-time, data-based marketing that can improve the customer's journey and increase consumers' interaction. According to Copeland (2024), AI is a system's ability to imitate the cognitive capabilities of the human mind, including its capacity to learn and reason, which shows why AI is highly useful in businesses that require personalization and interaction.

The COVID-19 pandemic has substantially expedited the remote work revolution, which has not only transformed workplace dynamics within technology businesses (Ghabban et al., 2024) but has also played a critical role in modifying consumer behavior and furthering the emergence of e-commerce. This paradigm shift emphasizes the interconnectivity of workplace changes and shifting customer preferences, ushering in a new era of digital interaction.

2.2 Theoretical Perspectives

The application of artificial intelligence (AI) in consumer behavior and marketing has attracted considerable interest in many theoretical frameworks. These theories provide a vital understanding of consumers' use and purchase decision-making processes regarding AI technologies and their brand-switching behavior. In this paper, we delve into major theories and how they have helped explain the role of AI in consumer behavior.

The Technology Acceptance Model (TAM) is well known for predicting technology adoption within the consumer behavior literature. TAM was developed by Davis (1989) and focuses on two important constructs: perceived usefulness and perceived ease of use. Research using TAM has highlighted how these factors relate to the adoption of products with incorporated AI (Panagiotopoulos & Dimitrakopoulos, 2018), chatbots (Kim & Kim, 2021), and service robots (Zhong et al., 2021). For instance, consumers are more likely to accept smart functions if they perceive them as beneficial and easy to use, thereby enhancing customer relations and e-commerce.

Another relevant model is the Expanded Technology Acceptance Model, developed by Venkatesh et al. (2003) based on the Unified Theory of Acceptance and Use of Technology (UTAUT). Subsequently, the second generation of UTAUT, developed by Venkatesh et al. (2012), extends this framework to consumer usage contexts, aiming to understand the consumer-level pull factors of technology. Performance expectancy and social influence are among the antecedents that directly impact AI adoption in service-oriented professions, while facilitating conditions deserve more research attention in AI adoption (Guggemos et al., 2020).

The Uses and Gratifications (U&G) paradigm, labeled as one of the most influential theories in communications research (Lin, 1996), posits that individuals actively seek media to fulfill utilitarian, need-satisfying, and intentional purposes—gratifications (Guo et al., 2008). In the e-commerce context, this framework assists in defining how consumers' psychological needs shape the characteristics of the media they expect and engage with, and what behavioral patterns result (Cowles et al., 2002). For example, consumers may select media based on content utility (availability of detailed product information), process utility (entertaining interaction with the platform), and social utility (opportunities to develop social networks). The fact that this theory suggests individuals seek media and technology that meet their needs helps explain why consumers turn to specific AI applications, providing valuable insights into consumers' choices and actions.

2.3 Literature Gap

Although several studies have been conducted related to the implementation of AI in consumer behavior, there are still many gaps in the literature, including consumer familiarity with AI concepts, the extent of reliance on AI, and the ethical aspects. To address these gaps, this literature review outlines specific areas that require further exploration, framed around key research questions:

AI's extensive adoption in consumer products is underexplored, and more research and surveys are needed to understand public knowledge and dependence on AI for purchasing decisions and suggestions. Knowledge of demographic factors, education, and experience can inform AI promotion and ethical AI development. Limited research on how AI influences consumer behavior, brand selection, and loyalty is essential for marketers who are interested in behavior-driven AI design.

Most of the existing literature is concerned with the first stage of use, namely, the decision to adopt AI, but there are few empirical investigations of the subsequent stages, including sustained use, satisfaction, and loyalty after long-term interactions with AI. This gap implies that there is a lack of research on the dynamics of the consumer–AI relationship and what causes consumers to continue or discontinue using AI. Such insights could be very useful in enhancing AI systems for better retention and, therefore, creating ongoing consumer-brand engagement.

2.4 Synthesis of Literature Findings and Theoretical Framework

The rise of Artificial Intelligence has pivoted consumer behavior studies by modifying consumer–brand relations, purchase decision processes, and brand loyalty formation. Researchers build their conceptual models regarding AI's impact on consumer behavior through theoretical applications of the Technology Acceptance Model (TAM), Unified Theory of Acceptance and Use of Technology (UTAUT), and Uses and Gratifications Theory (U&G).

Reviews demonstrate mounting consumer certainty about the practical applications of artificial intelligence, thus leading to increased activities in information searches and decision-making. UTAUT establishes that users rely on either performance expectations or social acceptance when deciding to utilize AI. Through the conceptual model, the constructs of familiarity and dependence serve as key factors that explain AI's method of collecting personal data for the prediction of consumer behavior to generate loyal customers. The findings are supported by TAM, as consumers' perceived usefulness drives both their trust development and purchase activity. The proposed framework unites UTAUT with U&G to explain how AI satisfies client needs and develops persistent relationships between customers and brands.

3 Methodology

3.1 Dataset

The target population for this survey includes individuals aged between 18 and 55 years and above who have experience with AI-driven marketing or have been exposed to AI-enabled recommendations and advertisements. A total of 54 respondents participated in the study, selected in light of practical constraints and the exploratory nature of the research. Despite the limited sample size, the participants possess academic backgrounds and a solid understanding of emerging technologies such as artificial intelligence, which enhances the relevance of their input. Among the respondents, 35 are postgraduates, 14 are graduates, and 5 are undergraduates, providing an informed foundation for analyzing attitudes and behaviors toward AI-driven marketing.

3.2 Research Design

This research focuses on consumers who have engaged with AI-enabled marketing or have come across AI-recommended advertisements or offers. An age bracket has been chosen to capture a wide range of population responses concerning levels of digital literacy and exposure to AI marketing practices. A convenience sampling method has been employed due to the ease of contacting participants through online platforms. The survey was conducted through Google Forms, and targeted participants were invited to complete the survey. According to the work of Vasantha Raju & Harinarayana (2016), Google Forms is beneficial for surveying because it is easy to create, share, and collect responses, has a high response rate, and is less susceptible to data input errors. While this sample may not be very large, it reflects the stance and actions of a diverse group of consumers. To achieve age diversity, participants were selected based on an understanding of how various age groups respond to AI marketing.

3.2.1 Theoretical Framework

In expanding the understanding of consumer attitudes toward AI usage within marketing communication, this paper employs a theoretical framework consisting of the Unified Theory of Acceptance and Use of Technology (UTAUT) and the Uses and Gratifications Theory (U&G), both of which capture technology acceptance factors as well as psychological and social needs.

Acceptance of IT is best captured by the UTAUT model developed by Venkatesh et al. (2003). This synthesized approach focuses on four core constructs: Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), and Facilitating Conditions (FC), which are closely related to Behavioral Intention (BI) and Use Behavior (UB) regarding new technology (Mohamed et al., 2021). The following hypotheses are developed based on the UTAUT model constructs:

- **H1**: Performance Expectancy (PE) positively influences consumer Behavioral Intention (BI) to engage with AI-driven marketing tools. \
- **H2**: Expectancy (EE) positively influences Behavioral Intention (BI) toward AI-driven marketing tools.
- **H3**: Social Influence (SI) positively affects Behavioral Intention (BI) to use AI-driven marketing, moderated by demographic factors (e.g., age, gender).
- **H4**: Facilitating Conditions (FC) positively influence Use Behavior (UB) for AI-driven marketing tools.

In addition to UTAUT, the Uses and Gratifications Theory (U&G)—originating in the 1940s and further developed in the 1970s—provides a framework for examining the psychological and social needs that drive media adoption (Ruggiero, 2000). When combined, UTAUT and U&G offer a dual perspective: UTAUT outlines the technological and social product factors that influence the adoption of AI, while U&G captures the psychological utilities offered by AI marketing tools to the consumer. This integration provides a strong evaluation framework for consumer attitudes toward AI in marketing by capturing both technology acceptance and the satisfaction of individual users' needs.

The following hypotheses are proposed to evaluate the integrated model:

- **H5**: Information-Seeking (IS) significantly and positively influences Behavioral Intention (BI) to engage with AI-driven marketing tools.
- **H6**: Convenience (CO) significantly influences Behavioral Intention (BI) to adopt AI-driven marketing tools.
- **H7**: Entertainment (EN) significantly and positively influences Behavioral Intention (BI) to interact with AI-driven marketing tools, moderated by demographic factors.
- **H8**: Ethical Concerns (EC) influence the relationship between Behavioral Intention (BI) and Use Behavior (UB).

The theoretical framework developed for the study is shown graphically in the following Figure 1.

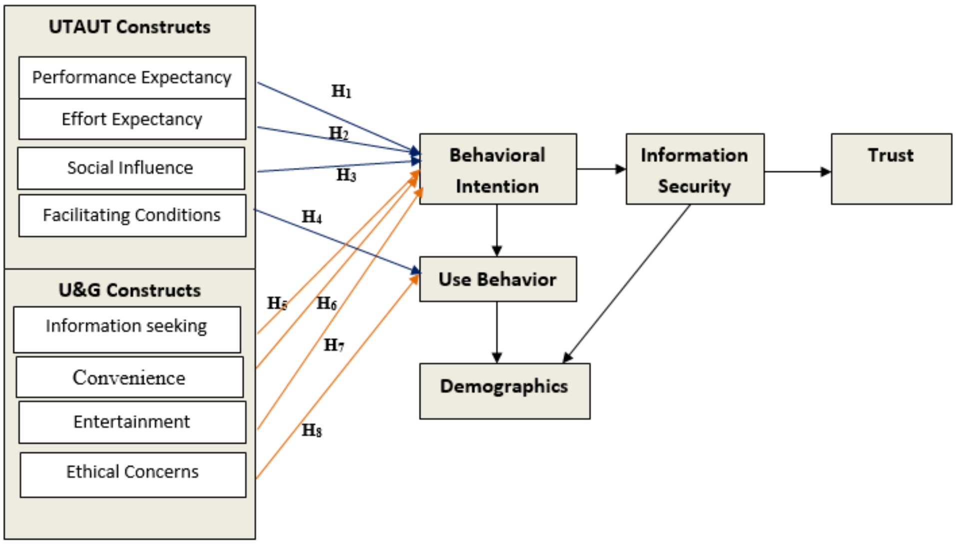

Figure 1: Conceptual Framework Illustration

3.3 Data Analysis

The current study applies reliability analysis and statistical analytical tools to analyze the data and test the hypotheses. These methods are employed to establish the extent of the research perspective on the study sample. Quantitative methods are valuable in research as they are used to score and appraise different events and variables. In this research, reliability tests, Chi-square analysis, and multiple regression are employed as methods of data analysis. These techniques are used to establish the reliability of the data, examine the relationships between two or more variables, and test the hypotheses. Stata software is used for these analyses.

3.3.1 Graphical Method

The study employs the use of graphs to simply present the analytical data. Categorical data in this study is summarized and graphically presented using bar charts and pie charts. Bar graphs are used to portray differences between one set and another or between sets of discrete data. These types of diagrams make it easier to understand how various categories of interest are connected. Although unlabeled, the length of the bars is proportional to the degree of satisfaction or another variable. In contrast, pie charts are used to display categories as a percentage of the whole. They offer a quick and easy way of translating the categories or segments into the overall strategic picture. By using both bar charts and pie charts, this study improves understanding of data, relationships, and distributions within and between variables. These graphical representations make the study more comprehensible and lend further clarity to the findings.

3.3.2 Reliability Analysis

3.3.2.1 Cronbach's Alpha

A Cronbach's alpha value of 0.60 to 0.70 is considered acceptable, while a higher value signifies greater reliability of the developed scale (Gliem & Gliem, 2003; Cortina, 1993). However, if the alpha is excessively high (e.g., above 0.90), it could indicate redundancy among items, so moderate values (0.70 to 0.90) are typically preferred.

Cronbach's alpha is a reliability coefficient rather than a statistical test. It can be mathematically expressed as:

$$\alpha = \frac{N\bar{c}}{\bar{v} + (N-1)\bar{c}}$$

Were,
N = No. of items
$\bar{c}$ = Average covariance between pair of items
$\bar{v}$ = Average variance.

3.3.2.2 Average Inter-Item Correlation

This approach is appropriate as it provides an alternative or supplementary measure of internal consistency, especially useful for shorter scales. Correlations between 0.15 and 0.50 indicate acceptable internal consistency without excessive redundancy among items. This method complements Cronbach's alpha and offers further validation for the reliability of the constructs.

3.4 Statistical Method

After the data analysis, statistical analytical methods were applied. These include independent sample t-tests and multiple linear regression.

3.4.1 Chi-Square

The chi-square test examines the relationship between AI-based advertisements and product selection, the influence of AI on targeted efforts, and consumer trends. It assesses the effect of tailored AI ads on purchase decisions and explores the associations with age, gender, and educational credentials. Additionally, it evaluates perceived risks related to the application of personal information for AI recommendations, highlighting the challenges marketers face in applying AI and understanding customer concerns.

3.4.2 Multiple Linear Regression

Since the study aims to examine relationships between several independent variables (e.g., Performance Expectancy, Effort Expectancy, Social Influence, Information-Seeking, Convenience, etc.) and the dependent variable, customer behavior, multiple regression analysis is highly appropriate. This method allows the study to test the influence of multiple predictors on each outcome variable, helping to validate the hypotheses by estimating the strength and direction of these relationships. Multiple regression can also incorporate moderating variables, such as ethical and privacy concerns, making it valuable for testing hypotheses in the UTAUT + U&G integrated model.

3.5 Ethical considerations

The study ensured that participants were given informed consent by issuing a pre-statement before the survey regarding the purpose of the study and guaranteeing that all data would remain anonymous. Participants were informed that they could withdraw from the survey at any point. Data confidentiality was maintained through anonymized responses; no personal identifying information was collected, other than age and general demographic data. The research followed all the provisions of the GDPR concerning participant data privacy. Furthermore, ethical approval was secured from the relevant institutional body overseeing the research project.

3.6 Empirical Framework

This study's empirical framework is based on the expanded UTAUT + U&G (Uses and Gratifications) model and the Unified Theory of Acceptance and Use of Technology (UTAUT) model. These frameworks allow for a detailed analysis of customer behavior and intentions regarding the use of AI-powered marketing tools. Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), and Facilitating Conditions (FC) are the four primary factors that impact Behavioral Intention (BI) and Use Behavior (UB) in the UTAUT model.

The following equation defines the connections between these constructs:

$$BI = \beta_1 * PE + \beta_2 * EE + \beta_3 * SI + \beta_4 * (PE \times Gender) + \beta_5 * (EE \times Gender) + \beta_6 * (SI \times Gender) + \beta_7 * (PE \times Age) + \beta_8 * (EE \times Age) + \beta_9 * (SI \times Age) + \beta_{10} * (PE \times Qualification) + \beta_{11} * (EE \times Qualification) + \beta_{12} * (SI \times Qualification) + \epsilon \quad (1)$$

Use Behavior (UB) is influenced by BI and FC, represented by:

$$UB = \alpha_1 * BI + \alpha_2 * FC + \alpha_3 * (FC \times Gender) + \alpha_4 (FC \times Age) + \alpha_5 * (FC \times Qualification)\epsilon \quad (2)$$

In this model, Performance Expectancy (PE) reflects consumers' perception of how well they believe AI understands their preferences compared to marketers. Effort Expectancy (EE) focuses on the extent to which consumers experience AI in marketing, for instance, through the use of customized advertisements and recommendation services. Social Influence (SI) targets AI-based pricing strategies in business and work-related decisions and also addresses consumers' views on the rise of personalized targeting and recommendations in recent years, shaped by current corporate values. Facilitating Conditions (FC) describe the extent of consumer ease with AI and the information gathering about their spending patterns for recommended products. In this case, Behavioral Intention (BI) examines the probability that AI-personalized ads will affect purchasing behavior. Lastly, Use Behavior (UB) assesses whether consumers use paid or unpaid versions of AI software, representing actual usage and measuring consumers' interest in specific types of AI-based personalization regarding their level of engagement.

In essence, the UTAUT + U&G model adds gratification constructs, which are: Information-Seeking (IS), Social Interaction (SI), Entertainment (EN), and Convenience (CO), derived from the U&G theory. These constructs have been included to capture the consumer's motivators for engaging with AI-driven marketing tools.

The relationships in this model are defined by the following equations:

$$BI = \beta_1 * PE + \beta_2 * EE + \beta_3 * SI + \beta_4 * IS + \beta_5 * EN + \beta_6 * CO + \beta_7 * (SI \times Gender) + \beta_8 * (SI \times Age) + \beta_9 * (SI \times Qualification) + \epsilon \quad (3)$$

$$UB = \alpha_1 * BI + \alpha_2 * FC + \alpha_3 * (FC \times Gender) + \alpha_4 (FC \times Age) + \alpha_5 * (FC \times Qualification) + \alpha_6 * SI + \alpha_7 * (SI \times Gender) + \alpha_8 * (SI \times Age) + \alpha_9 * (SI \times Qualification) + \epsilon \quad (4)$$

In the expanded model, Social Influence (SI) encompasses both UTAUT's social influence and U&G's social interaction, examining the role of AI tool pricing in business-related decisions and consumers' awareness of the rise in customized advertising. Information-Seeking (IS) captures consumers' stances on and beliefs about using AI in their lives and in general, as well as their expectations regarding AI advancements. Entertainment (EN) measures consumer opinions about the opportunities and threats associated with AI and reflects how much consumers enjoy these technologies. Convenience (CO) embodies consumers' apprehensions about how their information will be utilized in making recommendation decisions, while also considering whether privacy concerns would be sufficient to deter them from purchasing from specific brands.

These modifications to the empirical framework allow for a comprehensive examination of both technology acceptance and psychological gratification factors, enhancing the study's ability to analyze consumer behavior toward AI-driven marketing tools.

4 Results and Discussions

4.1 Graphical Analysis

In total, the research gathered 54 responses, divided by gender, age, and qualification level. Among the respondents, 20 are male and 34 are female (Figure 2), thus the majority of the dataset is female. By age, 33.3% of the responses are from the 35–45 years age group, which is the largest age group in the study. The second major age groups are 25–35 and 18–25 (Figure 3), which together account for 26 responses. Additionally, 18.5% of the responses are from the 45–55 years group, and there were no responses from the 55+ group. Regarding qualification, 35 respondents are postgraduates, 14 are graduates, and 5 are undergraduates.

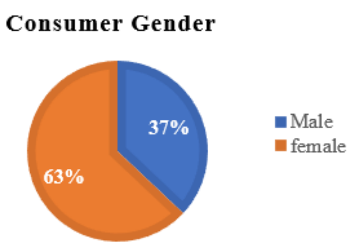

Figure 2: Gender Classification

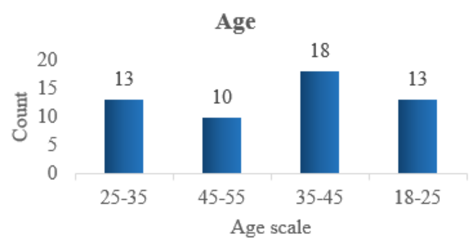

Figure 3: Age Classification

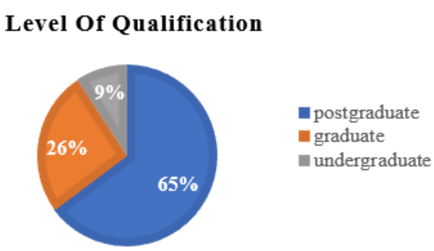

Figure 4: Level of Qualification

Influence Of AI-driven Insights on Targeted Marketing Strategies:

Most participants believe that AI-driven recommendations and advertisements are more relevant than traditional marketing approaches. A total of 53.7% agree, 44.4% remain neutral, and only 1.9% disagree. Most participants are also willing to allow the tailoring of ads for user satisfaction, with just 1.9% expressing disagreement. Overall, more than half of the participants agree with the relevance and efficacy of AI-driven recommendations.

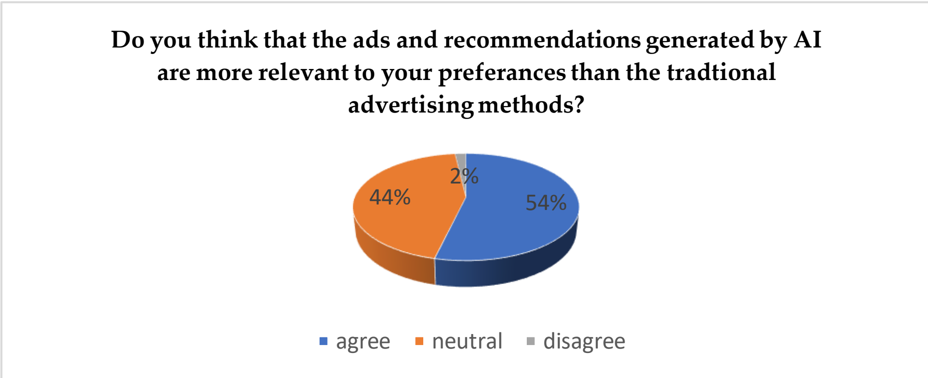

Figure 5: Perception of Respondents towards Recommendations Generated by AI

The Effectiveness of AI in Predicting Consumer Purchasing Patterns and Preferences:

The success of AI in predictive analytics is important to marketers. Figure 6 shows that 63% of respondents believe AI-based advertisements sometimes impact their purchasing decisions, while 16.7% report that they are influenced very often. A smaller percentage report that they are never or hardly ever influenced, indicating that while AI-based advertising is effective, it is not consistently so, and that consumer resistance and awareness can play a role.

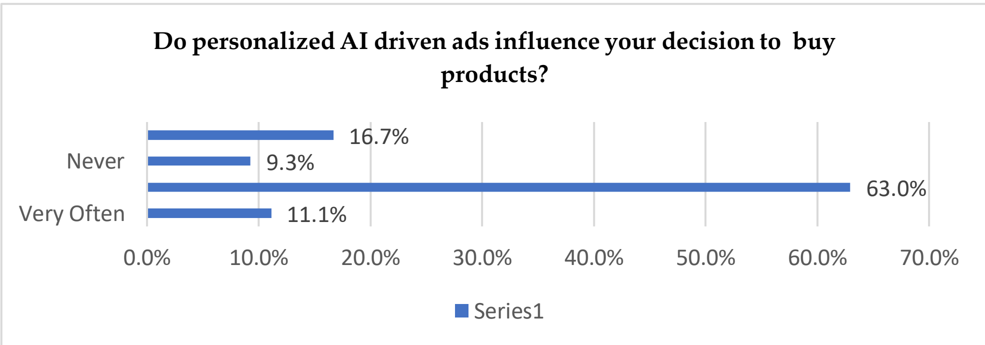

Figure 6: Consumer Purchasing Patterns and Preferences

Consumer Familiarity with AI-Assisted Marketing Suggestions:

Figure 7 demonstrates that 53.7% of respondents know a little about AI in marketing, 24.1% are very familiar, and 22.2% are not at all familiar. Most respondents are at least somewhat familiar with AI in marketing. This indicates that familiarity with AI-driven marketing techniques is relatively high, although a significant portion of respondents still lacks familiarity with these techniques.

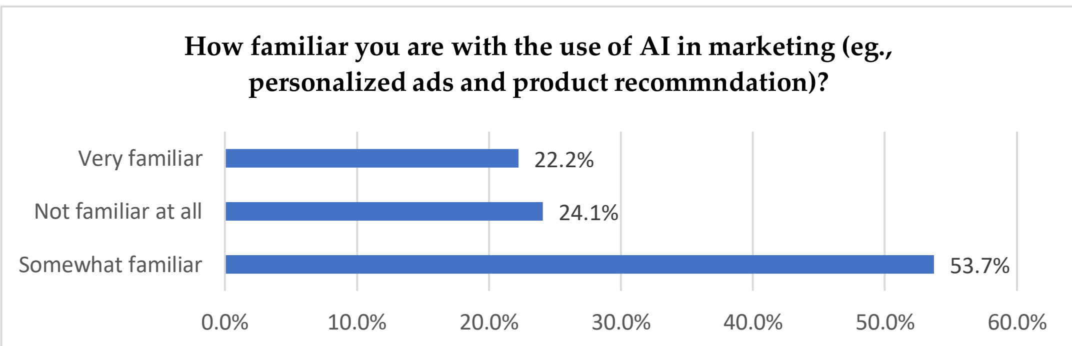

Figure 7: Consumer Familiarity of AI-Assisted Marketing

Challenges And Ethical Considerations for Marketers and Consumers:

Figure 8 shows that 89% of respondents agree, and Figure 8 indicates that companies should be more transparent in their collection and use of consumer data. Additionally, 9% are neutral, and 2% do not agree. The overwhelming majority of respondents believe that companies should be more transparent about their data practices. This reflects a clear consumer desire for more control over and understanding of how personal data is collected, stored, and used.

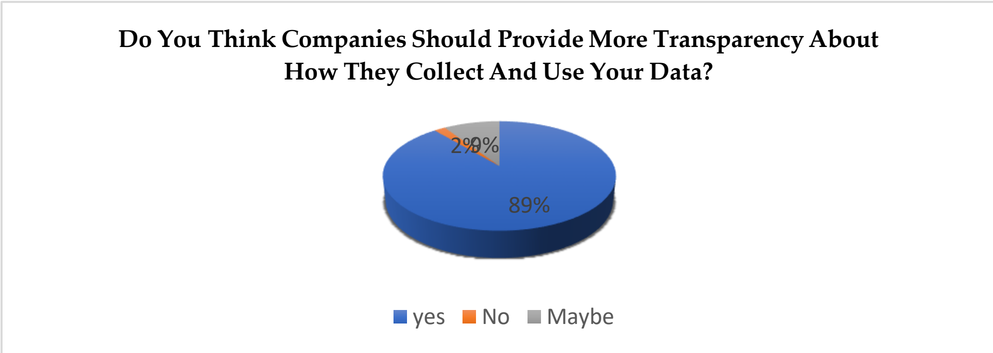

Figure 8: Consumer's Concern Regarding Ethical and Privacy Dilemmas

4.2 Reliability Analysis

4.2.1 Cronbach's Alpha and Average Inter-Item Correlation

The reliability of the dataset was determined by computing Cronbach's alpha coefficient, yielding a result of 0.6 for 16 items, suggesting that the questions in the form have moderate consistency and reliability (Table 1). A generally accepted rule is that an alpha of 0.6–0.7 indicates an acceptable level of reliability (Ursachi et al., 2015). The Average Inter-Item Correlation (AIC) is 0.364, which falls within the recommended range of 0.15 to 0.50. This suggests that the items are reasonably related and measure the same construct without being overly redundant.

Table 1: Reliability Analysis Results

Average interitem correlation	**0.364**
Number of items	16
Cronbach's alpha	0.6

4.3 Statistical Analysis

4.3.1 Chi-square Test

Chi-square test results demonstrate a statistically significant relationship between the ability of AI to use consumer preferences for analysis and the influence of AI-personalized advertisements on decision-making ($\chi^2 = 18.281$, $p = 0.032$). Consumers who depend on AI-derived purchase recommendations interact highly with tailored advertisements ($\chi^2 = 20.768$, $p = 0.002$), providing evidence of successful AI-based marketing. However, demographic variables such as age, gender, or education do not significantly affect AI advertisement effectiveness. Furthermore, privacy concerns related to AI do not result in brand avoidance, as shown by a non-significant Chi-square measure ($\chi^2 = 4.537$, $p > 0.05$).

Table 1: Chi-Square Statistics

Association	**Chi-Square**	**p-Value**
Personalized AI-driven ads influence decision-making, vs. AI, better understanding of consumer preferences	18.281	0.032***
Purchased products based on AI recommendations vs. Personalized AI ads influence decision-making	20.768	0.002***
Consumer demographics vs. Personalized AI-driven ads influence decision-making.		
- By Age	9.987	0.352
- By Gender	2.623	0.454
- By Qualification	7.7	0.261
Concern about AI using personal data vs. avoiding brands due to AI using personal data	4.537	0.338

Note ***, **, * indicates significance level at 1%,5% and 10% confidence interval.

4.3.2 Multiple Linear Regression

4.3.2.1 UTUAT Model

This paper investigates the effects of perceived ease of use (EE), social influence (SI), and the cross-level moderation effects of qualification and gender on behavioral intention (BI), with specific attention to purchase intention from personalized AI ads. EE has a positive effect on BI, as users who are comfortable using AI systems tend to interact more with AI-based personalized advertising. SI suggests that pricing influences business choices in selecting AI tools, and that product norms and social norms can discourage consumers from adopting AI systems. The relationship between EE and BI is moderated by gender, but with a negative coefficient, indicating that gender-specific methods in marketing AI tools could maximize the effectiveness of social influence messages. Qualification reduces the relationship between EE and BI, suggesting that educational levels may moderate the effect of perceived ease of use on behavioral intentions. These findings can be applied to modifying AI technology strategies by taking into account factors such as social pressure and demographic granularity, including gender and qualification.

Table 3: UTUAT Model 1 Estimation

Behavioral Intention (BI)	Coef.	Std. Err.	T	P>|t|
Performance Expectancy (PE)	-0.099	0.272	-0.370	0.716
Effort Expectancy (EE)	1.562	0.460	3.400	0.002***
Social Influence (SI)	-1.233	0.345	-3.580	0.001***
PE2* Gender	-0.180	0.138	-1.310	0.197
EE*Gender	-0.686	0.221	-3.100	0.003***
SI*Gender	0.806	0.208	3.880	0.000***
PE*Qualification	0.157	0.100	1.570	0.123
EE*Qualification	-0.322	0.177	-1.820	0.075*
SI*Qualification	0.236	0.160	1.480	0.147
PE*Age	-0.066	0.060	-1.090	0.281
EE*Age	0.053	0.113	0.470	0.638
SI* Age	0.035	0.090	0.380	0.702
Constant	2.067	0.457	4.520	0.000***
Prob > F	0.0012***			
R-squared	0.5084			
Adj R-squared	0.3646			

Note ***, **, * indicates significance level at 1%,5% and 10% confidence interval.

The research tests the interaction between Facilitating Conditions (FC) and User Behavior (UB) within the UTAUT model. The findings reveal that Behavioral Intention (BI) has a positive but insignificant relationship with UB, which may indicate the presence of other influential variables. The interaction is moderated by gender, such that positive views toward AI-enabled personalized recommendations play a more prominent role among certain groups. The relationship is also mediated by age, with younger users more readily accepting AI systems, while older users may require additional prompting. The model is significant at the 5% level, implying that these predictors capture a substantial portion of the variance in UB.

Table 2: UTUAT Model 2 Estimations

Use Behavior (UB)	Coef.	Std. Err.	t	P>|t|
Behavioral Intention (BI)	0.080	0.202	0.390	0.695
Facilitating Conditions (FC)	0.199	0.317	0.630	0.533
FC *Gender	0.347	0.120	2.890	0.006***
FC*Age	-0.199	0.062	-3.180	0.003***
FC*Qualification	0.000	0.108	0.000	0.997
Constant	1.728	0.664	2.600	0.012***
Prob > F	0.0257***			
R-squared	0.2275			
Adj R-squared	0.1470			

Note ***, **, * indicates significance level at 1%,5% and 10% confidence interval

4.3.2.2 Modified Theoretical Model

This research employs the integrated UTAUT model and U&G (Uses and Gratifications) model to analyze the effect of personalized AI-based advertisements on users' purchasing behavior. The study evaluates Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), and other variables such as Information-Seeking (IS), Entertainment (EN), and Convenience (CO). The negative sign of PE indicates that users who believe AI can better understand their preferences than human marketers are less likely to utilize personalized AI ads. Comfort level with AI used in everyday life, such as personalized advertisements and profiles, decreases perceived complexity and increases ease with AI technology. In contrast, CO exerts a negative influence on BI directly, which may indicate that individuals are not eager to be influenced by AI-enabled ads when making their own decisions. At the 5% significance level, these predictors explain a high proportion of the variability in Behavioral Intention (BI).

Table 3: Modified Model 1 Estimation

Behavioral Intention (BI)	**Coef.**	**Std. Err.**	**t**	**P>|t|**
Performance Expectancy (PE)	-0.206	0.076	-2.720	0.009***
Effort Expectancy (EE)	0.281	0.157	1.780	0.081*
Social Influence (SI)	-0.022	0.235	-0.090	0.926
Information-Seeking (IS)	-0.210	0.156	-1.350	0.184
Entertainment (EN)	0.050	0.102	0.500	0.623
Convenience (CO).	-0.219	0.110	-1.990	0.053*
SI* Gender	0.098	0.086	1.150	0.257
SI* Age	0.029	0.039	0.750	0.455
SI* Qualification	0.035	0.076	0.460	0.648
Contant	3.162	0.721	4.390	0.000***
Prob > F	0.0443***			
R-squared	0.3061			
Adj R-squared	0.1642			

Note ***, **, * indicates significance level at 1%,5% and 10% confidence interval

The analysis determines that Behavioral Intention (BI) profoundly impacts the Use Behavior (UB) of AI software usage, such that individuals with greater behavioral intentions are highly likely to adopt either paid or free versions. Social Influence (SI) is directly and positively related to UB and is statistically significant at the 5% level, implying that organizational or professional influence can shape users' decisions to incorporate AI tools. However, the role of SI in moderating the relationship between Qualification and UB is negative and insignificant at the 10% level. Across all three levels of social influence, the intensity of the effect on qualification decreases as educational levels rise. This suggests that highly educated individuals may rely more on their own judgment when deciding whether to adopt AI software.

Table 4: Modified Model 2 Estimations

Use Behavior (UB)	**Coef.**	**Std. Err.**	**t**	**P>|t|**
Behavioral Intention (BI)	0.575	0.318	1.810	0.077*
Facilitating Conditions (FC)	-0.727	0.596	-1.220	0.229
FC *Gender	0.363	0.238	1.530	0.134
FC*Age	-0.056	0.134	-0.420	0.678
FC*Qualification	0.309	0.224	1.380	0.175
Social Influence (SI)	0.896	0.433	2.070	0.044***
SI* Gender	-0.089	0.181	-0.490	0.626
SI* Age	-0.098	0.086	-1.140	0.259
SI* Qualification	-0.296	0.176	-1.690	0.099*
Constant	0.357	0.922	0.390	0.701
Prob > F = 0.0318**				
R-squared = 0.3208				
Adj R-squared = 0.1819				

Note ***,**, * indicates significance level at 1%,5% and 10% confidence interval

5 Conclusion

Artificial intelligence (AI) marketing has become extremely beneficial in the marketing field due to the tremendous increase in internet usage, offering personalized data and insights about customers. Big data and AI work together to precisely identify customer trends and preferences for businesses. Targeted advertisements and predictive activations are becoming cornerstones of customer relationship marketing strategies. However, these developments also raise moral concerns about data security, usage, disclosure, and customer trust. This study addresses customer perceptions of AI in marketing, its effect on immediate consumer purchases, consumer interactions, and the ethical challenges that could undermine trust in AI marketing systems.

In an increasingly AI-driven world, companies seeking to successfully implement AI technologies while preserving customer loyalty and trust must address these challenges. The study employs the chi-square test to examine the relationships between variables and reliability tests such as Cronbach's Alpha and Average Inter-Item Correlation to evaluate the validity of survey results. The theoretical framework integrates the Unified Theory of Acceptance and Use of Technology (UTAUT) with the Uses and Gratifications Theory (U&G), demonstrating how AI can build enduring relationships between brands and consumers, thus becoming an essential component of the contemporary marketing mix.

The chi-square analysis and reliability tests offer valuable insights into consumer attitudes and behaviors regarding AI marketing. Customers favor AI-powered recommendations and internet advertisements over traditional marketing tactics. The majority acknowledge that targeted advertisements have a favorable impact on their purchasing decisions, even though a smaller percentage have encountered AI-driven marketing. Notably, 89% of participants expressed a desire for greater control over their data, underscoring consumer demands for privacy and autonomy. Chi-square analysis further demonstrates a correlation between AI's ability to assess customer preferences, the efficacy of tailored ads, and improved decision-making across different age and gender groups. Importantly, while privacy remains a priority, consumers do not abandon brands solely over privacy concerns.

Regression models provide further insights into the benefits and challenges of AI-assisted marketing. The insignificance of Performance Expectancy (H1) indicates consumer skepticism about AI's ability to predict preferences, consistent with Venkatesh et al. (2003), who observed that performance expectancy is less influential when users are uncertain about a technology's efficacy. In contrast, Effort Expectancy (H2) positively influences Behavioral Intention, supporting Davis (1989) and Venkatesh et al. (2003), who emphasized the importance of ease of use in technology acceptance. Social Influence (H3) negatively affects Behavioral Intention, implying that external pressures may create resistance if AI marketing is perceived as intrusive—contrary to Gopinath and Narayanamurthy (2022), who found social influence to be a positive driver of AI adoption. Facilitating Conditions (H4) were found to be insignificant in predicting Use Behavior, deviating from Venkatesh et al. (2003), who highlighted their importance.

Additionally, gratification factors show mixed results: Information-Seeking (H5) and Entertainment (H7) were rejected, while Convenience (H6) was accepted but with a negative significance, suggesting that consumers prioritize utilitarian benefits over entertainment or psychological gratifications when engaging with AI marketing tools. This aligns with Sage Kelly et al. (2023), who found perceived convenience to be a stronger driver than entertainment. Ethical concerns (H8) emerged as significant barriers to the link between Behavioral Intention and Use Behavior, supporting findings by Martin et al. (2017) and Lwin et al. (2007) that privacy concerns are central to building trust in AI marketing environments.

These findings highlight the need for AI marketing research to move beyond emphasizing transactional advantages and focus on increasing the perceived value of AI technologies. The ability of AI to adapt to various consumer preferences, demographic diversity, usability factors, and purchase patterns remains critical. This supports Chaffey's (2019) suggestion that AI products should be tailored to meet specific consumer needs and preferences, and is reinforced by Huang and Benyoucef (2013), who emphasized the role of demographic factors in successfully leveraging AI-based marketing strategies to boost adoption and engagement.

5.1 Recommendations

Several key suggestions have been proposed to enhance the efficacy, acceptability, and ethical application of AI in marketing in light of the study's findings:

- **Improve Usability and Trust:**

Marketing strategists should address usability challenges associated with AI to effectively influence consumer behavior. This includes removing obstacles by making AI interfaces simpler to use, debunking misconceptions through transparent communication, and ethically utilizing demographic data to manage trust while fulfilling social and psychological needs. Employing the UTAUT and U&G frameworks has proven beneficial in examining consumer satisfaction and technology adoption. Although gratification factors do not have a major impact, AI functions can be enhanced to better satisfy deeper consumer demands for relevance, trust, and contentment. Consequently, in today's technologically advanced world, businesses can use AI to strengthen consumer relationships and foster brand loyalty.

- **Ensure Transparent and Ethical Data Handling:**

Given the high levels of concern regarding data privacy and transparency, businesses must adopt transparent and ethical data handling practices. Communicating openly about how data is collected, stored, and used will enable AI-based marketing strategies to achieve higher levels of consumer trust and engagement.

- **Enhance Accuracy and Relevance of AI Recommendations:**

Since behavioral intention was not significantly impacted by performance expectancy, AI recommendations should be made more accurate and relevant. This requires investing in more sophisticated algorithms and continuously incorporating actual user feedback to improve AI outputs.

- **Tailor AI Marketing to Demographic Factors:**

Marketers should tailor AI-specific marketing efforts based on demographic variables such as age, gender, and educational attainment, given the evidence that demographics moderate adoption behavior. Doing so can deepen relationships with target consumers and enhance message relevance.

- **Address Negative Social Influence:**

It is critical to alter public perceptions of AI in marketing, as social influence was found to negatively impact behavioral intention. Educational campaigns highlighting the advantages and ethical application of AI can be launched to reduce skepticism and increase social acceptance.

- **Balance Convenience with Ethical Engagement:**

While convenience is a strong motivator, it must be interpreted with caution. Marketers should avoid making AI tools overly invasive or manipulative in their pursuit of user engagement. Instead, users should be empowered with creative opt-in choices and offered customizable preference settings to maintain trust and satisfaction.

- **Directions for Future Research:**

Future research could explore the long-term effects of AI-based marketing on consumer trust and brand loyalty, particularly across diverse demographic groups. Further studies are recommended to investigate how AI can foster greater ethics and transparency, especially concerning culturally diverse consumer markets. Expanding the research to include broader and more representative consumer populations would help validate and refine the current findings. Moreover, exploring AI-based personalization techniques that can effectively address privacy concerns would provide businesses with pathways to maximize AI's potential while upholding ethical standards and customer trust.

- **Data Availability**

The data supporting the findings of this study are available from the corresponding author upon reasonable request.

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