Edelweiss Applied Science and Technology
ISSN: 2576-8484
Vol. 9, No. 2, 1228-1244
2025
Publisher: Learning Gate
DOI: 10.55214/25768484.v9i2.4745

Factors influencing purchase decisions on social media platforms: The role of explainable artificial intelligence

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Abstract: This study aims to measure the impact of privacy concerns and perceptions of personalization on purchase decisions on social media platforms. It focuses on the mediating role of attitudes toward advertising and the moderating role of Explainable Artificial Intelligence (XAI). The study investigates consumers who frequently shop on social media. The research model was implemented using an online questionnaire and direct interviews, yielding 515 valid responses. To assess the reliability of the measurement scales, SPSS 26 software was employed. The research hypotheses were tested, and the measurement and structural models were evaluated using AMOS 28. The proposed model is grounded in the Elaboration Likelihood Model (ELM), causal models, interpretability in human-AI interaction, computational privacy theory, and the Theory of Reasoned Action (TRA). The findings indicate that consumers' perceptions of personalized advertising content positively influence their attitudes toward advertisements. Privacy concerns negatively affect users' attitudes toward advertisements. Positive attitudes toward advertising, in turn, influence purchase decisions on social media. This study enriches the theoretical understanding of consumer behavior toward AI-enabled technological products and offers managerial implications for producers to enhance advertising quality and meet consumer demands in the context of social media shopping.

Keywords: *Explainable Artificial Intelligence, Perceived Personalization, Social Media Purchasing.*

1. Introduction

The rapid growth of social media platforms has significantly transformed how businesses approach advertising. As users are increasingly bombarded with content, advertisers face the challenge of cutting through the noise to effectively engage and influence potential customers. Personalization has emerged as a key strategy in digital marketing, allowing brands to tailor content to individual preferences and behaviors, thereby improving engagement and conversion rates. In the current digital era, advertising on social media platforms has become a vital component of marketing strategies for businesses in the e-commerce sectors. With the rapid advancement of artificial intelligence (AI), the personalization of advertising content has achieved unprecedented effectiveness. However, despite these clear benefits, the lack of transparency in AI operations has raised significant concerns regarding fairness and ethics in advertising.

AI can generate highly targeted advertising that resonate with specific audiences by analyzing vast amounts of data from users' social media activities. This personalization is achieved through sophisticated algorithms that assess user behavior, preferences, and interactions on social media platforms. For instance, AI can optimize ad placements by predicting which content will elicit positive emotional responses from users, thus driving engagement and conversion rates [1, 2]. Moreover, the use of generative AI in conversational marketing enables brands to engage in real-time, personalized

History: Received: 11 December 2024; Revised: 16 January 2025; Accepted: 21 January 2025; Published: 12 February 2025
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dialogues with consumers, further enhancing the relevance of advertisements [2, 3]. This dynamic interaction not only improves customer satisfaction but also increases the likelihood of purchase decisions being influenced by the personalized content presented to them. However, traditional AI algorithms often operate as "black boxes," providing limited transparency regarding how decisions are made. This lack of explainability can lead to consumer trust issues, potentially affecting their response to personalized advertising.

The ethical implications of AI in advertising cannot be overlooked. As organizations deploy AI to automate and optimize marketing strategies, they must also consider the ethical dimensions of these technologies. The use of AI in advertising raises questions about consumer privacy, data security, and the potential for bias in algorithmic decision-making [4]. XAI addresses these concerns by providing insights into how AI models operate, which can help mitigate data misuse fears and enhance consumer trust [5]. By making AI's decision pathways more transparent, advertisers can align their strategies with ethical standards, ultimately leading to more responsible marketing practices. Furthermore, the effectiveness of personalized advertising is significantly enhanced when consumers understand the rationale behind the recommendations they receive. Research indicates that when consumers perceive AI-driven advertisements as relevant and trustworthy, they are more likely to engage with the content and make purchasing decisions [6, 7]. XAI not only improves the interpretability of AI systems but also empowers consumers by allowing them to comprehend the factors influencing their ad experiences. This understanding can lead to a more positive perception of the brand and its offerings, thereby influencing purchasing behavior favorably.

The existing literature on XAI in marketing is limited and lacks comprehensiveness, with the aforementioned gaps either insufficiently addressed or still under debate. To bridge this research gap, this paper aims to develop a model to investigate users' attitudes toward social media advertising through their perceptions of XAI quality. The model includes perceptions of personalization, privacy concerns, attitudes toward advertising, and purchasing decisions. By exploring the relationship between XAI, advertising personalization, and purchase decisions, this study aims to provide valuable insights for marketers, enabling them to optimize their advertising strategies while fostering consumer trust and loyalty in the commerce sector as well as in the logistics industry. The following sections of the study will present the foundational theories related to the research topic, hypotheses, proposed research model, research methodology, results, and discussion. The final section will offer conclusions and managerial implications.

2. Literature Review and Research Model

2.1. The Elaboration Likelihood Model (ELM)

The Elaboration Likelihood Model is a critical framework for understanding how advertising content influences consumer purchasing decisions on social media platforms. ELM posits that individuals process persuasive information through two distinct routes: the central route and the peripheral route. The central route involves careful and thoughtful consideration of the information presented, typically employed in high-involvement decisions, while the peripheral route relies on superficial cues, such as visual elements or the attractiveness of endorsers, in low-involvement situations [8, 9]. This dual processing framework is particularly relevant in the context of social media, where users are often bombarded with a plethora of advertisements, necessitating a nuanced understanding of how different types of content can effectively engage consumers. Research indicates that the effectiveness of advertising on social media can vary significantly based on the level of consumer involvement with the product being advertised. For high-involvement products, where consumers are likely to engage in extensive information processing, advertisements that provide detailed, relevant content are more effective in persuading consumers [10, 11]. Conversely, for low-involvement products, peripheral cues such as celebrity endorsements or visually appealing graphics can significantly enhance the persuasiveness of the advertisement [12]. This distinction underscores the importance of tailoring advertising strategies to align with the target audience's level of involvement, thereby optimizing the likelihood of positive purchasing decisions. Moreover, the role of social media influencers and their perceived attractiveness can significantly impact consumer attitudes and behaviors. Studies have shown that when influencers are congruent with the product being advertised, they can serve as effective peripheral cues that enhance the persuasive power of advertisements, even in low-involvement contexts [10, 12]. This phenomenon is particularly relevant on platforms like Instagram and TikTok, where influencer marketing has become a dominant strategy for brands seeking to engage younger audiences. The ELM framework helps elucidate why consumers may respond favorably to advertisements featuring influencers, as these endorsements can evoke emotional responses that facilitate purchasing decisions [10, 12].

In addition to the content and presentation of advertisements, the context in which they are encountered also plays a crucial role in shaping consumer responses. For instance, the popularity of a post can serve as a peripheral cue that influences consumer perceptions and intentions. Research has demonstrated that advertisements with higher engagement metrics (likes, shares, comments) are perceived as more credible and appealing, thereby enhancing their effectiveness in driving purchasing decisions [13, 14]. This interplay between content, context, and consumer involvement highlights the complexity of consumer behavior on social media and the necessity for marketers to adopt a multifaceted approach when designing advertising campaigns.

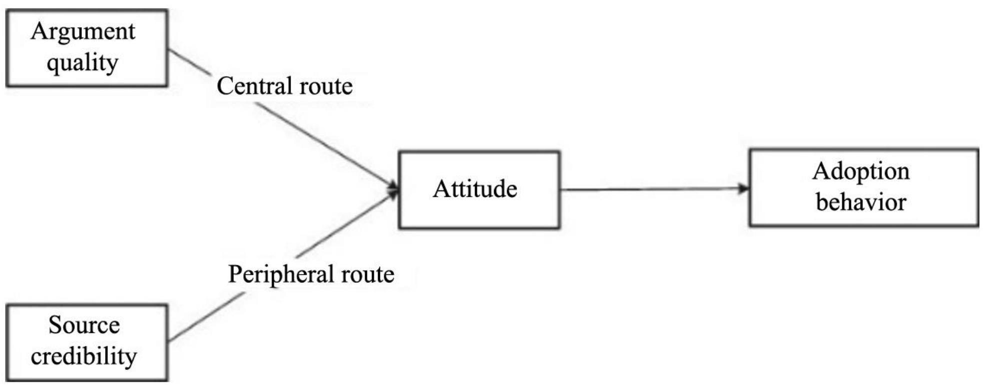

Figure 1.
The elaboration likelihood model.
Source: Cacioppo, et al. [15]

2.2. The Causal Models and Explainability in Human-AI (CMEH-AI)

Causal models provide a framework for identifying and analyzing the relationships between various consumer decision factors. For instance, AI systems can analyze consumer data to predict purchasing behavior, but without a clear understanding of the causal relationships at play, marketers may struggle to optimize their strategies effectively. By employing causal inference techniques, marketers can discern which aspects of their advertising campaigns are genuinely influencing consumer behavior, allowing for more targeted and effective marketing strategies. This is particularly relevant in social media contexts, where the rapid dissemination of information can lead to complex interactions between consumer perceptions and advertising content. Explainability in AI is crucial for fostering trust and enhancing user experience in human-AI interactions. As consumers become more aware of AI's role in shaping their purchasing decisions, the demand for transparency in how these systems operate increases. Explainable AI (XAI) initiatives aim to demystify AI decision-making processes, allowing consumers to understand the rationale behind personalized advertisements. This understanding can mitigate skepticism and enhance the perceived credibility of AI-driven recommendations, ultimately influencing purchasing decisions positively. For example, when consumers are informed about how their data is used to tailor advertisements, they are more likely to engage with the content and make informed purchasing choices.

The findings of Shin [16] highlight the dual role of causality and explainability in establishing trust, which ultimately influences user behavior. The study demonstrates that providing clear explanations of personalized suggestions or recommendations enhances user trust. According to Shin [16] an explainable system must ensure three key factors: fairness, clarity, transparency, and accountability. These factors are also discussed in studies by Meske, et al. [17]; Gerlings, et al. [18] and Shin and Park [19]. The three elements of fairness, transparency, and accountability in XAI foster corresponding user perceptions: perceived fairness, transparency, and accountability. These perceptions, in turn, influence users' trust in artificial intelligence [16]. Moreover, the integration of explainability into AI systems can help address ethical concerns related to data privacy and algorithmic bias. As AI technologies become more pervasive in marketing, ensuring that these systems operate transparently is essential for maintaining consumer trust. Ethical AI practices involve not only providing clear explanations of how AI systems function but also ensuring that these systems are designed to avoid reinforcing existing biases in advertising. This ethical consideration is particularly important in social media environments, where diverse consumer demographics interact with targeted advertising.

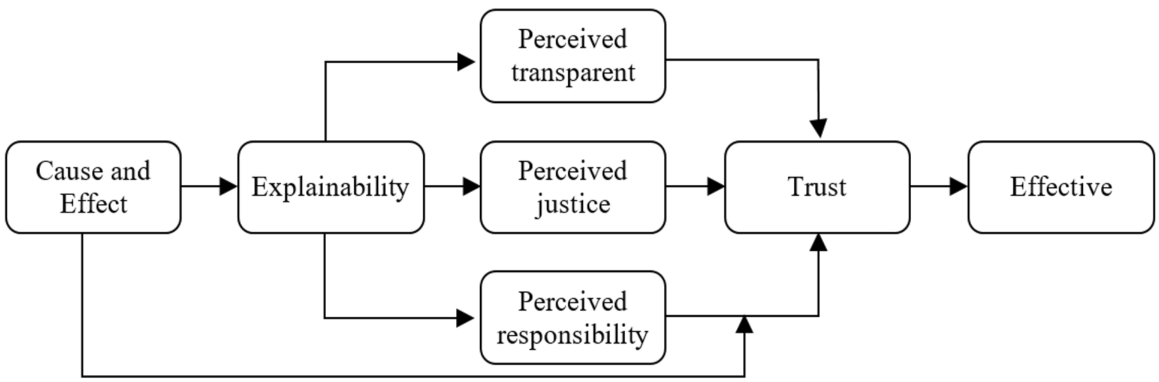

Figure 2.
The causal models and explainability in human-AI.
Source: Shin [16]

2.3. The Privacy Calculus Theory

Privacy Calculus theory plays a significant role in shaping purchasing decisions on social media platforms, particularly as consumers navigate the complexities of personalized advertising and data privacy. The intersection of privacy concerns and consumer behavior is critical, as individuals increasingly weigh the benefits of personalized recommendations against their apprehensions about data misuse and privacy violations. One of the foundational concepts in computational privacy theory is the "privacy paradox," which describes the discrepancy between consumers' stated privacy concerns and their actual online behaviors. Research indicates that while consumers express significant privacy concerns, they often fail to take protective actions when engaging in online transactions [20]. This paradox is particularly relevant in the context of social media, where personalized advertising relies heavily on user data. For instance, studies have shown that privacy concerns can inhibit consumers' willingness to engage with personalized recommendations, thereby negatively impacting their purchase intentions [21, 22]. This suggests that marketers must navigate a delicate balance between leveraging consumer data for personalization and addressing privacy concerns to foster trust and encourage purchasing behavior.

Computational models can provide valuable insights into user behavior regarding privacy and purchasing decisions. By employing formalized computational modelling, researchers can derive precise predictions about how privacy concerns influence consumer behavior in online contexts [23]. Such models can help identify the mechanisms through which privacy concerns affect purchasing decisions, allowing marketers to tailor their strategies accordingly. For example, understanding the factors that contribute to the privacy calculus where consumers weigh the perceived benefits of personalized advertising against the risks of privacy loss can inform the design of more effective advertising campaigns [24]. Moreover, the role of privacy signals in online advertising is crucial for shaping consumer perceptions and behaviors. Transparency regarding data usage and privacy policies can significantly influence purchasing intentions. Research has demonstrated that when consumers are presented with clear and accessible privacy information, they are more likely to incorporate privacy considerations into their purchasing decisions [25]. This highlights the importance of providing consumers with control over their data and clear communication about how their information will be used, which can mitigate privacy concerns and enhance trust in the advertising process [26, 27].

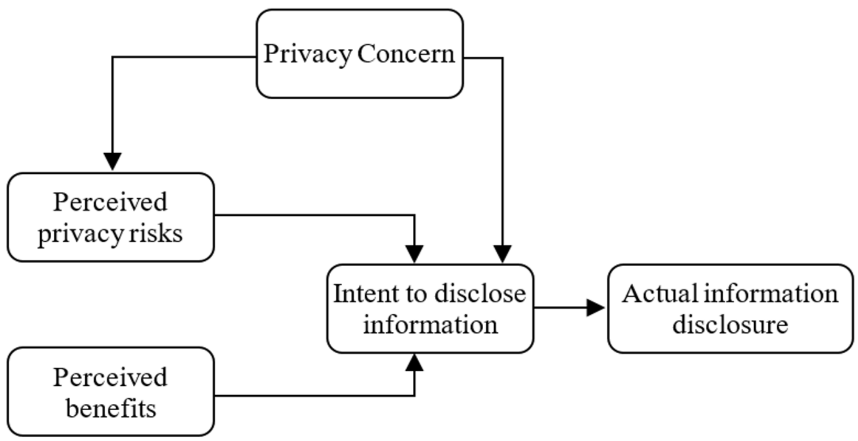

Figure 3.
The privacy calculus theory model.
Source: Culnan and Armstrong [28].

2.4. The Relationship between Perceived Personalization and Attitudes toward Personalized Advertising

Based on the scrutiny model theory [29], two information processing routes include the central route, which involves careful and thorough consideration of advertising content, and the external route, based on superficial signals at the surface level. The topic considers the ELM model as a tool to explain how consumers process personalized advertising on social networks influenced by AI. In personalized advertising, perceived personalization can lead to customers processing the central route [30]. According to Cacioppo, et al. [15], scrutiny is defined as the degree to which an individual thinks carefully about an argument. The depth and relevance of personalized content can drive more positive and lasting attitudes toward personalized advertising, increasing customer purchase intent. Therefore, the following hypothesis is proposed:

H_1: Perceived personalization positively impacts attitudes toward personalized advertising.

2.5. The Relationship between the Privacy Concerns and Attitudes Toward Personalized Advertising

Privacy concerns may trigger the peripheral processing route because it focuses on the credibility of the information source rather than the content. This aspect is consistent with the ELM view that peripheral cues (such as trust and credibility) can influence attitudes. The greater the privacy concern, the more negatively customers tend to react to personalized advertising [31, 32]. Therefore, the following hypothesis is proposed:

H_2: Privacy concerns negatively impact attitudes toward personalized advertising.

2.6. The Relationship between the Attitude Advertising and Purchase Decision

The relationship between attitudes toward advertising on social media platforms and purchasing decisions is a critical area of research, particularly as digital marketing continues to evolve. Numerous studies have explored how consumer attitudes toward social media advertising influence their purchase intentions, revealing various factors that mediate this relationship. One significant study by Genç and Turna highlights the mediating effect of attitudes toward online advertising in the context of social media addiction and online purchase intention. Their findings suggest that positive attitudes toward online advertisements can enhance consumers' purchase intentions, particularly among those with higher levels of social media addiction [33]. This underscores the importance of crafting advertisements that resonate positively with users to drive purchasing behavior.

Celebrity endorsements also play a crucial role in shaping consumer attitudes. Melati et al. found that the congruence between a celebrity endorser and the product being advertised significantly influences consumer attitudes and, consequently, their purchase intentions. The familiarity and credibility of the celebrity can enhance the effectiveness of the advertisement, leading to more favorable consumer responses [34]. This aligns with the notion that consumers are more likely to engage with advertisements that feature relatable and trustworthy figures. Furthermore, Yang et al. explored consumer attitudes toward online video advertisements on platforms like YouTube, demonstrating that factors such as creativity and emotional appeal significantly impact shopping intentions and purchase behavior. Their research indicates that engaging video content can lead to more favorable attitudes toward advertisements, ultimately influencing purchasing decisions [35]. This highlights the necessity for marketers to focus on the quality and creativity of their advertising content to capture consumer interest effectively. Therefore, the following hypothesis is proposed:

H_3: Attitude advertising positively impact Purchase Decision.

2.7. The Moderating Role of XAI Quality Perception on the Relationship between Perceived Personalization and Attitudes Toward Advertising

Investigating how XAI affects consumers' perceptions of personalization and their subsequent attitudes toward advertising is confirmed by Tsai, et al. [20] in their study. The authors found that when consumers were presented with explanations of how AI systems generated personalized recommendations, they developed higher trust in the AI. As a result, their perception of the personalization was enhanced, leading to a more positive attitude toward the advertising. The authors emphasized the importance of transparency in AI-driven personalization to improve consumer satisfaction and engagement with advertising content. XAI quality significantly improved users' trust in the advertising system, which in turn strengthened the relationship between perceived personalization and consumer attitudes toward advertising. Evans et al., explored how explanations enhanced consumers' perception of relevance, further improving consumers' ad experience [36].

Exploring the role of XAI based advertising on consumer engagement. The authors hypothesized that high quality XAI would enhance the perceived personalization of advertising and increase engagement and ad effectiveness [37]. Their findings supported this hypothesis, showing that consumers engaged more with personalized advertising when they understood how the AI systems arrived at their recommendations. Explainability provided clarity, enhancing the perceived relevance and boosting overall attitudes toward the advertising. Consumers were more likely to accept and appreciate personalized advertising when the AI systems provided clear, understandable explanations for generating customized content. XAI quality positively influenced perceived personalization, resulting in higher levels of ad acceptance and more favorable attitudes toward advertising in general [38]. Therefore, the following hypothesis is proposed:

H_4: Perceived quality of XAI moderates the relationship between perceived personalization and attitudes toward personalized advertising.

Edelweiss Applied Science and Technology
ISSN: 2576-8484
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DOI: 10.55214/25768484.v9i2.4745

2.8. The Moderating Role of XAI Quality Perception on the Relationship between Privacy Concerns and Attitudes Toward Advertising

Privacy concerns significantly influence individuals' attitudes toward personalized advertising [36]. Consumers often express concerns about the impact of AI technology on privacy, including personalized advertising [39]. XAI has attracted attention for its ability to bring transparency and interpretability to AI systems [38]. XAI can improve consumers' understanding of how AI algorithms make decisions, potentially alleviating privacy concerns associated with AI technology. The transparency provided by XAI can promote trust and reduce concerns related to data privacy [38]. Furthermore, the perceived quality of XAI may act as a moderator in the relationship between privacy concerns and attitudes toward personalized advertising. Therefore, the following hypothesis is proposed:

H_5: Perceived quality of XAI moderates the relationship between privacy concerns and attitudes toward personalized advertising.

Through a comprehensive review of the literature and relevant foundational theories, the authors identified a research gap pertaining to the topic under study. Based on this insight, they formulated a hypothesis and proposed a research model. The model integrates elements from the Elaboration Likelihood Model (ELM), the Cognitive-Motivational-Emotional Heuristic-AI (CMEH-AI), and Privacy Calculus Theory (Figure 4).

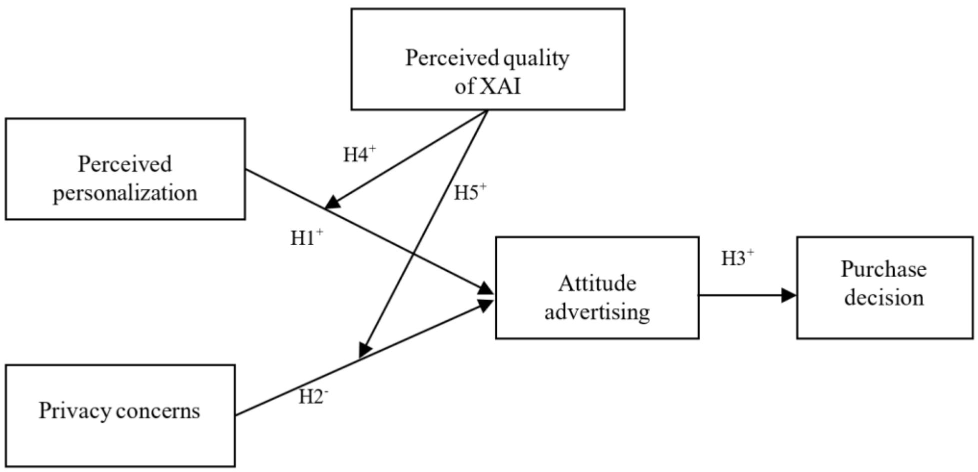

Figure 4.
Proposed research model.

3. Research Methods

3.1. Instrument Development

Scales are important tools for building survey questionnaires. Based on reviewing studies related to the topic, the authors inherited and synthesized the scales, adjusted the scales to suit the research context, and then carried out the following steps: data analysis and testing of research hypotheses. The measurement structures use a 5-point Likert scale, from 1 is completely disagree, to 5 is completely agree. Appendix 1 presents the measurement scales inherited from previous studies.

3.2. Data Collection

Data were collected through online survey methods using convenience sampling. More than 1,500 questionnaires were sent out via email and other communication channels, and after more than 2 months of sending, the number of responses received was 545 (36%). After cleaning and removing 20 invalid responses, the number of remaining questionnaires included in the official study was 525.

ISSN: 2576-8484
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3.3. Data Analysis

This study uses Structural Equation Modeling (SEM) to test the proposed research model. Linear structural models represent cause-and-effect relationships between independent and dependent constructs [40]. Therefore, using CB-SEM is entirely suitable for this study. The tool used to perform the analysis is AMOS 28 software, which uses a maximum likelihood estimation method. SPSS 26 was used for exploratory factor analysis (EFA). Confirmatory factor analysis (CFA) and average variance extracted (AVE) were used to evaluate the measurement model.

4. Research Results

4.1. Profile of the Sample

The statistical results of the research sample show that female demographics account for 64% of the sample, male demographics account for 36%, this ratio shows that women tend to shop on social media more than men. Regarding age distribution, people under 18 years old account for 6.3%, from 18 to 35 years old account for 59.2%, from 35 to 50 years old account for 26.1% and people over 50 years old account for 8.4%.

Regarding income, the collected data shows that customers with income under 10 million VND account for 12.2%, from 10 to 20 million account for 63.2%, from 20 to 30 million account for 18.3%, over 30 million account for 6.3%. For the question 'Are you satisfied with shopping on social media?', the number of people answering Yes is 375, accounting for 71% and the number of people answering No is 150, accounting for 29%. Table 1 shows detailed statistics of the research sample.

Table 1.
Research sample size and structure.

Characteristics	Frequency	Percentage
Gender		
Male	189	36
Female	336	64
Age		
Under 18 years old	33	6.3
18-35 years old	311	59.2
35-50 years old	137	26.1
Over 50 years old	44	8.4
Income (million VND)		
Under 10	64	12.2
From 10 to under 20	332	63.2
From 20 to 30	96	18.3
Over 30	33	6.3
Are you satisfied with shopping on social media?		
Yes	375	71
No	150	829

4.2. Assessment of Measurement Model

The analysis was performed in two steps. Step one analyzes each independent factor to more clearly determine the contents that must be considered in testing the scale's reliability. Step two uses the oblique rotation method to test the convergent and discriminant validity of all variables in the model. The criteria for calculating the reliability of variables are as follows: the threshold value of Cronbach's Alpha coefficient and composite reliability is 0.7 [40]. Initially, the analysis encompassed 32 variables. However, after a meticulous examination of Cronbach's Alpha reliability, it was found that the values of the three variables SYS1, PEU1, and SAT5 were all small and unreliable. Consequently, these variables were eliminated from the model, resulting in a refined structural model analysis with 29 variables. Notably, the smallest alpha value is 0.711, corresponding to the smallest value of CR, which is 0.811. All of these elements adhere to the standard, further validating the model.

For convergent validity, the AVE threshold is 0.5, and the minimum factor loading is 0.6 [41]. The EFA results of all variables show that the research model's concepts achieve convergent and discriminant validity. The results of the variance analysis extracted using EFA for the scales are presented in a summary in Table 2.

Table 2.
Reliability and validity measures.

Variables	Items	Loading	C.A	CR	AVE
Purchase decision (PD)	PD1	0.767	0.86	0.863	0.559
	PD2	0.701			
	PD3	0.695			
	PD4	0.793			
	PD5	0.778			
Perceived of personalization (PP)	PP1	.792	0.87	0.875	0.583
	PP2	.651			
	PP3	.817			
	PP4	.804			
	PP5	.706			
Attitude advertising (AA)	AA1	.792	0.84	0.836	0.560
	AA2	.704			
	AA3	.700			
	AA4	.641			
Privacy concerns (PC)	PC1	.849	0.86	0.857	0.601
	PC2	.752			
	PC3	.711			
	PC5	.760			
Perceived quality of XAI (PQ)	PQ1	.708	0.82	0.825	0.541
	PQ2	.731			
	PQ3	.764			
	PQ4	.744			

The results of the CFA analysis presented show that the critical model is suitable because the general goodness-of-fit indexes are: Chi-Square/df =1.248 (<3); GFI = 0.959; CFI = 0.991 (>0.9); TLI = 0.989 (>0.9); RMSEA = 0.022 (<0.08) meets the requirement (Figure 2).

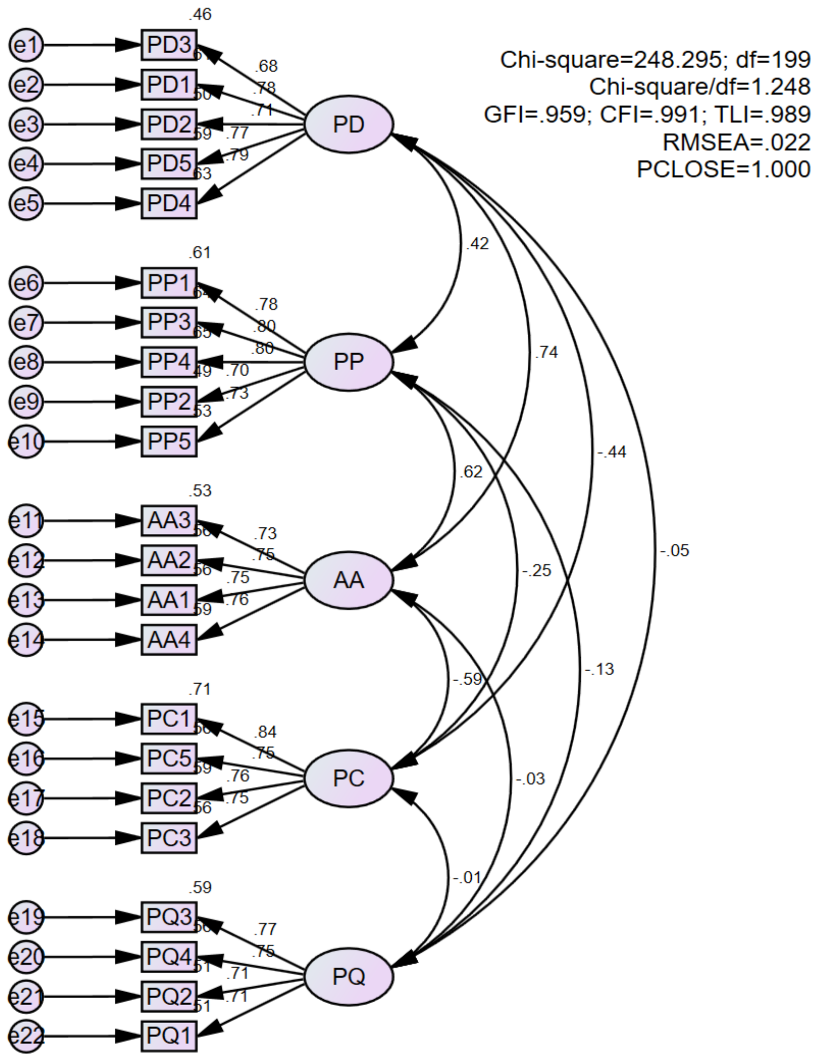

Figure 5.
CFA model.

The results of the discriminant validity test are presented in Table 3; the square root of AVE is larger than the correlation value in the rows and columns. Therefore, according to Fornell-Larcker criteria [42], the theoretical model's research concepts meet the discriminant validity requirement.

Table 3.
Discriminant validity test.

Items	PD	PP	AA	PC	PQ
PD	0.748				
PP	0.424	0.764			
AA	0.736	0.618	0.749		
PC	-0.441	-0.249	-0.593	0.775	
PQ	-0.106	-0.147	-0.034	-0.016	0.735

4.3. Structural Model and Hypotheses Test

Five hypotheses were developed to validate the conceptual framework of the study. The results of the analysis are presented in Figure 3. The overall fit values of the model all meet technical requirements: GFI = 0.965; TLI = 0.987 (>0.9); CFI = 0.989 (>0.9); RMSEA = 0.053 (<0.08) meets the requirements.

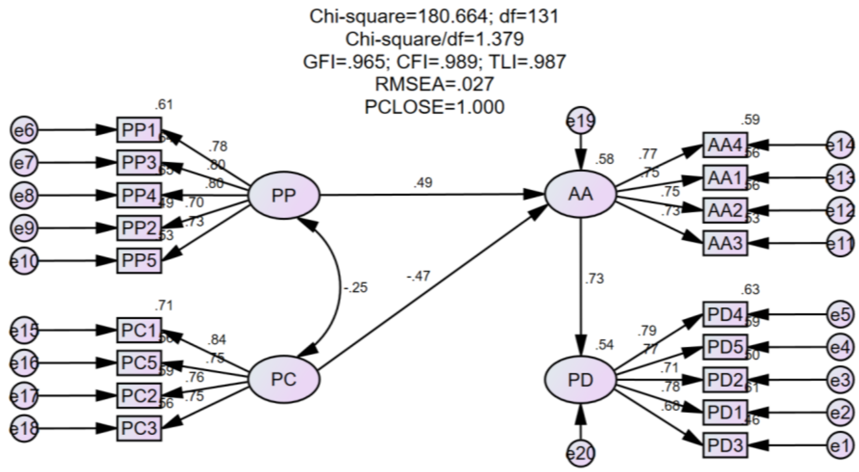

Figure 6.
Test research hypotheses using SEM.

Research results show that the factors of PP, PC have a positive impact on the AA; AA has a positive effect on the PD Table 4.

Table 4.
Regression weights of theoretical relationships.

Hypothesis	Relationship			Wei	S.E.	C.R	p	Conclusion
H1	AA	<---	PP	0.377	0.036	10.461	***	Accepted
H2	AA	<---	PC	-0.319	0.031	-10.250	***	Accepted
H3	PD	<---	AA	0.701	0.058	12.050	***	Accepted

```
Model Summary
          R       R-sq        MSE          F        df1        df2          p
       .540       .291       .320     71.371      3.000    521.000       .000

Model
              coeff         se          t          p       LLCI       ULCI
constant      3.590       .025    144.016       .000      3.541      3.639
F_PP           .432       .034     12.870       .000       .366       .498
F_PQ           .024       .037       .644       .520      -.049       .097
Int_1          .130       .056      2.342       .020       .021       .239

Product terms key:
 Int_1    :        F_PP      x        F_PQ

Test(s) of highest order unconditional interaction(s):
       R2-chng          F        df1        df2          p
X*W       .007      5.487      1.000    521.000       .020
```

Figure 7.
Results of moderating variables on the relationship between PP and AA.

4.4. Moderator Variable Analysis Results

Variable Int_1 has a t-test p_value of 0.020 < 0.05 which is statistically significant, variable PQ plays a moderating role in the impact of PP on AA. The regression coefficient of the moderating impact is 0.130 > 0, so when PQ increases, PP will have a stronger impact on AA.

Model Summary

R	R-sq	MSE	F	df1	df2	p
.587	.344	.296	91.190	3.000	521.000	.000

Model

	coeff	se	t	p	LLCI	ULCI
constant	3.584	.024	150.884	.000	3.537	3.630
F_PC	-.465	.030	-15.754	.000	-.523	-.407
F_PQ	-.055	.035	-1.558	.120	-.125	.014
Int_1	.084	.037	2.297	.022	.012	.157

Product terms key:

Int_1 : F_PC x F_PQ

Test(s) of highest order unconditional interaction(s):

	R2-chng	F	df1	df2	p
X*W	.007	5.276	1.000	521.000	.022

Figure 8.
Results of moderating variables on the relationship between PC and AA

Variable Int_1 has a t-test p_value of 0.022 < 0.05 which is statistically significant, variable PQ plays a moderating role in the impact of PC on AA. The regression coefficient of the moderating impact is 0.084 > 0, so when PQ increases, PC will have a weaker impact on AA.

5. Discussion

Hypothesis 1 (H1): The perceived personalization of advertising positively impacts attitudes toward advertising. The results confirm this hypothesis, indicating that consumers' perceptions of personalization in advertising foster positive attitudes. This aligns with the findings of [30], who demonstrated that well-personalized content enhances engagement and positive reception of advertising. Similarly, Cacioppo, et al. [15] found that personalized content in advertising to deeper processing and stronger attitudes toward advertising, thus supporting this study's findings.

Hypothesis 2 (H2): Privacy concerns negatively impact attitudes toward personalized advertising. This study's findings support this hypothesis, with privacy concerns decreasing positive attitudes toward advertisements. This outcome is consistent with van Ooijen, et al. [32] and Lina and Setiyanto [31] who noted that increased privacy concerns lead to skepticism and reluctance towards advertisements. Further support comes from Van Doorn and Hoekstra [43] who discussed how privacy concerns create barriers in consumer trust, thereby affecting attitudes.

Hypothesis 3 (H3): Attitudes toward advertising positively impact purchasing decisions. The study results confirm this, showing that positive attitudes directly enhance purchasing decisions. This is in line with Genç and Turna [33] who found that favorable attitudes toward advertisements on social media platforms significantly boost purchase intentions, particularly among active social media users. Melati, et al. [34] also highlighted that consumer attitudes are crucial in influencing decisions, especially when the ad content is engaging or features credible figures, reinforcing this study's outcome.

Hypothesis 4 (H4): Perceived quality of XAI moderates the relationship between perceived personalization and attitudes toward advertising. Findings confirm that high-quality XAI enhances consumers' perception of personalization, thereby improving their attitudes toward advertisements. These results are consistent with Tsai, et al. [20], who emphasized the importance of transparency in AI systems to build trust and positively influence consumer perceptions. Similarly, Huang and Wang

ISSN: 2576-8484
Vol. 9, No. 2: 1228-1244, 2025
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[37] demonstrated that when AI explanations are clear, they enhance the relevance of personalized advertising and foster better engagement, which aligns with the findings of this study.

Hypothesis 5 (H5): Perceived quality of XAI moderates the relationship between privacy concerns and attitudes toward advertising. The results support this hypothesis, showing that effective XAI quality can mitigate negative impacts caused by privacy concerns. This finding resonates with Vilone and Longo [38], who argued that XAI improves transparency, which in turn alleviates privacy-related skepticism. Evans, et al. [36] also noted that transparency through XAI has the potential to reduce privacy-related fears, supporting this study's conclusions.

6. Conclusions

Based on the research findings, this study concludes that perceived personalization and privacy concerns significantly influence consumer attitudes toward advertising, which subsequently impacts purchasing decisions on social media platforms. Specifically, the positive impact of perceived personalization highlights the value of tailored content in creating favorable consumer attitudes and driving engagement. Conversely, privacy concerns negatively affect attitudes toward advertising, underscoring the importance of addressing consumer apprehensions about data usage in personalized marketing efforts.

The study also confirms that the quality of XAI plays a moderating role in these relationships. High quality XAI enhances perceptions of personalization by increasing transparency, thereby building consumer trust and improving attitudes toward AI-driven advertisements. Furthermore, XAI quality mitigates the adverse effects of privacy concerns, showing that when consumers understand AI decision-making processes, they are more likely to respond positively to personalized advertising.

The distribution of this study holds significant importance and value in providing insights into how Explainable Artificial Intelligence (XAI) technology can enhance the effectiveness of personalized advertising on social media platforms, thereby influencing consumer purchase decisions. Investigating the role of XAI in advertising not only helps mitigate concerns about the lack of transparency in AI but also expands understanding of how factors such as trust and transparency can drive consumer engagement and increase conversion rates in digital marketing strategies.

The value of this research lies in the development of a model that analyzes the relationship between XAI, personalized advertising, and purchase decisions, offering valuable insights for marketers. The research findings can aid in optimizing advertising strategies, fostering consumer trust, and enhancing customer loyalty. Furthermore, the study will clarify factors such as privacy concerns and their relationship with consumer attitudes toward advertising, thereby providing practical conclusions and recommendations for managers and marketing professionals in developing more transparent and effective advertising strategies.

While this study offers important insights, several limitations should be noted. First, the research sample was geographically limited to specific urban areas in Vietnam, which may limit the generalizability of the findings to broader populations. Expanding the survey scope to include diverse regions and cultural contexts could enhance the robustness and applicability of the results. Second, the study focused on consumers between the ages of 18 and 60, potentially overlooking the attitudes and behaviors of younger or older demographics. Future research could include a wider age range to capture variations in responses across different generational groups. Lastly, this study primarily examined technical and emotional factors influencing consumer behavior in AI-driven advertising but did not account for evolving technological or social factors, such as changes in privacy regulations or AI capabilities. Future research could explore additional variables, such as regulatory impacts or ethical considerations, to provide a more comprehensive understanding of the factors shaping consumer responses to AI-powered personalization.

In summary, while these findings contribute to the theoretical and practical understanding of consumer attitudes toward AI-driven advertising, addressing these limitations will provide a more nuanced perspective on how personalization, privacy, and explainability shape consumer behavior across various contexts and demographic groups.

Transparency:

The authors confirm that the manuscript is an honest, accurate, and transparent account of the study; that no vital features of the study have been omitted; and that any discrepancies from the study as planned have been explained. This study followed all ethical practices during writing.

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Appendix 1.

Instruments development.

No	Variable	Instruments	References
1	Perceived of Personalization (PP)	PP1:I believe the ad is customized to my needs	[44]
		PP2: Overall, this ad is suitable for my situation	
		PP3: This ad makes me feel like I'm the only customer	
		PP4. I think this ad allows me to order products specifically designed for me	
		PP5: This ad offers purchasing recommendations tailored to my needs	
2	Privacy Concerns (PC)	PC1: Can users feel secure about providing sensitive information to Facebook?	[45]
		PC2: Do users feel secure about posting personal information on someone's personal Facebook?	
		PC3: Do users feel secure about sending personal information via Facebook messenger service?	
		PC4: Do users feel secure about keeping someone's personal information on Facebook confidential?	

3	Perceived Quality of XAI (PQ)	PQ1: I feel that the tool works well.	[46] [47]
		PQ2: I feel secure that when I rely on the tool, I will get the correct answer.	
		PQ3: The tool is effective in that it works very quickly.	
		PQ4: This tool is very reliable. I can trust that it is always right.	
4	Attitude Advertising (AA)	AA1: Interesting advertisement	[48] [49]
		AA2: Advertising is trusted	
		AA3: The advertisement has attracted attention	
		AA4: I like to see product information on my Facebook	
5	Purchase Decision (PD)	PD1: I am interested in the content brands post on social media.	[50] [51] [52]
		PD2: Promotions on social media motivate me to buy products.	
		PD3: I will to buy products that are advertised on social media.	
		PD4: Positive reviews on social media influence my purchasing decisions.	
		PD5: Comments on social media influence my purchasing decisions.	