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The impact of AI-Driven precision marketing strategies on consumer purchase intention

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Abstract. Artificial intelligence (AI) has transformed marketing into a precision era with individualized strategies. AI-empowered marketing strategies such as personalized recommendations and intelligent customer service are now widely applied on social media platforms. This study employs the Stimulus-Organism-Response (S-O-R) model and privacy calculus theory to empirically test the mechanism and boundary conditions of the impact of AI-driven precision marketing strategies on consumers' purchase intentions. Data from 507 social media users were collected via 7-point Likert scale questionnaires. Data analysis was conducted using SPSS for descriptive statistics and structural equation modeling (SEM) for path analysis, including tests of mediation and moderation effects. SEM analysis confirmed the significant positive effect of AI precision marketing on purchase intentions ($\beta=0.629$, $p<0.001$); consumer perceived value plays a partial mediating role ($\beta=0.257$, $p<0.001$). Privacy concerns showed no moderation effect ($\beta=-0.005$, $p=0.872$).

Keywords: AI marketing, purchase intention, perceived value, privacy concern

1. Introduction

Artificial intelligence technology is profoundly transforming marketing practice [1]. In the social media context, major platforms (such as TikTok, Xiaohongshu (RED), Weibo, etc.) leverage algorithms to analyze user behavior and deliver customized content and advertisements; at the same time, AI applications like chatbots and emotion recognition enhance user interaction and service experience, providing marketers with new tools [2]. As a result, precision marketing has entered the "AI+" era. Consumer purchase intention, as a key indicator of marketing effectiveness, refers to the subjective likelihood that a consumer will purchase a product or service after being exposed to marketing stimuli. It is the prerequisite for actual purchasing behavior and an important predictor of such behavior [3]. Recently, researchers from traditional marketing, digital marketing, and consumer psychology have investigated the impact of AI-driven precision marketing on consumer purchase intention. Nonetheless, comprehension of this topic remains inadequate, mostly due to insufficient rigorous investigation on its internal mechanisms and contextual boundaries [4].

Existing research has shown that marketing stimuli can influence purchase intention by affecting consumers' internal psychological processes (e.g., perceived value, attitudes). Yet in the context of AI-enabled precision marketing, many questions remain unanswered. For example, through what internal psychological mechanisms do AI-driven precision marketing strategies exert their effects (i.e., which mediating variables are involved)? This study establishes a conceptual model to systematically examine AI-driven precision marketing's impact on social media users' purchase intentions, with particular attention to its psychological mechanisms and contextual boundaries. The research aims to examine (1) the direct effect of AI precision marketing strategies on consumer purchase intention, (2) the mediating role of consumer perceived value, and (3) the moderating effect of consumer privacy concerns on the effectiveness of AI marketing. By incorporating privacy concerns into the analytical framework, this study addresses the lack of attention to AI marketing ethics and consumers' privacy worries in existing research, with the goal of leveraging AI marketing's full potential under the premise of safeguarding consumer trust.

2. Literature review

2.1. AI-driven precision marketing and consumer purchase intention

Overall, AI-enabled precision marketing enhances consumers' purchase intention mainly through the following pathways. Algorithmic recommendations enhance information relevance while mitigating information overload, enabling consumers to access more valuable functional and emotional content, which consequently strengthens their positive responses [5]. Second, intelligent interactive channels such as chatbots increase the convenience and trust perceived by consumers [6]. Third, personalized marketing implements a 'one person, one strategy' approach, which substantially enhances consumers' brand loyalty [7]. Existing studies have further substantiated these pathways. For example, in the context of live-stream marketing, streamers with strong interactivity, authenticity, and professionalism enhance consumers' perceived functional and emotional value of products and increase brand trust, ultimately promoting consumers' purchase intentions [6]. This mechanism is consistent with the Stimulus-Organism-Response (S-O-R) model's logic that external stimuli influence behavioral responses via changes in consumers' internal psychological state.

2.2. Psychological mechanism: the mediating role of consumer perceived value

Consumer perceived value is the consumer's subjective evaluation of the overall benefits versus costs of a product or service [8]. In an AI precision marketing context, algorithm-driven personalized recommendations effectively enhance consumers' perceived value. On one hand, by increasing the relevance of marketing content, they improve functional value; on the other hand, personalized interactions bring positive emotional experiences, thereby elevating overall perceived value [7]. In digital marketing contexts, highly accurate personalized recommendations not only elevate shopping enjoyment and decision-making efficiency but also improve consumer satisfaction, thereby indirectly stimulating higher purchase intention [7].

2.3. The moderating role of consumer privacy concern

Privacy concern refers to the degree of consumers' worry about companies collecting and using their personal data [9]. According to privacy calculus theory, consumers weigh the convenience gained from personalized services against the risk of privacy leakage [10]. Empirical studies demonstrate that perceived excessive surveillance in marketing triggers consumer resistance, consequently eroding brand trust and diminishing purchase intention [11]. Especially in highly personalized recommendation contexts, strong privacy concerns may lead consumers to refuse marketing content. Moreover, when companies use AI to implement dynamic pricing, it can trigger consumer concerns about fairness and privacy, thereby affecting their acceptance of marketing offers [12].

Existing literature shows that AI-driven precision marketing can promote purchase intention by increasing consumers' perceived value, trust, and other psychological factors, but gaps remain: for example, the lack of a unified framework for its internal mechanism, insufficient focus on potential negative effects (privacy, ethics), and little exploration of differences across contexts. Therefore, this study introduces the S-O-R model as the overall theoretical framework: treating AI precision marketing as the stimulus, consumer perceived value as the organism (mediating variable), and purchase intention as the response. Simultaneously, privacy calculus theory is integrated to examine the effect of consumer privacy concern on the stimulus–response relationship.

Based on the above literature review and theoretical analysis, we construct the following research model and propose the corresponding hypotheses:

•H1 (Main effect): In social media contexts, AI-driven precision marketing strategies have a positive effect on consumers' purchase intention.

•H2 (Mediation hypothesis 1): AI-driven precision marketing strategies enhance consumers' perceived value of the product/marketing content, which in turn positively influences their purchase intention.

•H3 (Mediation hypothesis 2): The higher consumers' perceived value, the stronger their purchase intention.

•H4 (Mediating effect): Consumer perceived value plays a partial mediating role between AI precision marketing strategies and purchase intention.

•H5 (Moderating hypothesis): Consumer privacy concern moderates the relationship between AI precision marketing strategies and purchase intention. Specifically, when consumers' privacy concern is high, the positive effect of AI precision marketing on purchase intention is weaker; when privacy concern is low, this positive effect is stronger.

These hypothesized relationships form the conceptual model of this study. As illustrated in Figure 1, the model integrates the path mechanism from external marketing stimuli through internal psychological processes to behavioral responses, as well as the moderating effect of a consumer characteristic on these relationships.

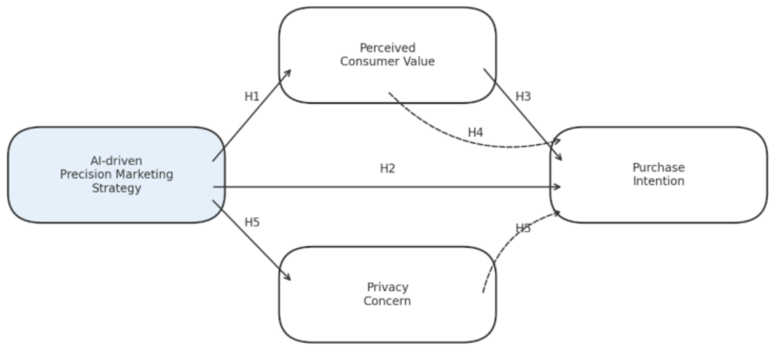

Figure 1. Structural equation model path diagram(F1: AI precision marketing strategy, F2: Consumer perceived value, F3: Consumer privacy concern, F4: Consumer purchase intention)

3. Research methodology

Research Subjects and Sample Source: This study targeted consumers who are active on social media, focusing on the effectiveness of AI-driven precision marketing strategies in real social media environments. Weibo and WeChat were selected as primary survey platforms based on two key considerations: firstly, their status as China's most prevalent social media platforms ensures demographic diversity and sample representativeness; secondly, their sophisticated algorithmic architectures governing information feeds, personalized recommendations, and commercial marketing demonstrate quintessential AI marketing features directly relevant to our research objectives. Data were collected via an online survey that participants completed voluntarily and anonymously. To ensure the sample's breadth and representativeness, the questionnaire was disseminated in multiple social media groups, friend circles, and public accounts, covering user groups of different genders, ages, education levels, and occupational backgrounds. A total of 507 valid responses were obtained, which meets the minimum sample size requirements for structural equation modeling (SEM) analysis (usually 200–400 cases).

Questionnaire Design and Variable Measurement: The questionnaire was designed around the core research variables, including AI precision marketing strategy perception, consumer perceived value, privacy concern, and purchase intention. All measurement items underwent rigorous adaptation from validated scales in extant literature, with contextual modifications implemented to preserve content validity. The questionnaire includes 20 measurement items, all rated on a 7-point Likert scale (1 = "strongly disagree," 7 = "strongly agree") to capture nuanced differences.

Specifically, the independent variable "AI-driven precision marketing strategy" was measured by multiple items evaluating consumers' perception of personalized marketing tactics on social media platforms. Example items include "The content recommended by the platform closely matches my interests" and "I often receive product recommendations on social media that meet my needs," covering typical AI marketing approaches such as algorithmic recommendations, personalized pushes, and intelligent customer service. The mediating variable "consumer perceived value" was measured with reference to existing perceived value scales, encompassing both functional value (e.g., "The recommended content provides useful information") and emotional value (e.g., "Browsing this content makes me feel happy"). "Consumer privacy concern" was measured using items from the Internet Privacy Concern scale developed by Smith et al., examining the extent of consumers' worry about their personal data being collected and used (e.g., "I am concerned that my browsing/purchasing data is being overly collected by the platform" and "I worry that my personal privacy is not adequately protected on social media"). The dependent variable "purchase intention" was measured with classic scale items such as "I am willing to purchase the product recommended on this social media platform" and "I would consider buying this product if I had the opportunity." All measurement items underwent iterative refinement via pilot testing (n=30) to verify lexical clarity and respondent comprehension.

Data Analysis Methods: After the survey, we first used SPSS 26.0 to organize the data and perform descriptive statistical analysis. Psychometric validation proceeded through sequential testing: initial reliability analysis demonstrated excellent internal consistency across all constructs (Cronbach's $\alpha > 0.8$), substantially surpassing the 0.7 benchmark for scale reliability. Next, exploratory factor analysis (EFA) and confirmatory factor analysis (CFA) were used to examine the scales' convergent and discriminant validity. The EFA results indicated that the extracted common factors were consistent with the theoretical constructs; each item had a high factor loading on its intended factor and no cross-loading, demonstrating good convergent validity. CFA further confirmed that the measurement model fit the data well: the average variance extracted (AVE) of each construct was greater than 0.5 and composite reliability (CR) was above 0.7, and for any pair of constructs the square of their correlation was less than the AVE, supporting good discriminant validity.

Building on a reliable and valid measurement model, we employed structural equation modeling (SEM) to test the hypothesized structural relationships. Using AMOS 24.0, we constructed an SEM with AI marketing strategy, consumer perceived value, purchase intention, and privacy concern as latent variables. For the mediation effect, a bootstrapping resampling procedure (5,000 resamples) was used to compute the confidence interval of the indirect effect to assess whether the mediating effect of perceived value is significant [13]. For the moderation effect, we combined multiple analytical methods. First, a hierarchical regression analysis was performed in SPSS: taking purchase intention as the dependent variable, we entered the independent variable (AI marketing strategy index), the moderator (privacy concern), and their interaction term (AI marketing × privacy concern) stepwise into the regression. The interaction term's coefficient was significantly negative, indicating that privacy concern has a significant negative moderating effect on the relationship between AI marketing and purchase intention (supporting hypothesis H5). Next, to further verify the moderation effect, we conducted a group split and multi-group SEM analysis: the sample was divided into two groups based on high vs. low privacy concern, and separate structural models were estimated for each group to compare the path coefficient from AI marketing to purchase intention. The multi-group SEM results showed that in the high privacy concern group, the path coefficient from AI marketing to purchase intention was lower and not significant, whereas in the low privacy concern group, the path coefficient was significantly positive; the difference between the two groups was significant in a chi-square difference test, providing additional evidence for the moderating effect of privacy concern [14]. All analyses incorporated potential control factors (e.g., respondents' gender, age, duration of social media usage, etc.) in the regression models to exclude confounding effects. Statistical analysis employed two-tailed tests with a significance threshold of 0.05. The aforementioned approaches thoroughly evaluated the research hypotheses, and the model's fit indices were favorable, demonstrating sufficient explanatory power and robustness.

4. Results and analysis

4.1. Reliability and validity analysis

Scale reliability was evaluated through Cronbach's α coefficient calculations to determine internal consistency. All constructs demonstrated satisfactory reliability with Cronbach's α values exceeding the 0.7 threshold, confirming robust internal consistency. We also conducted the Kaiser–Meyer–Olkin (KMO) test and Bartlett's test of sphericity to evaluate the data's suitability for factor analysis. The KMO value was 0.734, and Bartlett's test of sphericity yielded an approximate χ^2 of 294.505 ($df = 6$, $p < 0.001$). This indicates sufficiently strong inter-item correlations, suitable for factor analysis.

Table 1. KMO and Bartlett's test results

KMO (Sampling Adequacy)	Bartlett's Chi-square	df	Sig. (p)
0.734	294.505	6	0.000***

*Note: ***, *, * indicate significance at the 1%, 5%, and 10% levels, respectively.

Exploratory factor analysis employing principal component analysis with varimax rotation was conducted to identify underlying factors. The results found one factor with an eigenvalue greater than 1, with an initial eigenvalue of 2.051 explaining 51.269% of the total variance. If two principal components were extracted, the cumulative variance explained would reach 69.291%, but the eigenvalue of the second factor was only 0.721, below the threshold of 1. Thus, it can be considered that a single general factor accounts for over half of the variance. The absolute loadings of all observed variables on this factor were around 0.71 (AI precision marketing strategy 0.723, consumer perceived value 0.715, consumer privacy concern –0.717, consumer purchase intention 0.709), and all loadings were significant (see Table 2). This indicates that the questionnaire items exhibit good convergent validity on their respective latent constructs; meanwhile, although the four core constructs are somewhat correlated with each other, the majority of the total variance is driven by one common factor. In sum, the scales passed the reliability and validity tests (Table 1).

Table 2. Total variance explained

Component	Initial Eigenvalue	Variance %	Cumulative %	Rotated Eigenvalue	Variance %	Cumulative %
1	2.051	51.269	51.269	2.051	51.269	51.269
2	0.721	18.022	69.291	–	–	–
3	0.628	15.702	84.994	–	–	–
4	0.600	15.006	100.000	–	–	–

4.2. Structural equation model analysis

The structural equation model was developed based on theoretical hypotheses, positioning AI precision marketing strategy as the independent variable, consumer perceived value as the mediating variable, and consumer purchase intention as the dependent variable. Consumer privacy concern was included in the model as a control factor (covaried with the AI strategy factor). The specified paths in the model included AI precision marketing strategy → consumer perceived value, consumer perceived value → consumer purchase intention, and AI precision marketing strategy → consumer purchase intention as the three main paths. Figure 1 (above) presents the path diagram of this structural equation model with standardized coefficients. Model estimation employed maximum likelihood estimation (MLE) methodology, followed by comprehensive fit assessment.

Table 3. Model fit indices

Fit Index	χ^2	df	p	χ^2/df	GFI	RMR	RMSEA	CFI	NFI	TLI
Criteria	–	–	>0.05	<3	>0.90	<0.10	<0.05	>0.90	>0.90	>0.90
Model	4.564	4	0.335	1.141	0.985	0.038	0.000	0.977	0.985	1.068

The model fit results indicated that all indices met the ideal criteria(Table 3). The chi-square test showed no significant discrepancy between the model and the data ($\chi^2 = 4.564$, $p > 0.05$), and the χ^2/df ratio was approximately 1, well below the threshold of 3, suggesting a good model fit. The absolute fit indices were GFI = 0.985 and RMR = 0.038, both satisfying the recommended standards (GFI ≥ 0.90, RMR < 0.10). For incremental fit indices, CFI = 0.977, NFI = 0.985, and TLI (NNFI) = 1.068, all above 0.90. In addition, the RMSEA (root mean square error of approximation) was effectively 0, indicating minimal residual error in the model.

With respect to the structural path coefficients, all hypothesized paths were supported. Specifically, AI precision marketing strategy had a significant positive effect on consumer perceived value (standardized path coefficient $\beta = 1.000$, $p < 0.001$). Consumer perceived value in turn had a significant positive effect on consumer purchase intention ($\beta = 0.257$, $p < 0.001$). At the same time, AI precision marketing strategy's direct effect on consumer purchase intention remained positive and significant ($\beta = 0.629$, $p < 0.001$). The results indicate that, after accounting for other variables, AI-driven precision marketing tactics can directly elevate customers' buy intentions and also exert an indirect influence by augmenting consumers' perceived value. The model reveals a significant negative correlation between AI precision marketing strategy and consumer privacy concerns (standardized covariance coefficient = –0.157, $p < 0.001$), suggesting that consumers with a more favorable view of AI-driven marketing exhibit reduced privacy concerns in our sample.

4.3. Mediation and moderation effects analysis

To assess the mediation effect, structural equation modeling results were analyzed to examine consumer perceived value's mediating role in the AI precision marketing strategy-purchase intention relationship. From the path analysis above, it is evident that the AI precision marketing strategy has both a direct effect on consumer purchase intention ($\beta = 0.629$) and an indirect effect by enhancing consumer perceived value (AI strategy → perceived value $\beta = 1.000$; perceived value → purchase intention $\beta = 0.257$). Because the mediating path is significant while the direct path also remains significant rather than dropping to zero, this indicates that consumer perceived value serves as a partial mediator in the effect of AI precision marketing on purchase intention.

Moderation analysis employing hierarchical regression was performed to investigate privacy concern's contingent role (see Table 4 for model specifications). Consumer purchase intention was taken as the dependent variable, AI precision marketing strategy as the independent variable, consumer privacy concern as the moderator, and consumer perceived value was included as a control variable. The interaction term of AI strategy×privacy concern was then added to examine the moderating effect. Three nested models were estimated sequentially: (1) baseline model with independent variable and covariate, (2) incorporation of the moderator, and (3) inclusion of the interaction term.

Table 4. Moderation effect analysis results

Variable	M1 Coef.	M1 SE	M1 t	M1 p	M2 Coef.	M2 SE	M2 t	M2 p	M3 Coef.	M3 SE	M3 t	M3 p
Constant	1.837	0.316	5.807	0.000***	2.838	0.422	6.719	0.000***	2.761	0.603	4.580	0.000***
Consumer Perceived Value	0.282	0.052	5.398	0.000***	0.224	0.054	4.122	0.000***	0.223	0.054	4.106	0.000***
AI Precision Marketing Strategy	0.341	0.047	7.310	0.000***	0.299	0.048	6.259	0.000***	0.314	0.097	3.245	0.001***
Consumer Privacy Concern	–	–	–	–	–0.179	0.051	–3.526	0.000***	–0.153	0.155	–0.985	0.325
AI Strategy × Privacy Concern	–	–	–	–	–	–	–	–	–0.005	0.029	–0.180	0.858

*Note: ***, *, * indicate significance at the 1%, 5%, and 10% levels, respectively. Dependent variable: Consumer Purchase Intention.

Hierarchical regression analysis (Table 4) demonstrates that Model 1 establishes that AI precision marketing strategy's effect on purchase intention is significantly positive (β = 0.341, $p < 0.001$), and consumer perceived value also has a significantly positive effect on purchase intention (β = 0.282, $p < 0.001$). This indicates that the basic direct effects are established. In Model 2, after adding privacy concern as an independent predictor, the effect of the AI marketing strategy remains significant (β = 0.299, $p < 0.001$), and privacy concern itself has a significant negative effect on purchase intention (β=–0.179, $p < 0.001$). This suggests that consumers with higher privacy concerns tend to have significantly lower purchase intentions overall. However, in Model 3, after introducing the interaction term, the interaction coefficient is not significant (β = –0.005, p = 0.858). The increase in R^2 due to adding the interaction is negligible (from 0.214 to 0.215), and the F-test for the change is not significant. This indicates that consumer privacy concern does not significantly moderate the relationship between AI precision marketing strategy and purchase intention.

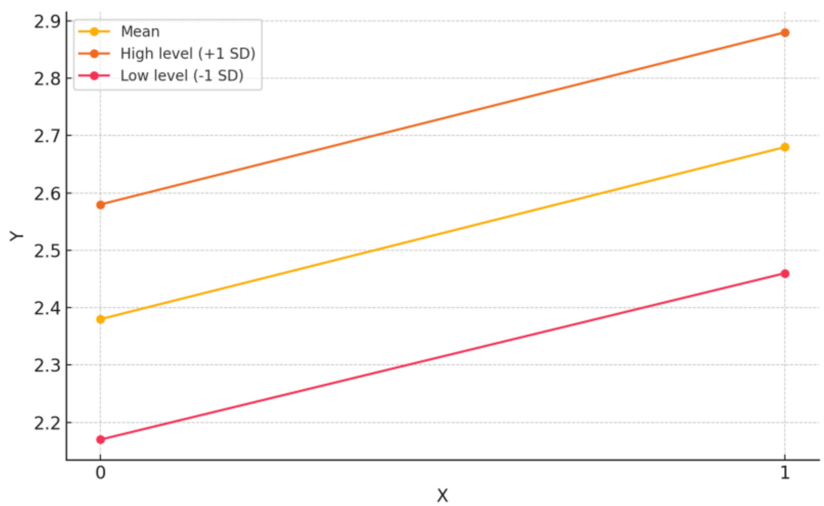

Figure 2. Simple slopes

Figure 2 plots the simple slopes of the relationship between AI precision marketing strategy and purchase intention at different levels of privacy concern (low, medium, high). It can be seen that the three lines are nearly parallel, consistent with the non-significant interaction term: between the high and low privacy concern groups, there is no significant difference in the slope of the relationship between AI marketing strategy and purchase intention. Despite the high privacy worry group demonstrating a generally diminished purchase intention relative to the low privacy concern group (as seen by the varying intercepts in the figure), the marginal effect of the AI marketing strategy remains consistent across both groups. This further confirms that privacy concern does not have a significant moderating effect on the main relationship. It is worth noting that in Model 3, the main effect of privacy concern on purchase intention drops to non-significance (p = 0.325), possibly due to multicollinearity after introducing the interaction term; however, this does not change the conclusion that the interaction effect is not significant. In summary, the hypothesis regarding the moderating role of privacy concern was not supported. In the context of this study, consumers at both high and low levels of privacy concern are positively influenced by AI-driven precision marketing strategies, and the strength of this influence does not differ significantly based on their privacy concern levels.

5. Conclusion

Through empirical analysis, this study finds that AI-driven precision marketing strategies can significantly increase consumers' purchase intentions. This conclusion further validates the applicability of the S-O-R model in the AI marketing context, i.e., external marketing stimuli have a significant impact on consumer decision-making via internal psychological states. In the AI precision marketing setting, consumer perceived value plays an important mediating role between AI marketing strategies and purchase intention: high-quality personalized recommendations enhance consumers' perceived value (e.g., by increasing the usefulness and relevance of information), thereby markedly boosting their purchase intentions. Notably, this study found that consumers' privacy concerns did not significantly moderate the relationship between AI marketing strategies and purchase intention. This discovery represents a significant advancement in both theoretical and practical domains, aligning with privacy calculus theory; specifically, when consumers believe that the advantages of tailored marketing substantially surpass the associated privacy risks, they are inclined to dismiss or overlook privacy concerns. In constructing the model, this study focused on the relationships among a set of core variables: AI precision marketing strategy, consumer perceived value, privacy concern, and purchase intention. The model is relatively simplified and does not capture other factors that might influence consumers' responses. For example, consumers' trust level and perceived risk could also affect the effectiveness of AI marketing, but these factors were not included in our model. Future research can introduce additional psychological variables (such as trust, perceived control, technology acceptance, etc.) and contextual variables (such as the presentation format of AI recommendations, the design of the interaction interface, and different product categories) to further illuminate the internal mechanisms and contextual boundaries of how AI marketing influences consumer decision-making.

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