

ORIGINAL ARTICLE

The impact of artificial intelligence-based advertisement placement on consumer purchase sentiment

Xue Guo¹, Xuerui Han^{2,*}¹Faculty of Health and Wellness, City University of Macau, Macao 999078, China²Department of Applied Psychology and Human Development, University of Toronto, Toronto M5S1A1, Ontario, Canada**ABSTRACT**

The advertising industry is embracing artificial intelligence technologies to improve the accuracy and effectiveness of advertisements. In today's digital marketing field, artificial intelligence (AI)-based ad implementation has become a key strategy to increase consumers' purchase intention. In terms of consumers' perceived value, how to effectively influence consumers' perceived benefits, risks and final purchase decisions through intelligent ad implantation has become a hot topic. This study explores advertisement implantation based on AI and its impact on consumers' perceived value and purchase intention. Results indicate that personalized and relevant AI-driven ad placements significantly enhance perceived benefits, thereby increasing purchase intent. Additionally, ad delivery through reputable platforms mitigates perceived risks, further fostering positive purchase sentiment. Conversely, certain ad display methods may not consistently enhance perceived benefits and could detract from consumer engagement if not well-aligned with audience expectations. These findings offer strategic insights into optimizing AI applications in digital advertising, underscoring the importance of aligning ad content with consumer expectations to maximize positive emotional responses and drive purchasing behavior.

Key words: artificial intelligence, advertisement implantation, consumer purchase emotion

INTRODUCTION

The use of artificial intelligence (AI) has enhanced the targeting capabilities (Chap, 2022) and improved the personalization of content (Hari Krishna *et al.*, 2023), enabling advertisements to display the most appropriate message to the right consumer at the right time (Bhuvaneswari *et al.*, 2024). The technological advances in AI have provided industries with unprecedented marketing tools and have demonstrated significant effectiveness in increasing consumer purchase intentions (Bhatia, 2023).

Ad implantation by AI technology mainly processes and parses large-scale consumer behavioral data through

statistical analytics and pattern recognition algorithms, which include information such as consumers' online activity records, shopping habits, social media interactions, and geographic locations. Based on the data, AI algorithms are able to construct fine-grained consumer profiles and predict the attractiveness of specific advertising content to particular consumer groups (Anica-Popa *et al.*, 2021; Kietzmann *et al.*, 2018). For example, machine learning techniques can be used in practice to identify which visual elements, copy styles, or product presentations are most likely to attract specific age or interest groups, thus enabling a high degree of content customization across different advertising campaigns (Guo & Ye, 2023; Phay, 2019). In addition, AI is able to instantly adjust advertising

***Corresponding Author:**

Xuerui Han, Department of Applied Psychology and Human Development, University of Toronto, Toronto M5S1A1, Ontario, Canada. Email: sherryxr.han@mail.utoronto.ca; <https://orcid.org/0000-0001-5682-9238>

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parameters, display frequency, display time, and placement by analyzing users' online behavior and feedback in real time to ensure optimal ad delivery (Khamaj & Ali, 2024). Meanwhile, the application of AI in the ad creation process can improve the efficiency of ad production and enhance the relevance and attractiveness of ad content (Aliyah *et al.*, 2023), such as natural language generation technology that can automatically generate attractive ad copy, which provides strong support for the marketing of enterprises.

It is known that consumers' purchasing decision-making process is influenced by their perceived values, including perceived benefits and perceived risks (Kim *et al.*, 2008; Liu *et al.*, 2013). Perceived benefits are usually associated with the expected benefits of a product or service, while perceived risks involve negative consequences. Thus, the application of AI can optimize advertising content to strengthen consumers' positive perceptions through accurate data analysis and then dynamically adjust marketing strategies to respond to consumers' rapidly changing needs. Furthermore, marketing communication theory emphasizes the impact of the way information is delivered on the recipients of the information (Kolwas & Domański, 2023). Based on AI, advertisers can analyze a large amount of consumer data to determine the most effective way of displaying advertisements, whether it is visually appealing or content-targeted, which can significantly improve the attractiveness and persuasiveness of advertisements (Chaitanya *et al.*, 2023). Meanwhile, the multistep flow theory of communication science suggests that "opinion leaders" or "key nodes" in the flow of information play a decisive role in the acceptance and re-transmission of information. In digital marketing, the application of AI makes this choice more scientific and efficient, ensuring that advertising messages are received by consumers in the most influential environment (Baek, 2023).

In summary, this study aims to explore the influence of AI-based advertisement placement on consumers' perceived value and purchase intentions. Although prior research has demonstrated AI's general effectiveness and growing role in personalized advertising, limited studies have focused on how AI-based ad placement specifically impacts the stages of consumer engagement in the purchasing decision process. This study seeks to address this gap by examining consumer responses across the attention, interest, desire, and action (AIDA) model, a widely used marketing communication framework that segments the consumer journey into four stages (Wei *et al.*, 2022). By applying the AIDA model, this study investigates how AI-driven ad placement shapes each of these engagement stages, particularly focusing on how consumers perceive the value and risks associated with ads. This approach provides insight into optimizing ad strategies to align with the AIDA stages, thus offering

practical guidance for marketing fields aiming to enhance consumer purchase sentiment through AI.

The impact of advertisement implantation on consumers' perceived value

In general, ad insertion aims to seamlessly integrate advertising content into media content to reduce consumer resistance and increase advertising effectiveness. In this study, consumers' perceived value refers to the worth of a product or service as evaluated by the consumer, encompassing both perceived benefits and perceived risks. Perceived benefits include factors such as price, quality, and the utility of the advertised product or service, while perceived risks refer to potential drawbacks or uncertainties associated with the product or service, such as financial, functional, or social risks (Lee *et al.*, 2021). With the advancement of AI technology, ad insertion has more accurately targeted specific groups of consumers to effectively increase their perceived value (Stone *et al.*, 2020). AI-driven ad implantation utilizes consumer data analytics to tailor advertising content closely to consumer behavior patterns, effectively enhancing personalization and engagement (Kietzmann *et al.*, 2018).

Information processing theory (Schaeppdrijver *et al.*, 2022) suggests that consumers engage in the process of encoding, storing, and retrieving information when they are exposed to advertising messages and that this process is largely dependent on the degree of relevance and personalization of the information. AI technology optimizes the information processing process by providing customized advertising content, enabling consumers to absorb and reflect on the advertising message more efficiently, which makes them more likely to engage in purchasing behavior (Pearson, 2019). In addition, expectation confirmation theory (Chie *et al.*, 2023) suggests that consumer satisfaction is determined by the difference between expectations and actual experience. AI's ad implantation can maximize consumer satisfaction and loyalty by accurately predicting consumer expectations and delivering an ad experience that matches them. When consumers' actual experience exceeds their expectations, their perceived value, including benefits and risks, increases, making them more likely to respond positively to the advertised product or service.

Influence of advertisement display methods on consumers' perceived value

The concept of advertisement display methods refers to the various ways in which advertisements are presented to consumers, incorporating visual, textual, and interactive elements to optimize consumer engagement (McQuarrie & Mick, 1999; Scott, 1994). Unlike advertisement implantation, which focuses on the strategic

placement of ads within media to enhance visibility, display methods emphasize the presentation details, such as color schemes, font styles, image selection, and copywriting, tailored to resonate with specific consumer preferences. With the extensive application of AI, advertisement presentations have become increasingly intelligent and dynamic. This AI-driven approach not only personalizes ad content and timing but also adapts creative elements to align with individual aesthetic preferences (Haleem *et al.*, 2022). For instance, AI can adjust the colors, fonts, images, and ad copy to appeal to different demographic segments, enhancing relevance and fostering emotional connection with the audience. Highly customized displays can increase the attractiveness of advertisements, significantly enhance their effectiveness, and increase consumers' perceived benefits by precisely matching their needs and interests (Olsen & Pracejus, 2020). In addition, these benefits can be further categorized into functional benefits, such as the utility and relevance of the product or service; emotional benefits, which refer to the positive feelings elicited by the advertisement; and social benefits, which involve the perceived enhancement of the consumer's social status or relationships (Rasoolimanesh *et al.*, 2020). By precisely matching consumer needs and interests, AI-driven advertising displays can amplify these benefits, fostering a stronger connection between the consumer and the brand.

Motivation theory (Wang *et al.*, 2021) suggests that when an advertisement is displayed in a way that is highly aligned with consumers' expectations and needs, it can stimulate consumers' intrinsic motivation and drive them toward purchasing behavior. AI, through data analysis to determine consumers' behavioral patterns and preferences, is able to design advertising presentations that match consumers' expectations, thereby increasing consumers' acceptance of and response to advertising content (Babatunde *et al.*, 2024). In addition, cognitive load theory (Young *et al.*, 2014) emphasizes that consumers have certain cognitive capacity limitations in receiving and processing information. The application of AI can reduce unnecessary cognitive load by optimizing the visual and textual elements of advertisements, making advertising information easier to digest and understand and thus improving the efficiency and effectiveness of information delivery (Huang & Rust, 2021). For example, language and design can be adapted to different population groups, making the information easier to process and increasing the likelihood of favorable consumer responses. Such optimizations enhance the efficiency and effectiveness of ad delivery, maximizing the potential for consumer conversion. However, it is important to note that while personalized ad displays can offer substantial benefits, they may also introduce perceived risks. Excessively personalized ads may prompt concerns regarding data privacy, with

consumers potentially feeling their personal information is being overused or improperly accessed. This privacy risk may offset the positive impact of personalized advertisements, ultimately diminishing the perceived value and acceptance of the ads. To counterbalance these concerns, advertisers must consider transparency and ensure that personalization aligns with consumer expectations to maintain trust and acceptance.

Impact of advertised brands on consumers' perceived value

The way a brand is presented in an advertisement and the consumers' preconceived perceptions of that brand together determine the success or failure of the advertisement's effectiveness. Brand equity theory suggests that the value of the brand itself derives from its physical product and also from the awareness, perceived quality, brand loyalty and other intangible assets associated with the brand (Nadeem *et al.*, 2021). Advertisements that effectively emphasize these assets can significantly enhance a consumer's perceived value by reinforcing the brand's promise of quality, dependability, and relevance. For instance, an ad highlighting a brand's innovative features and long-standing reputation in the market can increase functional benefits, while storytelling approaches that evoke emotion can enhance emotional benefits. Storytelling in advertising typically involves constructing a narrative that resonates with the target audience's values, aspirations, or everyday experiences. This may include presenting a relatable character, a problem-solution journey, or an emotional transformation arc that connects the brand with meaningful human experiences.

Brand trust is the consumer's confidence that the brand fulfills its promises. High brand trust significantly reduces consumers' perceived risk and increases their willingness to purchase branded products (Lassoued & Hobbs, 2015). Trust is built on consistent brand performance and positive consumer experiences, communicated through consistent and honest advertising (Lau & Lee, 1999). Meanwhile, Social Identity Theory (Han *et al.*, 2023) states that consumers tend to purchase brands that reflect or enhance their social identity. When advertisements are effectively aligned with consumers' social identity and values, they can enhance consumers' attraction to the brand and thus increase purchase intentions. By effectively integrating elements of brand equity, brand trust, and social identity into advertising strategies, brands can significantly enhance consumers' perceived value. This involves not only highlighting tangible attributes like product quality but also leveraging emotional and social connections to build a stronger relationship with the consumer.

Influence of advertising platform on consumers' perceived value

Ad delivery platform is the channel of information

transmission and profoundly influences the effect of advertisement reception, thus directly impacting the perceived value of consumers. Different platforms influence the visibility, interactivity and consumer acceptance of advertisements through their unique user base, technical characteristics and content forms. On the one hand, the technological capability of the platform determines the degree of personalization and customization of advertisements, and technologically advanced platforms are able to use complex algorithms to push the most relevant advertisements to users, improving the targeting and efficiency of advertisements (Chen & Hsieh, 2012). For example, social media platforms display customized advertisements by analyzing users' interaction records and preferences, and a high degree of personalization can strengthen the attractiveness of advertisements, thus enhancing consumers' perceived benefits. On the other hand, user groups on different platforms have different consumption habits and preferences, which determine that certain types of advertisements are more effective on specific platforms (Liao *et al.*, 2021). For example, short-video platforms like Jieyin and Kwai attract younger users with fast-paced, visually captivating content, making them ideal for promoting fashion, gaming, tech gadgets, and lifestyle products. By leveraging trends, influences, and interactive content, brands create engaging campaigns with strong emotional appeal. Professional networks like LinkedIn, favored by high-income professionals, excel at advertising career-focused products such as executive education and recruitment services. These platforms build trust and authority with their professional tone. E-commerce platforms like Amazon and Taobao focus on transaction-driven users, effectively showcasing promotions, reviews, and bundled deals to address purchasing intent. By tailoring advertisements to each platform's audience and strengths, brands enhance relevance, perceived benefits, and engagement, fostering stronger consumer connections (Olsen & Pracejus, 2020).

Model construction

The modeling system demonstrates the influence path from different features of advertisement delivery to consumers' purchase intention. As shown in Figure 1, the model includes four independent variables: AI ad insertion, advertisement display method, advertising brand, and ad delivery platform. These variables influence two mediating factors: Consumer perceived benefits and consumer perceived risk. Both of them affect the outcome, which is the willingness to buy. This model explains how AI-based advertising strategies may guide consumer decisions.

Advertising characteristics are subdivided into AI advertisement insertion, advertisement display method,

advertisement brand, and advertisement delivery platform, which are hypothesized to directly affect customers' perceived value, that is, perceived benefits and perceived risks. Perceived benefits are further subdivided into functional, emotional, and economic benefits, which are the perceived benefits that consumers receive directly or indirectly from advertising (Lee, 2020). Direct benefits may include functional advantages, such as learning about a product's specific features or cost-saving promotions. Indirect benefits encompass emotional connections the advertisements foster or the sense of value consumers feel toward a brand, even when not actively purchasing. Perceived risks are subdivided into data privacy risks, misleading risks, risks of negative brand associations and content relevance risks, which are risk factors that tend to impede consumers' willingness to buy (Lăzăroiu *et al.*, 2020). The model highlights the importance of considering the full range of factors when developing an advertising strategy that enhances positive consumer perceptions (*i.e.*, benefits) while minimizing potential risk perceptions as a way to optimize advertising effectiveness and ultimately drive sales.

Research questions and hypotheses

Based on the conceptual framework and the identified relationships among AI-based advertisement placement, perceived informativeness, perceived intrusiveness, brand attitude, and consumer purchase sentiment, this study addresses the following research questions: (1) RQ1—how does AI-based advertisement placement influence consumers' purchase sentiment? (2) RQ2—does perceived informativeness mediate the relationship between AI-based advertisement placement and brand attitude? (3) RQ3—does perceived intrusiveness negatively impact brand attitude and consumer sentiment?

To empirically test these questions, the following hypotheses are proposed: (1) H1—AI-based advertisement placement has a positive effect on perceived informativeness. (2) H2—AI-based advertisement placement has a negative effect on perceived intrusiveness. (3) H3—perceived informativeness positively affects brand attitude. (4) H4—perceived intrusiveness negatively affects brand attitude. (5) H5—brand attitude positively influences consumer purchase sentiment. (6) H6—perceived informativeness and perceived intrusiveness mediate the relationship between AI-based advertisement placement and brand attitude.

METHOD

Questionnaire design and recovery

The AIDA model (Baber, 2022; Wong *et al.*, 2024), a widely used framework in Western salesmanship, provides an essential structure for designing the

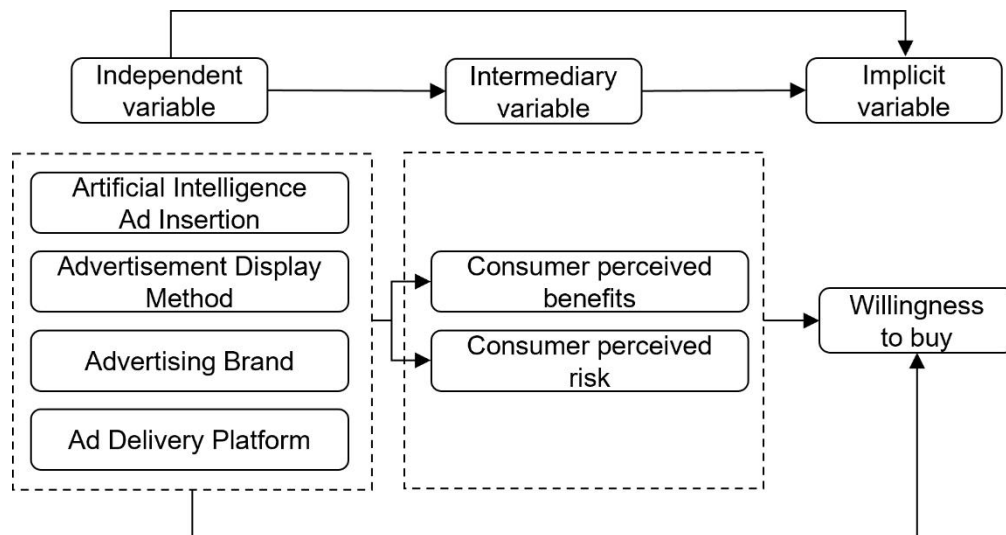


Figure 1. Structural equation model of this study.

questionnaire used in this study. AIDA represents four stages that a consumer typically experiences during the advertising engagement process. "A" stands for attention, meaning that the advertisement captures the consumer's awareness, making them notice the content. "I" represents interest, where the advertisement is engaging enough to evoke a sense of curiosity or intrigue in the consumer. "D" signifies desire, as the ad content stimulates a consumer's want or need for the product or service. Finally, "A" stands for action, where the consumer is motivated to make a purchase or take a tangible step toward acquisition (Wei *et al.*, 2022). To align with the AIDA model, AI-based ad implantation is primarily expected to influence the attention and desire stages. At the attention stage, personalized and context-relevant ads increase initial user engagement. At the desire stage, algorithmic targeting enhances the perceived value of the product by showing tailored content that meets consumers' needs and expectations. Accordingly, our questionnaire includes measures for both AI-driven relevance and emotional engagement to capture its effects across AIDA stages.

To ensure that the questionnaire captured each of these psychological stages thoroughly, the study included questions specifically targeting consumer AIDA, allowing the research to cover the entire process from initial ad exposure to the potential purchase action. Fortenberry *et al.* (2020) further extended the AIDA model by exploring the functions of advertising using 14 questions. Drawing on this expanded version of the AIDA model, this study designed questions focusing not only on the AIDA stages but also on dimensions such as brand credibility and advertising platform trustworthiness to assess how these factors impact consumer acceptance and engagement with ads. The questionnaire

consisted of a total of 21 questions, divided across multiple dimensions. Each AIDA stage—AIDA—was allocated 5 questions designed to measure specific consumer responses and attitudes toward these stages. Additionally, each dimension aimed to capture key elements of consumer perceived value, aligning with the research question on how perceived value affects consumer behavior.

In the "attention" stage, the goal is to assess whether the AI-based advertisement successfully captures the viewer's notice. This was measured using three dimensions: AI advertising relevance, advertising attractiveness, and AI ad attention. These dimensions focus on the perceived relevance of content, its visual appeal, and how effectively it draws initial focus. In the "interest" stage, the study evaluates how the format and delivery of the advertisement generate engagement. Three dimensions were used: Ad display innovation, interactive display interest, and display innovation curiosity. These reflect user responses to the ad interactivity, novelty, and the degree to which ad format sparks curiosity. In the "desire" stage, the focus shifts to emotional and attitudinal factors that might create a psychological desire for the advertised product. Here, four dimensions were used: Brand trust, brand buying interest, positive brand buying propensity, and perceived benefits (including functional, emotional, and economic benefits). These capture how brand perception and product value contribute to forming a purchase desire. Finally, the "action" stage measures actual purchase intent. It includes variables such as willingness to buy, trust in advertising platforms, platform preferences, and perceived risks (*e.g.*, data privacy, misinformation, negative brand associations). These help evaluate how likely consumers are to act upon their desire and

proceed to purchase behavior under various advertising conditions.

The study was conducted in the form of a Likert 5-point scale (*i.e.*, 1 meaning "strongly disagree" and 5 meaning "strongly agree"), shown in Table 1.

Data collection

A total of 169 questionnaires were distributed over a two-week period using a multi-channel online approach, including email invitations, social media promotions, and outreach through partner organizations. Specifically, emails were sent to university students, alumni mailing lists, and corporate mailing groups affiliated with marketing and technology sectors. Social media platforms used included WeChat, LinkedIn, and Facebook, where online flyers and anonymous survey links were posted in relevant interest groups and discussion forums to attract a diverse participant base.

Participation was voluntary and anonymous. To ensure data quality, only respondents who met the inclusion criteria—being over 18 years old and having at least occasional exposure to online advertisements—were allowed to complete the survey. Responses were excluded if they exhibited straight-lining, extremely short completion time (under 90 seconds), or more than 20% missing data.

After screening, 150 valid responses were retained, yielding an effective response rate of 88.8%. The demographic breakdown of the valid sample, including age, gender, education level, and frequency of online ad exposure, is presented in Table 2.

Participants were primarily concentrated in the 25-44 age group, including 106 young and middle-aged adults. This demographic is typically active on social media platforms and represents a key target audience for digital advertising (Chou *et al.*, 2009). The gender distribution is relatively balanced, and more than half of the participants have bachelor's degrees. Over 50% of the participants were office workers. Although students (15.3%) and retirees (10.0%) represent smaller portions of the sample, their inclusion brings additional diversity to the dataset, offering insights from less traditionally represented consumer groups. Similarly, freelancers (22.7%) may contribute unique perspectives due to the flexible and digitally-oriented nature of their professions.

Data analysis

In this study, multiple analytical techniques were used to ensure a comprehensive and accurate interpretation of consumer responses to AI-based advertisements. Firstly, Cronbach's alpha reliability analysis was conducted to evaluate the internal consistency across questionnaire items. Following this, Kaiser-Meyer-Olkin (KMO) and

Bartlett's test of sphericity were applied to assess the suitability of the data for factor analysis. A KMO value close to 1 suggests a high level of shared variance among items, confirming that the data has sufficient correlation for factor analysis (Kaiser, 1974). Bartlett's test further supports this by determining if the correlation matrix is significant, thereby validating that the dataset is structured appropriately for identifying underlying factors. Next, factor loading analysis was employed to reveal the correlation between each item and its respective factors, indicating the weight or contribution of each item to its associated dimension. This analysis clarifies which specific dimensions—such as perceived benefits, perceived risks, and brand trust—are best captured by the corresponding survey items, thereby validating the structure of the measurement model and supporting the construct validity of the scales. High factor loadings suggest that the variables strongly contribute to the identified factors, providing insights into the elements that most impact perceived value and consumer engagement with AI-driven advertisements.

Structural equation modeling (SEM) was utilized to explore the relationships among latent variables, such as perceived benefits, perceived risks, and willingness to purchase. SEM allows for testing the hypothesized pathways between advertisement characteristics and consumer responses, effectively illustrating how different advertising features influence perceived value and drive purchase decisions.

RESULTS

Cronbach's alpha reliability

The analysis began with Cronbach's alpha reliability test to assess the internal consistency across the questionnaire items. The standardized Cronbach's α coefficient of the questionnaire reached 0.978, which showed a very high internal consistency, indicating that the questionnaire items were very stable and that there was a good coordination between the questions (Table 3).

Most of the questions demonstrated high reliability values, with Cronbach's α coefficients all exceeding 0.95, indicating excellent internal consistency. However, a few items—such as "data privacy risk" (CITC = 0.658) and "negative brand association risk" (CITC = 0.639)—showed relatively lower corrected item-total correlations, suggesting that these questions were slightly less consistent with the overall construct compared to other items in the questionnaire. Nonetheless, the presence of these questions was still necessary for the comprehensiveness of consumers' multidimensional responses to advertising characteristics. This questionnaire demonstrated a high degree of reliability and measurement accuracy and was considered suitable for

Table 1: Questionnaire design

Measurand	Measuring dimensions	Measuring dimensions	Related items
Argument	AI-ad insertion? Planted advertisement	AI advertising relevance	I think AI-based ad placement makes the content more relevant
		AI advertising attractiveness	I think AI-based ad placement improves the appeal of ads
		AI ad attention	When ads are implanted through an AI, I'm more likely to focus on ad content
	Advertisement display method	Ad display innovation	I like the ads are displayed in innovative form
		Interactive display interest	I am more interested in products when ads are interactive
		Display innovation curiosity	The innovation of advertising display methods has increased my curiosity about products
	Advertising brand	Brand trust	I have more trust in the advertising of famous brands
		Brand buying interest	The advertising of well-known brands can arouse my interest in buying more
		Positive brand buying propensity	I tend to buy products from brands that show a positive image in advertising
	Ad delivery platform	Trust in reputation platforms	Advertising ads on a reputable platform will increase my trust in advertising
		Common platform preferences	I prefer to see ads on my usual social media platforms
X		Platform security acceptance	The professionalism and security of the platform have affected my acceptance of advertising
Metavariable	Perceived benefits	Functional interest	Advertising has enabled me to understand that products can significantly solve practical problems
		Emotional benefits	Through advertising, I feel the emotional satisfaction of a certain product
		Economic benefits	The price of the products made me feel a financial benefit
	Perceived risk	Data privacy risk	I fear that AI-based ads will violate my privacy
		Misleading risk	Misleading information in the ads can make me skeptical about the product
		Negative brand association risk	Brand ads related to negative news made me feel at risk about buying the brand
Dependent variable	Willingness to buy	Benefit-related willingness to buy	If advertising makes me feel like a high perceived interest, I will probably buy the product
		Risk-related willingness to buy	If the perceived risk in the ad is low, I am more likely to buy the advertised product
		Advertising-related willingness to buy	Considering all aspects of the advertising, I would consider buying the products displayed in the ads

AI, artificial intelligence.

Table 2: Demographic characteristics of participants (N = 150)

Characteristics	Subcategory	Number of people	Percentage
Age groups	18-24	20	13.4%
	25-34	53	35.3%
	35-44	53	35.3%
	45-54	24	16.0%
Gender	Man	60	40.0%
	Woman	90	60.0%
Educational level	Senior middle school	37	24.7%
	Undergraduate course	83	55.3%
	Master's degree or above	30	20.0%
Careers	Student	23	15.3%
	Office worker	78	52.0%
	Liberal professions	34	22.7%
	Retire	15	10.0%

Table 3: Results of Cronbach's α reliability analysis

Measuring dimensions	CIT	Item deleted α coefficient	Cronbach α coefficient
AI advertising relevance	0.883	0.976	0.978
AI advertising attractiveness	0.779	0.977	
AI ad attention	0.862	0.976	
Ad display innovation	0.891	0.976	
Interactive display interest	0.875	0.976	
Display innovation curiosity	0.852	0.976	
Brand trust	0.766	0.977	
Brand buying interest	0.884	0.976	
Positive brand buying propensity	0.847	0.976	
Trust in reputation platforms	0.822	0.976	
Common platform preferences	0.854	0.976	
Platform security acceptance	0.842	0.977	
Functional interest	0.895	0.976	
Emotional benefits	0.787	0.977	
Economic benefits	0.868	0.976	
Data privacy risk	0.658	0.978	
Misleading risk	0.783	0.977	
Negative brand association risk	0.639	0.978	
Benefit-related willingness to buy	0.829	0.976	
Risk-related willingness to buy	0.772	0.977	
Advertising-related willingness to buy	0.891	0.976	

AI, artificial intelligence; CIT, correction total correlation.

further analyzing the impact of advertising characteristics on consumers' perceived value.

KMO and Bartlett's test of sphericity

The KMO value is a measure of the proportion of variance shared between the observed variables, and the closer the value is to 1, the higher the correlation between the variables, the more suitable it is for factor analysis (Effendi *et al.*, 2019; Shrestha, 2021). A KMO value of 0.6 and above is usually considered acceptable. The KMO value of 0.931 indicated a high degree of commonality between the variables and was suitable for factor analysis (Table 4).

The results of Bartlett's test of sphericity supported the applicability of the data. The approximate χ^2 value of this test is 4550.85 with a degree of freedom of 210 and a P -value < 0.001 , indicating the variables in the data are independent of each other. This result proved that there was sufficient correlation between the variables in the data to be suitable for factor analysis.

Factor loading results

In this study, the effect of advertising characteristics on consumer perception and behavior was explored through factor analysis. The results of the analysis showed that the data structure was clear and supported a three-factor model that explained 84.19% of the total variance. The rotation after factor analysis made the

explanation more in line with the theoretical expectation, where the first factor was mainly concerned with the relevance and attractiveness of the advertisement content, the second factor focused on the trust and preference of the brand and the platform, and the third factor was significantly related to the consumer's risk perception (Table 5).

Specifically, AI ad relevance, AI ad attention, and display innovation curiosity showed loadings coefficients on the first factor of 0.82, 0.81, and 0.80, respectively, indicating that these variables were strongly correlated with the relevance and appeal of the ad content, in line with the expectation that these variables were directly associated with how ads could be improved in terms of relevance and personalization through AI technology. On the second factor, brand purchase interest and commonly used platform preference showed higher loadings of 0.808 and 0.685, respectively, pointing out that consumers' brand preference and their exposure to ads on commonly used platforms were important factors influencing their purchase decisions. Reputable platform trust and platform security acceptance also loaded significantly on this factor, emphasizing that platform reputation and security were key factors influencing consumers' ad acceptance. The third factor was mainly concerned with perceived risk, in which the loading coefficients of suspicion of misleading information in advertisements and negative news brand risk reach 0.86

Table 4: KMO and Bartlett's test of sphericity

Test	Statistics / value	df	P
KMO price	0.931	-	-
Bartlett's test of sphericity	4550.853	210	< 0.001

KMO, Kaiser-Meyer-Olkin.

Table 5: Factor loading results

Variable name	Factor load factor			Common degree (common factor variance)
	factor 1	factor 2	factor 3	
AI advertising relevance	0.827	0.352	0.227	0.859
AI advertising attractiveness	0.297	0.842	0.297	0.886
AI ad attention	0.816	0.252	0.355	0.856
Ad display innovation	0.784	0.435	0.204	0.846
Interactive display interest	0.355	0.792	0.252	0.816
Display innovation curiosity	0.804	0.263	0.392	0.869
Brand trust	0.797	0.408	0.116	0.816
Brand buying interest	0.355	0.808	0.196	0.818
Positive brand buying propensity	0.847	0.328	0.216	0.872
Trust in reputation platforms	0.695	0.513	0.162	0.773
Common platform preferences	0.576	0.685	0.085	0.807
Platform security acceptance	0.632	0.530	0.281	0.759
Functional interest	0.800	0.375	0.282	0.861
Emotional benefits	0.406	0.801	0.151	0.830
Economic benefits	0.855	0.336	0.171	0.872
Data privacy risk	0.405	0.135	0.864	0.930
Misleading risk	0.520	0.285	0.707	0.852
Negative brand association risk	0.088	0.617	0.711	0.893
Benefit-related willingness to buy	0.805	0.302	0.224	0.789
Risk-related willingness to buy	0.397	0.812	0.124	0.832
Advertising-related willingness to buy	0.781	0.386	0.292	0.844
Characteristic root value (before rotation)	14.845	1.674	1.160	-
Variance interpretation rate (before rotation)	70.691%	7.971%	5.524%	-
Cumulative variance interpretation (before rotation)	70.691%	78.662%	84.186%	-
Characteristic root value (after rotation)	8.912	5.997	2.770	-
Variance interpretation rate (after rotation)	42.437%	28.556%	13.193%	-
Cumulative variance interpretation (after rotation)	42.437%	70.993%	84.186%	-
Bart spheroid value Admidia	4550.852			-
df	210			-
P	< 0.001			-

AI, artificial intelligence.

and 0.71 respectively, highlighting consumers' high sensitivity to the truthfulness of advertisement content and the clarity of brand image.

Estimation of parameters of the research path model

In this study, the effects of advertising characteristics such as ad implantation, ad display method, ad brand and ad delivery platform on consumers' perceived benefits, perceived risks and purchase intentions were

assessed through structural equation modeling (Table 6). Data for the advertising characteristics were collected through survey items measuring ad placement relevance (advertisement implantation), visual and interactive elements (advertisement display method), brand familiarity and trust (advertisement brand), and platform effectiveness (advertisement delivery platform). Perceived benefits were computed from participants' evaluations of utility and quality, perceived risks from concerns like financial or functional uncertainties, and

Table 6: Model regression coefficient table

Factor (latent variable)	Analysis items (explicit variables)	Non-standardized coefficients	Standardization coefficient	Standard error	Z	P
Advertising implant	Perceived benefits	0.492	0.692	0.135	3.633	< 0.001
Advertisement display method	Perceived benefits	-0.039	-0.048	0.027	-1.461	0.044
Advertising brand	Perceived benefits	0.016	0.023	0.034	0.476	0.634
Ad delivery platform	Perceived benefits	0.561	0.733	0.138	4.058	< 0.001
Advertising implant	Perceived risk	0.242	0.412	0.064	3.787	< 0.001
Advertisement display method	Perceived risk	0.389	0.582	0.169	2.305	0.021
Advertising brand	Perceived risk	0.247	0.423	0.132	1.867	0.062
Ad delivery platform	Perceived risk	0.241	0.384	0.084	2.862	0.004
Advertising implant	Willingness to buy	0.492	0.692	0.135	3.633	< 0.001
Advertisement display method	Willingness to buy	-0.039	-0.048	0.027	-1.461	0.144
Advertising brand	Willingness to buy	0.016	0.023	0.034	0.476	0.634
Ad delivery platform	Willingness to buy	0.561	0.733	0.138	4.058	< 0.001

purchase intentions from responses indicating purchase likelihood. SEM captured the relationships between these variables to assess their direct and indirect effects.

The high coefficient of advertisement implantation indicated that with the high relevance of advertisement content to consumers' personal interests and needs, consumers' perceived benefits were significantly enhanced. At the same time, the innovative and interactive nature of the way the ads were displayed significantly increases consumers' curiosity and engagement with the ads, further reinforcing the effectiveness of the ads.

Perceived risk is handled in such a way that although advertising features such as the use of AI raise certain privacy concerns. This is reflected in the model through the negative path coefficients. Specifically, the advertisement display method has a significant positive impact on perceived risk with a standardized coefficient of 0.582 ($P = 0.021$), and ad delivery platform also contributes to perceived risk with a standardized coefficient of 0.38 ($P = 0.004$). However, the overall reduction in perceived risk due to high trust can be inferred from the strong positive coefficients of factors like ad delivery platform on willingness to buy ($\beta = 0.733$, $P < 0.001$) and perceived benefits ($\beta = 0.733$, $P < 0.001$), which suggests that high trust significantly reduces consumers' risk concerns and thus promotes purchasing behavior. Overall, the results of the model test emphasize the importance of enhancing the relevance and innovation of advertisements while

building and maintaining brand and platform trust in the development of advertising strategies. These factors not only directly increase consumers' perceived benefits, but also indirectly drive consumers' purchase decisions by reducing risk perception.

Based on the model regression coefficients, a summary of these path coefficients is shown in Table 7 below.

This study reveals the impact of AI-based ad implantation on consumers' perceived benefits, perceived risks, and purchase intentions, with the strength and direction of influence demonstrated by each pathway providing insight. The positive impact of ad implantation and ad delivery platform on perceived benefits is significant, with standardized coefficients of 0.692 and 0.733, respectively, and the significant increase in perceived benefits when the ad content is highly relevant to the specific needs of the consumer, as well as when the ads are delivered through reputable platforms, both directly contribute to the consumer's willingness to purchase. For ad display methods, although their impact on perceived benefits is statistically significant, it is implied that certain ad display methods may not effectively enhance consumers' perceived benefits, or may cause aversion due to their promotional methods being too aggressive or not in line with the target group's preferences, suggesting that ad designers need to give more consideration to consumer acceptance and preferences when innovating ad display methods. In terms of perceived risk, the positive effects of ad implantation and ad delivery platforms are also very

Table 7: Summary of path coefficients

Variable path	Non-standardized coefficients	Standardization coefficient	P	Result
Ad implantation → perceived benefit	0.492	0.692	< 0.001	Be in favor of
How ads are displayed → perceived benefit	-0.039	-0.048	0.044	Be in favor of
Advertising brand → perceived benefit	0.016	0.023	0.634	Unsupported
Advertising delivery platform → perceived benefits	0.561	0.733	< 0.001	Be in favor of
Ad implantation → perceived risk	0.242	0.412	< 0.001	Be in favor of
How ads are displayed → perceived risk	0.389	0.582	0.021	Be in favor of
Advertising brand → perceived risk	0.247	0.423	0.062	Unsupported
Advertising delivery platform → perceived risk	0.241	0.383	0.004	Be in favor of
Ad implantation → willingness to buy	0.492	0.692	< 0.001	Be in favor of
How ads are displayed → willingness to buy	-0.039	-0.048	0.144	Unsupported
Advertised brands → willingness to buy	0.016	0.023	0.634	Unsupported
Advertising platform → willingness to buy	0.561	0.733	< 0.001	Be in favor of

significant, showing that these advertising features play a positive role in reducing consumers' perceived risk. Trusted and safe platforms significantly reduce consumers' concerns about ad content and enhance ad effectiveness. In the sample of this study, the brand factor may not have directly influenced consumers' purchase decisions, suggesting that consumers may pay more attention to the quality and relevance of the advertising content itself than to the brand alone when encountering an advertisement.

DISCUSSION

This study reveals several key findings through an in-depth analysis of the impact of AI-based ad implantation on consumer purchase sentiment. The results show that the application of AI significantly enhances the personalization and targeting of advertisements, improves the attractiveness of advertisements, and effectively increases the perceived benefits to consumers (Kulkarni *et al.*, 2020), which in turn positively affects purchase intention. However, if advertisements are inserted at emotionally incongruent moments or without aligning with real-time viewer sentiment, they may disrupt the user experience and reduce ad effectiveness (Li *et al.*, 2022). While optimization of ad insertion and delivery platforms can significantly reduce consumers' perceived risk, ads displayed in ways that do not properly match consumers' expectations and preferences may have a negative impact (Hashim & Zolkepli, 2014). This highlights the need to give more consideration to consumers' psychological and emotional responses when using AI for advertising innovation, and to ensure that the effects of the technology application match consumers' actual experiences (Ziakos & Kydros, 2022). Brand influence was less significant than expected in this study, which may indicate that traditional brand influence may be waning in the face of highly personalized and targeted advertising strategies (Wen *et al.*,

2022). Consumers seem to be more inclined to make purchasing decisions based on the appeal of the actual content and personalized experience, rather than relying solely on brand name (Ghosh, 2022).

Consumer preferences and acceptance of advertising content vary significantly across regions, so advertising strategies must be highly flexible and adaptable (Kumar *et al.*, 2016). AI, by analyzing big data in real time, can identify these differences and adapt advertising content to better meet the needs of different consumer groups (Hill *et al.*, 2012). The flexible use of such strategies may be the key to improving advertising effectiveness in the global marketplace. As consumers become more aware of privacy protection, while AI technologies can enhance the relevance and effectiveness of advertisements through accurate data analytics (Malygina *et al.*, 2020), opaque data collection and processing processes may trigger consumer concerns and resentment (Shah & Nasnodkar, 2021). Therefore, transparent data management and the implementation of privacy protection measures are legal and ethical requirements and necessary to gain consumer trust and optimize advertising effectiveness (Segev *et al.*, 2014).

While the widespread use of AI has led to increased efficiency and accuracy, it can also lead to over-commercialization and user fatigue. Advertisers need to consider their social responsibility while pursuing technological innovation to ensure that advertising practices not only pursue economic benefits but also consider social values and consumer well-being (Grant *et al.*, 2015).

However, there are several limitations in this study related to participant recruitment, study design, and data analysis. First, the participant sample may lack sufficient representativeness, as it was primarily composed of individuals with relatively higher educational levels and concentrated in certain occupations (*e.g.*, office workers).

This limited diversity in demographic attributes—such as education level, occupation, and age group—may restrict the generalizability of the findings. Participants from different socio-economic backgrounds may interpret AI-based advertisements differently or exhibit varying levels of trust and engagement, potentially influencing the observed relationships.

Second, although cultural diversity was considered, in the context of China where this study was conducted, diversity in lifestyle, professional roles, and digital media literacy may play a more significant role in shaping consumer sentiment than cultural or ethnic background. Future studies should aim to recruit more demographically diverse participants across regions, industries, and life stages to better reflect the heterogeneity of consumer perspectives.

Third, the study focused primarily on attitudinal responses—such as perceptions of informativeness, intrusiveness, and brand trust—rather than actual consumer behavior or purchase decisions. While attitudes are important predictors, they do not always translate directly into action. Future research could integrate behavioral data, such as click-through rates, purchase intent tracking, or controlled experiments, to triangulate self-reported sentiment with observed consumer behavior.

Lastly, the use of traditional statistical analysis methods may limit the depth of insights into complex interactions among variables. Incorporating advanced data mining or machine learning models in future studies could enhance the precision of predictions and uncover nuanced patterns or latent relationships that go beyond linear assumptions.

CONCLUSION

This study thoroughly explored how AI-based ad implantation affects consumers' purchase sentiment, and through structural equation modeling analysis, revealed the impact of advertising characteristics such as ad implantation, display mode, brand, and delivery platform on consumers' perceived benefits and risks, and further analyzed how these perceptions are transformed into actual purchase sentiment and willingness. The results of the study show that the choice of ad implantation and delivery platform plays a key role in enhancing consumers' positive purchase sentiment, and these factors significantly increase consumers' perceived benefits and effectively reduce perceived risks, which in turn promotes the formation of purchase intention. Specifically, AI-based ad implantation significantly increased consumer attraction and acceptance of ads by providing highly relevant and personalized ad content,

which enhanced consumers' emotional responses and positive purchase decisions. However, the study also found that ad displays that fail to match well with consumers' preferences and acceptance can negatively affect consumers' perceived benefits and even trigger consumer resistance, thereby inhibiting purchase intentions. In conclusion, this study provides a concrete direction for optimizing advertising strategies, *i.e.*, while pursuing technological innovation, ensuring the personalization and relevance of advertisement content to maximize its positive impact on consumers' emotions, thus effectively promoting consumers' purchasing behaviors.

Based on the results that advertisement implantation with AI influences consumers' purchasing emotions, this study recommends the following: (1) Ad producers should use AI technology to deeply mine and analyze consumer behavioral data and preference patterns in order to create more accurate and targeted ad content. For example, by analyzing consumers' shopping history, browsing habits, and social media activities in order to customize the display of products or services that are most relevant to consumers' current needs, they can increase the attractiveness of their ads and significantly improve their conversion rates. (2) In view of the negative impact that advertising displays may have on consumers' emotions and perceived benefits, ad producers pay more attention to consumer acceptance and experience when designing the form and content of advertising displays, including avoiding the use of overly aggressive or easily off-putting visual and copywriting strategies, while exploring more innovative forms of expression that elicit positive emotional responses. For example, the use of storytelling to present advertising content can establish a stronger connection with consumers on an emotional level and enhance the infectious power of advertising.

DECLARATIONS

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None.

Author contributions

Guo X: Conceptualization, Methodology, Formal analysis, Writing—Original draft preparation, Visualization. Han X: Data curation, Software, Validation, Investigation, Writing—Review and Editing, Supervision, Project administration.

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Ethics approval

Not applicable.

Informed consent

Participation was voluntary and anonymous. To ensure data quality, only respondents who met the inclusion criteria—being over 18 years old and having at least occasional exposure to online advertisements—were allowed to complete the survey. Responses were excluded if they exhibited straight-lining, extremely short completion time (under 90 seconds), or more than 20% missing data.

Conflict of interest

The author has no conflicts of interest to declare.

Use of large language models, AI and machine learning tools

No AI tools were used.

Data availability statement

All data has been included in this paper.

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