RESEARCH ARTICLE

The Impact of AI-Driven Predictive Marketing on Purchase Intentions Among Social Media Users

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Abstract
This study investigates the behavioral impact of AI-driven predictive marketing on social media users' purchase intentions. Grounded in a multidimensional framework, the research examines the roles of predictive personalization, algorithmic trust, and anticipatory engagement in shaping consumer behavior in digitally mediated environments. A quantitative methodology was employed, utilizing data collected from 265 active social media users through a structured survey. Statistical analysis, including multiple regression, revealed that predictive personalization and anticipatory engagement significantly influence purchase intention, whereas algorithmic trust alone does not yield a direct effect. The findings suggest that consumer behavior is increasingly influenced by proactive, personalized AI content that resonates with individual preferences and anticipated needs. This reinforces the necessity for marketers to prioritize real-time personalization and context-sensitive outreach. The study contributes to marketing scholarship by integrating cognitive, emotional, and technological dimensions of AI application and offers strategic insights for digital marketers operating within socially networked ecosystems.

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I- Introduction

The emergence of artificial intelligence (AI) in digital marketing has fundamentally reshaped the way brands interact with consumers, particularly through the rise of AI-driven predictive marketing. This innovative approach enables firms to forecast consumer behavior, personalize interactions, and optimize marketing campaigns by analyzing large volumes of data in real time. Within the context of social media, predictive marketing not only enhances the relevance of promotional content but also influences users' decision-making processes, from awareness to purchase intent. Despite its growing adoption, the psychological and behavioral implications of such AI-powered strategies remain underexplored. In this context, the central research question becomes: To what extent does AI-driven predictive marketing influence the purchase intentions of social media users? (Elsevier.com, 2022; Fovet-Rabot, 2015, p.1; Picot & Macioce, 2022, p.23).

This inquiry is grounded in the hypothesis that the effectiveness of predictive marketing stems from three interrelated components: predictive personalization, anticipatory engagement, and algorithmic trust. It assumes that these dimensions, by enhancing perceived relevance, interactivity, and technological credibility, positively influence consumer intention to purchase. To test this hypothesis, it is necessary to examine how prior studies have addressed these factors and what empirical insights they offer.

In their study, Shoukat et al. (2024) investigated the role of psychological concerns—especially privacy and intrusiveness—in shaping AI users' perceived usefulness and behavioral intentions. Drawing on a sample of 488 Saudi users and the Theory of Planned Behavior, they found that privacy concerns indirectly affect user intention through perceived usefulness. The emphasis here was on user anxiety and technological trust, rather than direct personalization effects (Shoukat, et al., 2024).

In contrast, Ghufran and Ahmad (2025) assessed AI-driven marketing's effect on purchase behavior through consumer attitude and motivation. Using 577 responses from Indian consumers and structural equation modeling, they demonstrated that consumer motivation significantly mediates between attitude and purchase behavior. This study emphasized cognitive mediation and behavioral intention but did not isolate personalization or predictive engagement as distinct constructs (Ghufran & Waqar Ahmad, 2025).

A complementary perspective was offered by Beyari and Hashem (2025), who examined AI's role in enhancing the customer experience via social media personalization in the MENA region. Based on 893 responses, their findings confirmed that real-time personalized content and influencer matching improve user satisfaction and purchase intent. The study strongly supports the current hypothesis, particularly the predictive personalization and engagement dimensions (Beyari & Tareq Hashem, 2025).

Aryaa et al. (2025) added a behavioral marketing lens, analyzing how social enjoyment, conveyed through influencer-generated content, affects purchase intentions for electronic products. Their questionnaire of 299 social media users showed a strong correlation between entertaining AI-assisted content and consumer attitudes, suggesting that affective engagement is as critical as algorithmic accuracy. Although algorithmic trust was not explicitly measured, emotional resonance with AI-curated content played a pivotal role (Arya, et al., 2025).

From another angle, Areeb and Areeb (2025) assessed AI-powered chatbots and predictive analytics and their effects on decision-making. With a smaller sample of 60, the study confirmed that personalization and response efficiency increase engagement. However, the authors noted the limitations of AI's emotional intelligence, a factor that could hinder long-term trust—a significant point concerning algorithmic transparency (Areeb & Sarim Areeb, 2025).

Similarly, Kazmi et al. (2025) studied consumer privacy concerns and their impact on the effectiveness of AI personalization tools. Using mixed methods (surveys and interviews), they found that trust, satisfaction, and perceived value mediate the relationship between AI use and consumer behavior. Their findings underscore the importance of balancing personalization with privacy, reinforcing the conceptual need for trustworthiness in predictive systems (Kazmi, et al., 2025).

Finally, Patil et al. (2024) focused on AI tools like chatbots and predictive analytics in digital marketing, noting that real-time interaction and personalization can increase conversion rates by 200–300%. The study also highlighted geographic variations and trust concerns, concluding that while AI enhances user engagement and ROI, security and ethical issues persist, particularly when AI operates in opaque or overly aggressive ways (Patil, et al., 2024).

These studies reveal both converging and diverging trends. While most affirm the positive impact of AI on purchase intentions, their theoretical foci, samples, and methodologies vary. Shoukat, Kazmi, and Areeb centered their analyses on privacy and trust; Ghufran and Aryaa on motivation and affect; while Beyari and Patil focused on real-time engagement and personalization. None of the studies, however, unified all three dimensions—predictive personalization, algorithmic trust, and anticipatory engagement—into a single empirical model, which constitutes the unique contribution of the current research.

In response to these theoretical and empirical gaps, this study proposes a quantitative design, surveying 265 social media users. Through regression analysis, it assesses how AI-powered personalization, trust, and proactive engagement collectively influence the formation of purchase intentions in AI-mediated environments. By doing so, the study aims to synthesize and advance prior knowledge, offering both academic and practical implications for marketers navigating the digital economy.

AI-Driven Predictive Marketing: A Conceptual Overview

In the rapidly evolving digital economy, AI-driven predictive marketing has emerged as a transformative paradigm within the domain of strategic marketing and consumer analytics. Rooted in the capabilities of machine learning, natural language processing, and big data mining, this form of marketing leverages artificial intelligence to forecast consumer behaviors, preferences, and needs with increasing precision (Lal, et al., 2025, P 1987) . Unlike traditional marketing strategies that rely on historical segmentation or generic content delivery, predictive marketing uses real-time data inputs and algorithmic modeling to anticipate what customers want before they explicitly express it. It reflects a shift from reactive promotional strategies to proactive, anticipatory engagement tailored to the individual consumer level (Modi & Hassan Raza Chowdhary, 2025. P 662).

The core principle behind predictive marketing is data-informed personalization—the idea that brands can construct hyper-relevant experiences by learning from vast volumes of structured and unstructured data (Zare, Annur Islam Sifat, & Mumtaz Karatas, 2025. P 93). AI algorithms detect behavioral patterns across digital touchpoints—such as browsing history, click behavior, time spent on content, sentiment in messages, and even biometric responses—to make probabilistic predictions about future purchasing decisions. In doing so, marketers can send timely offers, tailor content dynamically, and allocate resources more efficiently. This not only enhances customer experience but also increases conversion rates, customer lifetime value, and brand loyalty. However, the effectiveness of predictive marketing hinges on the integration of its key dimensions, each of which captures a specific aspect of how AI influences marketing outcomes.

1. Predictive Personalization

The first and perhaps most visible dimension of AI-driven predictive marketing is predictive personalization. This refers to the system's ability to curate and deliver individualized content, product recommendations, or promotional messages based on inferred consumer preferences (Chandrakumar, 2024, p 4473). By employing deep learning techniques, AI systems are capable of constructing comprehensive user profiles that adapt over time (Amosu, et al., 2024, p. 789; Shabani et al., 2024, p. 2300; Ojika et al., 2023, p. 127). For example, a predictive model might learn that a customer responds positively to limited-time offers on weekends and thus prioritize such promotions accordingly. This dimension not only reduces consumer search costs but also fosters a sense of being "understood" by the brand, which enhances affective engagement.

In this regard, recent literature indicates that marketing campaigns (Personalized Marketing) driven by consumer data analytics demonstrate significantly greater effectiveness compared to generic campaigns, potentially yielding conversion rates up to 20% higher (Islam, Reza E Rabbi Shawon, & Md Sumsuzoha, 2023, p 751).

Predictive personalization also extends into dynamic website interfaces, adaptive pricing models, and responsive advertising formats. However, it carries inherent risks, particularly when personalization becomes overly intrusive or fails to reflect the evolving identity of the consumer. Therefore, marketers must calibrate the depth and timing of personalized interventions to avoid the "creepiness effect," (Rajaobelina, et al., 2021, p. 2340) where personalization becomes counterproductive.

2. Algorithmic Trust and Transparency:

The second dimension is algorithmic trust and transparency, which pertains to the degree to which consumers believe in and are willing to rely on AI-generated predictions and recommendations. While predictive marketing can deliver remarkable efficiency, it operates within a "black box" for most consumers, who are often unaware of how and why certain content appears in their digital feeds (Kumar & Manoj Daya, 2025, p 147; Choung, Prabu

David, & Arun Ross, 2022, p. 1731) .

Consumers are more likely to act on AI recommendations when they perceive them as unbiased, accurate, and grounded in legitimate data usage. Accordingly, organizations must strive to implement explainable AI (XAI) technologies that offer users clarity regarding how predictions are formulated. This imperative is reinforced by Liao and Vaughan (2023), who define transparency in this context as the system's ability to provide stakeholders with a clear understanding of the model's capabilities, limitations, and operational mechanisms—thereby enabling informed decision-making (Shabankareh, et al., 2025, p 7).

Algorithmic transparency is not just an ethical imperative but also a strategic one, as it directly influences brand credibility and user compliance. When trust is compromised—whether due to data misuse, poor predictions, or lack of disclosure—engagement declines and reputational risks rise. As René F. Kizilcec demonstrates that individuals' trust in technological systems is influenced by the degree of transparency these systems provide. Transparency can reinforce positive perceptions of reliability, but it may also trigger skepticism if it alters users' beliefs about system performance. In this context, trust is understood as a confident expectation in a risk-laden environment, wherein users assume their vulnerabilities will not be exploited (Kizilcec, 2016, p 2390).

3. Anticipatory Engagement

The third dimension is anticipatory engagement, which reflects the proactive nature of AI systems in reaching out to consumers before a need is consciously articulated. Unlike reactive campaigns that respond to overt consumer behavior, anticipatory engagement enables marketers to initiate communication based on signals that precede explicit intent " From Reactive to Predictive "(Cerejo & Miguel Carvalhais, 2020, p 346). For instance, a predictive model might detect early signs of interest in wellness products based on shifts in search queries and app usage, prompting the system to introduce relevant content or offers ahead of competitors.

This capability positions brands not only as responsive but as intuitively aligned with consumer rhythms. It transforms the consumer journey from a linear funnel into a dynamic, AI-curated experience. However, anticipatory strategies must be employed with nuance: if the system misinterprets behavioral cues, or if consumers perceive such targeting as manipulative, the result can be resistance or distrust. Successful anticipatory engagement thus requires a delicate balance between intelligent forecasting and user-centered respect.

Purchase Intentions Among Social Media Users: A Behavioral Perspective

In contemporary marketing scholarship, purchase intention represents one of the most crucial psychological constructs for predicting actual consumer behavior. It refers to an individual's conscious plan or willingness to purchase a specific product or service in the near future. It is also regarded as a behavioral driver that reflects the consumer's readiness to engage in a purchase action (Ullah, Faisal Gulzar, & Ali Agar Shahzad, 2025, p 70). Within digital ecosystems—particularly on social media platforms—purchase intentions have become increasingly complex, shaped not only by traditional marketing stimuli but also by real-time, personalized, and algorithmically driven interactions. As users navigate these highly dynamic platforms, their behavioral responses are often molded by content visibility, peer influence, and the seamless integration of promotional messaging into social and recreational spaces (Alam, et al., 2024,p 833).
Social media users exhibit distinctive consumer characteristics that differentiate them from traditional shoppers. They are exposed to an overwhelming volume of marketing stimuli, often delivered in the form of curated ads, influencer content, and native recommendations (Poleac & Alexandra-Niculina Gherguț-Babii, 2024,pp 70-71). In this context, the formation of purchase intentions becomes a cognitively and emotionally mediated process, influenced by the perceived relevance, trustworthiness, and timing of the promotional content. Users who feel that an offer is specifically tailored to their interests—without being invasive—are more likely to progress from attention to consideration, and eventually to intention. Thus, social media does not merely act as a communication channel; it serves as a psychological environment where perceptions are shaped, preferences are formed, and decisions are preconditioned.

Moreover, purchase intention on social media is not an isolated variable but rather a node within a larger behavioral framework. It is commonly modeled as an outcome of various antecedents such as perceived usefulness, perceived enjoyment (Roy, Murshedul Arafin, & Jubayer Ahmed, 2025), attitude toward the advertisement, brand engagement, and peer influence. In the case of AI-driven predictive marketing, these factors converge to create a seamless consumer experience where perceived personalization, predictive accuracy, and algorithmic trust directly contribute to the formation of purchase intentions. For instance, a user may form an intention to buy a product not because of traditional brand familiarity, but due to the psychological resonance of the AI-generated message with their latent needs.

A unique feature of purchase intentions within social media environments is their real-time fluidity. Intentions may fluctuate within short time frames, depending on the emotional tone of the feed, social proof (likes, shares, comments), and even algorithmic content curation. Therefore, predictive models that seek to anticipate or influence purchase intentions must account for both the temporal sensitivity and the multidimensionality of social media users' psychological states. Unlike static intention in offline contexts, digital purchase intentions are frequently interrupted or reinforced by the platform's interactive design and by ongoing social feedback loops.

II– Methods and Materials:

This section outlines the methodological framework employed in the present study, detailing the procedures for sample selection, variable operationalization, data collection, statistical treatment, and hypothesis testing. Methodological rigor was ensured to enable reproducibility and to strengthen the empirical validity of the findings.

Population and Sampling

The study targeted social media users across various age groups who exhibit high levels of engagement with digital platforms, particularly social networking sites. This population was considered especially relevant given the study's focus on AI-driven marketing experiences and technology-informed purchase intentions. A random sampling technique was employed, ensuring that participants possessed at least a minimum level of digital literacy and active usage of social media (defined as no less than two hours per day on platforms such as Instagram, TikTok, and Facebook). The final sample consisted of 265 valid respondents who voluntarily completed the online survey via Google Forms over a period of approximately eight weeks.

Variables and Operational Definitions

The study comprises two principal variables:

The independent variable: is AI-driven predictive marketing, defined as the utilization of artificial intelligence algorithms to forecast consumer preferences and deliver personalized marketing content accordingly. This variable was assessed using a composite scale adapted to the context of social media marketing. The final construct comprised 17 items distributed across three dimensions: algorithmic trust, predictive personalization, and proactive engagement.

Dependent Variable: Purchase Intentions, operationalized as the degree to which users express a deliberate willingness to purchase a product or service featured on social media platforms. A scale consisting of 12 items was incorporated, based on established and validated measures of purchase intentions.

Each item was measured using a five-point Likert scale, ranging from 1 (Strongly Disagree) to 5 (Strongly Agree). Internal consistency for each construct was verified using Cronbach's Alpha .As All items on the AI-driven predictive marketing scale exceeded a Cronbach's alpha coefficient of 0.82, while the items on the purchase intention scale surpassed 0.74. These values indicate a high level of internal consistency across both measurement instruments used in the study.

Data Collection Procedure

Data were collected between November and December 2024. The survey was distributed online via social media platforms, including groups, pages, and sponsored advertisements, to ensure a diverse representation within the study sample. Participants were informed of the academic purpose of the research, and their anonymity was assured in accordance with ethical research guidelines. Incomplete or partially filled responses were excluded, resulting in a final valid sample of 265 participants.

Data Summarization and Descriptive Statistics

The initial phase of analysis involved descriptive statistics to profile the sample and summarize the data. Frequencies and percentages were used for categorical variables (e.g., gender, education level), while means and standard deviations were calculated for the scale items. The average overall score for AI-driven predictive marketing was $M = 3.64$, $SD = 0.49$, and for purchase intention $M = 3.68$, $SD = 0.48$, indicating a moderately high perception of marketing personalization and a generally favorable intention to purchase.

Statistical Tools and Hypothesis Testing

To examine the effect of the independent variable on the dependent one, path coefficients (β), standard errors, and statistical significance (p-values) were calculated. The significance threshold was set at $p < 0.05$.

III- Results and discussion :

In alignment with the study's empirical objectives, this section presents a structured examination of the data to evaluate the psychometric validity of the measurement instruments, describe participant responses, and test the proposed hypotheses. The analysis begins with reliability diagnostics using Cronbach's Alpha to assess internal consistency across the key constructs. This is followed by descriptive statistics, offering a snapshot of central tendencies and dispersion measures for each variable under investigation. Finally, regression modeling—both simple and multiple—is employed to evaluate the predictive power of the three dimensions of AI-driven marketing (algorithmic trust, predictive personalization, and anticipatory engagement) on consumer purchase intentions.

Table (1): Cronbach's alpha

Item	N phrases	N	Cronbach's alpha
AI-Driven Predictive Marketing	17	265	0.829
Algorithmic Trust and Transparency	06	265	0.766
Predictive Personalization	06	265	0.766
Anticipatory Engagement	05	265	0.778
Purchase Intentions	12	265	0.749

Source: SPSS results

Table (1) provides the internal consistency reliability coefficients (Cronbach's alpha) for each of the major constructs used in the study, based on responses from a sample of 265 social media users. As The construct AI-Driven Predictive Marketing, comprising 17 items, recorded a Cronbach's alpha of 0.829, which indicates excellent internal consistency. This suggests that the items used to measure the overarching concept of predictive marketing based on artificial intelligence are highly interrelated and dependable in assessing the underlying construct.

The first subdimension, Algorithmic Trust and Transparency, consisting of 6 items, yielded a Cronbach's alpha of 0.766. This score is within the acceptable-to-good range, demonstrating that the items used to capture users' perceptions of algorithmic reliability, fairness, and transparency are sufficiently coherent to be treated as a unified scale.Similarly, Predictive Personalization, which also includes 6 items, recorded an identical alpha value of 0.766, further validating its internal reliability. This indicates that respondents consistently evaluated the personalization aspects of AI—such as tailored advertisements or recommendations—across the scale's items. The third dimension, Anticipatory Engagement, based on 5 items, exhibited a Cronbach's alpha of 0.778, denoting a solid level of reliability. This supports the conclusion that the measure accurately reflects the extent to which AI tools engage users proactively, by predicting their future needs and behaviors.

Lastly, the Purchase Intentions construct, which includes 12 items, achieved a Cronbach's alpha of 0.749. Although slightly lower than the other scales, it still surpasses the commonly accepted threshold of 0.70, indicating that the scale remains statistically reliable for assessing users' behavioral intention to purchase based on their interactions with AI-driven marketing.

Table (2): Characteristics of the Study Sample

Description	Frequency	Percentage

Gender	Male	91	34.3%
	Female	174	65.7%
Age	>30	135	50.9%
	31- 40	75	28.3%
	41-50	29	10.9%
	<51	26	9.8%
Marital status	Married	123	46.4%
	Single	138	52.1%
	Divorced	2	0.8%
	Widowed	2	0.8%
Total		265	100%

Source: SPSS

Table (2) outlines the demographic characteristics of the study's sample, which consisted of 265 respondents. The variables include gender, age, and marital status, with both frequency counts and corresponding percentages provided.

The gender distribution reveals a female-dominated sample, with 91 males (34.3%) and 174 females (65.7%). This demographic skew may reflect broader trends in social media usage or responsiveness to digital surveys, particularly among younger, tech-savvy users. Similarly, the marital status of the sample was relatively balanced: 123 participants (46.4%) were married, while 138 (52.1%) were single. Only a small fraction of respondents were divorced or widowed (0.8% each), suggesting a predominantly non-disrupted household structure within the sample.

In terms of age, the largest proportion of respondents (50.9%) were aged 30 or below, positioning them as digital natives—arguably the most relevant demographic for research on AI-driven marketing. Respondents aged 31 to 40 accounted for 28.3%, those aged 41 to 50 made up 10.9%, and individuals above 50 constituted only 9.8%, indicating limited representation from older social media users.

From a theoretical standpoint, the demographic profile of the sample aligns well with the intended focus of the study—namely, understanding the effects of AI-driven predictive marketing on digitally engaged, socially active consumers. The predominance of respondents under the age of 30 strengthens the study's emphasis on digital youth, who are both the most active users of social media and the most susceptible to algorithmic personalization and anticipatory marketing strategies. In parallel, the near-equal representation of single and married individuals introduces an additional analytical dimension, allowing for the examination of how lifestyle factors may mediate the effectiveness of predictive marketing. For instance, single respondents may be more responsive to AI-generated content related to entertainment, fashion, or aspirational living, while married participants might exhibit greater sensitivity to content centered on home, family life, or long-term planning.

In conclusion of this analysis, the demographic composition of the sample provides a robust and theoretically sound foundation for examining how AI-driven predictive marketing influences consumer behavior across varied user segments. The diversity in gender and marital status, coupled with the youth-heavy structure of the sample, reinforces the study's relevance to understanding intelligent marketing within socially networked environments.

Table (3): Descriptive statistics

Item	N of Items	Sample size	mean	Median	standard deviation

AI-Driven Predictive Marketing	17	265	3.64	3.58	0.491
Algorithmic Trust and Transparency	6	265	3.81	3.83	0.556
Predictive Personalization	6	265	3.77	3.66	0.572
Anticipatory Engagement	5	265	3.30	3.20	0.863
Purchase Intentions	12	265	3.68	3.66	0.489

Source: SPSS

Table (3) summarizes the descriptive statistics for the main constructs involved in the study, based on data collected from 265 social media users. The analysis includes the mean, median, and standard deviation for each construct, providing a snapshot of the central tendency and variability of the participants' responses.

The overall construct of AI-Driven Predictive Marketing, composed of 17 items, showed a mean score of 3.64 and a median of 3.58, with a standard deviation of 0.491. These values suggest that, on average, participants moderately agreed with statements reflecting their perceptions of AI-based marketing efforts, with a relatively low level of dispersion, indicating consistent responses.

Within this construct, Algorithmic Trust and Transparency had the highest mean score of 3.81 and a median of 3.83, alongside a standard deviation of 0.556. This indicates a strong perception of trust and transparency in the algorithms used for marketing on social media, with moderate variation among respondents.

Predictive Personalization exhibited a mean of 3.77 and a median of 3.66, with a standard deviation of 0.572. These values reflect a generally positive attitude toward the personalization capabilities of AI-driven marketing tools, suggesting users feel that content is well-aligned with their preferences, although with slightly greater variability in perceptions compared to algorithmic trust. The dimension Anticipatory Engagement had the lowest mean of 3.30 and a median of 3.20, with a higher standard deviation of 0.863. This shows that while participants' perceptions of proactive AI engagement were somewhat lower, the diversity of responses was notably higher, indicating varying degrees of acceptance and awareness of anticipatory marketing behavior.

Finally, the dependent variable, Purchase Intentions, showed a mean of 3.68, a median of 3.66, and a standard deviation of 0.489. These results indicate that, on average, participants tended to agree with statements related to their intention to make purchases as a result of their exposure to predictive marketing efforts on social media, with fairly low variability among responses.

These descriptive statistics offer key behavioral insights into how digital youth engage with AI-driven marketing mechanisms across social media platforms. First and foremost, the elevated mean values across all constructs suggest a positive perception and acceptance of predictive marketing powered by artificial intelligence. The digital youth cohort—often considered tech-savvy and data-aware—appears receptive to marketing content that is perceived as relevant, tailored, and technologically intelligent.

The strong ratings for Algorithmic Trust and Predictive Personalization affirm that trust remains a critical psychological precursor to the effectiveness of AI-based marketing. When users believe that the algorithmic processes behind recommendation engines are transparent and accurate, they are more likely to develop positive attitudes toward the content and, subsequently, the brand. This reinforces the theoretical frameworks linking trust with behavioral intention in digital environments. The anticipatory engagement dimension recorded a noticeably lower mean score, suggesting the presence of a cognitive gap—meaning that some users may not fully understand how these systems function or lack sufficient insight into their underlying mechanisms. This lack of clarity may generate a sense of ambiguity and skepticism. Moreover, the broader dispersion of responses indicates a more polarized perception among participants.

Lastly, the moderately high level of Purchase Intentions indicates that AI-driven marketing mechanisms—when designed with trust, personalization, and engagement in mind—can successfully influence behavioral outcomes. The low standard deviation underscores that this effect is consistently perceived across the sample, adding weight to the predictive power of AI in shaping consumer decisions.

Table (4): Coefficients

Independent variables	Dependent variable	R	R-deux ajusté	F	B	Sig
AI-Driven Predictive Marketing	Purchase Intentions	0.595	0.347	47.671	0.571	0.000

Source: SPSS

The regression model presented in the table (4) aims to assess the impact of AI-Driven Predictive Marketing and its key dimensions on the Purchase Intentions of social media users. The simple regression results show a correlation coefficient (R) of 0.595, indicating a moderately strong positive relationship between the independent and dependent variables. This means that as perceptions of AI-based predictive marketing increase, so do users' intentions to engage in purchasing behaviors.

The model explains a significant portion of the variance in purchase intentions, as reflected by the adjusted R-squared value of 0.347. This implies that approximately 34.7% of the variance in purchase intentions is accounted for by the predictive marketing construct, a notable outcome in behavioral marketing research. The F-value of 47.671 with a p-value of 0.000 confirms the overall statistical significance of the model, meaning the predictor contributes meaningfully to explaining the dependent variable. The unstandardized coefficient (B = 0.571) suggests that for every unit increase in AI-driven predictive marketing perception, purchase intentions are expected to rise by approximately 0.571 units, assuming all other variables remain constant.

Table (5): Descriptive statistics

Independent variables	Dependent variable	Beta	T	Sig
Constante	Purchase Intentions	-	8.402	0.000
Algorithmic Trust and Transparency		0.129	1.085	0.279
Predictive Personalization		0.428	3.599	0.000
Anticipatory Engagement		0.172	3.429	0.001

Source: SPSS results

The second part of the multiple regression model breaks down the composite construct of AI-driven predictive marketing into its three principal dimensions to evaluate their individual contributions to predicting purchase intentions. This multiple regression model offers a more nuanced understanding of how each specific element of AI-driven marketing influences consumer behavior on social media platforms.

The constant term was significant ($T = 8.402$, $p < 0.001$), providing a meaningful baseline for the regression equation. The dimension Algorithmic Trust and Transparency recorded a Beta of 0.129, a T-value of 1.085, and a p-value of 0.279, indicating that its influence is not statistically significant. This suggests that, although trust in and clarity of algorithms may be important conceptually, it did not emerge as a reliable predictor of purchase intentions in this sample.

Conversely, Predictive Personalization exhibited a strong and statistically significant effect, with a Beta coefficient of 0.428, T-value of 3.599, and a p-value of 0.000. This result shows that personalized marketing content that aligns with user preferences and behavioral data significantly enhances purchase intent. Similarly, Anticipatory Engagement contributed significantly to the model, with a Beta of 0.172, T-value of 3.429, and p-value of 0.001, reflecting a positive relationship between proactive AI interaction and the likelihood of purchasing behavior.

The overall significance of the AI-driven predictive marketing construct underscores the central role of advanced marketing technologies in shaping consumer behavior. That a third of the variance in purchase intentions is explained by this single construct ($R^2 = 0.347$) confirms its substantial influence in the digital marketing ecosystem. However, the decomposition of the model reveals important nuances. Predictive Personalization emerges as the most powerful predictor, suggesting that consumers are highly responsive to content that reflects their preferences, browsing history, and contextual behavior. This aligns with prior research emphasizing the persuasive power of personalized experiences, particularly in high-choice environments like social media where attention is fragmented and competition for user engagement is intense.

Anticipatory Engagement, the second significant predictor, highlights the growing effectiveness of AI systems that anticipate user needs before they are explicitly expressed. Its strong statistical weight implies that users not only recognize proactive engagement strategies but also value them when they feel intuitive and contextually relevant. This suggests a psychological shift in user expectations, where AI is increasingly seen not just as a reactive tool but as a predictive assistant in the decision-making process. Conversely, the non-significant effect of Algorithmic Trust and Transparency reveals a critical insight: trust alone may not directly influence purchase intentions unless it is paired with actionable value (e.g., personalization or anticipation). While users might expect a degree of trustworthiness in automated systems, it appears that functional utility overrides mere transparency in shaping behavioral outcomes. This finding encourages marketers and developers to focus more on experience optimization than mere algorithmic disclosure.

In conclusion, this regression analysis demonstrates that AI-driven predictive marketing is a powerful tool in influencing consumer behavior, particularly through its ability to personalize and anticipate user needs. These insights not only reinforce the importance of investing in advanced AI capabilities but also call attention to the evolving criteria by which users evaluate the effectiveness and persuasiveness of marketing in digital environments.

IV- Conclusion:

This study set out to explore the extent to which AI-driven predictive marketing can shape purchase intentions among active social media users. Through a multi-dimensional analysis incorporating algorithmic trust, predictive personalization, and anticipatory engagement, the research has demonstrated that artificial intelligence not only transforms marketing practices technically but also reconfigures how consumers psychologically engage with promotional content. The results underscore that personalization and proactivity—not mere algorithmic transparency—are the driving forces behind consumers' willingness to purchase in AI-mediated environments.

One of the most compelling findings of this study lies in the dominant predictive power of personalized content. Participants responded most favorably to marketing efforts that mirrored their preferences and behavioral patterns, reinforcing the idea that consumers value relevance and resonance over general exposure. This confirms the theoretical frameworks in consumer behavior that prioritize individual-centric experiences as critical to intention formation. Furthermore, anticipatory engagement emerged as a statistically significant contributor to purchase intentions, reflecting a shift in consumer expectations—from reactive content delivery to predictive and context-aware marketing interactions. Users appear increasingly open to AI systems that intuitively sense their needs, provided such interventions are respectful and well-calibrated.

On the other hand, the dimension of algorithmic trust did not exert a significant direct effect on purchase intention. This finding offers a nuanced insight: trust—as an abstract construct rooted in concepts such as transparency, fairness, and accuracy—is not sufficient on its own to shape consumer behavior unless it is translated into tangible cognitive value or a clear psychological impact for the user. In today's digital landscape, consumers do not base their decisions solely on whether systems are trustworthy or fair; rather, they are more strongly influenced by the functional value these systems deliver and how well the outcomes align with their personal needs and lived experiences. In other words, it is not enough for an algorithm to be reliable; the user must perceive its outputs as useful, relevant, and contextually responsive. This finding underscores the importance of shifting smart marketing strategies toward optimizing user-centered experiences, rather than relying solely on conceptual assurances of algorithmic integrity.

From a practical standpoint, the study highlights several implications for marketers and developers. First, investment in intelligent personalization technologies should remain a strategic priority. Second, the timing, tone, and contextual sensitivity of AI-generated content are critical levers in increasing user receptivity. Third, the success of predictive marketing depends not only on algorithmic sophistication but also on ethical sensitivity—balancing data-driven proactivity with user autonomy and trust.

Based on the above, AI-driven predictive marketing represents a powerful behavioral catalyst in the evolving digital economy. When intelligently designed and responsibly deployed, such systems can foster meaningful consumer-brand relationships, enhance engagement, and ultimately drive conversion. Future research should further investigate the long-term implications of anticipatory systems on consumer autonomy, emotional trust, and ethical perceptions, particularly as AI technologies become more embedded in everyday digital life.

Based on these findings, the study offers the following practical recommendations for marketers, AI developers, and digital strategists:

1. Prioritize investment in predictive personalization systems that adapt in real time to evolving user behavior and preferences.

2. Design anticipatory engagement mechanisms that are context-sensitive, ethically grounded, and respectful of user autonomy.

3. Move beyond algorithmic transparency as a rhetorical promise toward creating tangible, value-rich user experiences that directly enhance trust through usefulness and relevance.

4. Continuously monitor user feedback and behavioral signals to refine AI-driven marketing models and ensure long-term acceptance and effectiveness.

Research limitations

Despite its contributions, this study is not without limitations. Theoretically, it focused solely on three dimensions of predictive marketing without considering emotional or cultural variables that might moderate user responses. Methodologically, the study relied on cross-sectional survey data, which may not capture long-term changes in user behavior. Moreover, the sample consisted primarily of active social media users under the age of 30, limiting the generalizability of results to broader age groups or less digitally engaged populations.

For future research, longitudinal designs could be employed to track behavioral shifts over time. Additionally, comparative studies across demographic groups and cultural contexts could further refine understanding of how AI-driven marketing is perceived and acted upon in diverse environments. Researchers may also investigate ethical dimensions more explicitly, including user consent, data fatigue, and perceptions of autonomy in algorithm-mediated interactions.

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